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A Conceptual Framework for Integrating 3D Laser Scanning and Building Information Modeling (BIM) for Automated Dimensional Quality Control

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ABSTRACT

The increasing demand for construction accuracy, accountability, and digital integration has highlighted the limitations of traditional quality control (QC) systems, which often rely on manual measurements and subjective assessments. This study introduces a novel conceptual framework for automating dimensional quality control by integrating 3D laser scanning, Building Information Modeling (BIM), and a rule-based workflow to optimize deviation identification. The proposed system enables a methodical workflow that records as-built conditions of real physical structures using 3D laser scanning, aligns this data with the digital design model, and implements established criteria to automate dimensional quality control for model-based comparisons by encoding rule-based and project tolerances based on compliance standards and criteria, and to evaluate their implementability in real-world construction. A mixed-methods approach was employed, involving a synthesis assessment of theories and concepts from previous studies, and expert validation was implemented to refine the framework and operational definitions. The conceptual framework includes: data acquisition, data processing and registration, model integration and alignment, and deviation detection. Theoretically, the framework enhances model-driven construction theory by formalizing continuous, rule-based quality control workflows that are dynamically aligned with real-world conditions. It offers a scalable, auditable solution for deviation detection, minimizes rework, and accelerates acceptance decisions. Future work will focus on empirical validation within active projects, development of standardized rule libraries in accordance with project specifications, and integration of predictive analytics to facilitate intelligent, real-time decision-making. This research provides a novel theoretical framework and a practical approach for automated, data-driven quality control in modern construction.

Keywords: Dimensional quality control; Building Information Modeling (BIM); 3D laser scanning; automation

INTRODUCTION

Quality Control (QC) in construction refers to the systematic processes ensuring construction compliance with standards and specifications (CIDB, 2021, 2024; H. Li et al. 2020; T. Li et al. 2021; Musarat et al. 2024; Saif et al. 2024). The process involves monitoring (H. Li et al. 2020; Musarat et al. 2024; Saif et al. 2024), assessing (H. Li et al. 2020; T. Li et al. 2021) and validating that materials, workmanship and construction methods comply with industry standards and project specifications to mitigate defects, enhance durability and ensure structural integrity.

Dimensional quality in construction is essential for ensuring safety, performance and durability of constructed structure. Deviations from design specifications might compromise load distribution, joint alignment, and the overall structural integrity of a building (Q. Wang et al. 2018). Despite technological advancement, QC practices in the construction sector continue to be primarily manual, resulting in expensive rework, schedule delays, and inconsistent documentation. The traditional reliance on tape measures, spirit levels and visual inspection lacks the accuracy and repeatability (Son & Han 2021; J. Wang et al. 2015; Xiong et al. 2013).

To address these shortcomings, innovative digital tools specifically Building Information Modeling (BIM) and 3D laser scanning provide a path for automated, data-rich quality control. With the emergence of Industrial Revolution (IR) 4.0 and Construction Revolution (CR) 4.0, digital technologies such as 3D laser scanning and BIM (CIDB 2020) offer new possibilities for transforming quality control processes. BIM is a centralized digital platform that integrates design, construction and maintenance data, enhancing collaboration (Becker et al. 2019), and traceability (Choi et al. 2024). Integrating 3D laser scanning for accurate site conditions capture with other digital tools, such as enables the development of an automated, rule-based system for deviation analysis.

This study presents a conceptual framework for the implementation of an integrated BIM-3D laser scanning workflow with rule-based analysis, aiming to optimize deviation identification while minimizing reliance on manual inspection. Accordingly, the objectives are to develop automated dimensional quality control methods for model-based comparisons by encoding rule-based and project tolerances into a parameterized model that generates pass/fail indicators and to evaluate their implementability in real-world construction. This integration supports broader objectives in digital construction, encompassing traceability through the generation of auditable evidence, automation by minimizing manual measurements, and improved project outcomes by facilitating the early identification of non-conformities, decreasing rework, and aiding prompt, evidence-based acceptance decisions.

METHODOLOGY

This study adopted a mixed-methods research methodology that integrated a literature synthesis with expert validation to formulate and enhance a conceptual framework for automated dimensional quality control. The method consisted of three (3) interconnected phases. Phase one: synthesis of literature through examination of peer-reviewed literature, and industrial standards to identify the key concepts, variables, and operational definitions. This phase provided the theoretical basis of the framework and ensured its conformity with best practices and international standards. Phase two: development of the conceptual framework from the organized literature into a preliminary framework. Each module in the preliminary framework was decomposed into quantifiable variables to ensure traceability and reproducibility. Phase three: the preliminary framework was enhanced through organized discussions with domain experts, including a BIM Manager from Autodesk, a 3D laser scanner specialist, a project manager from Malaysia Marine and Heavy Engineering, Malaysia, an engineer from Malaysia Public Works Department (PWD), and a PWD assistant engineer. Feedback emphasized operational definitions, practicality, and variable interdependencies, resulting in iterative enhancements and ensuring that the framework is both scientifically robust and practically applicable.

BIM FOR QUALITY CONTROL

Building on the need for digital solutions, BIM in construction has transformed design, construction, and facility management in the architectural, engineering, and construction (AEC) sector. scholarly attention towards BIM has increased, indicating its central role in the construction digitalization. Recent studies underscore BIM's crucial role in facilitating digital transformation in the construction sector, especially with the incorporation of modern technologies like 3D laser scanners, artificial intelligence, machine learning, Internet of Things (IoT), and cloud computing (Srivastava et al. 2022; Almatared et al. 2024; Saleh et al. 2024). The Covid-19 epidemic expedited the adoption of BIM, since remote communication and digital workflow became essential for project continuity (Saif et al. 2024).

BIM facilitates the development and administration of digital representations of the physical and functional characteristics of structures. The implementation of this technology in construction quality control has accelerated due to its ability to centralize information, simulate construction sequences, and integrate multidisciplinary inputs. Previous studies have demonstrated BIM in clash detection (Srivastava et al. 2022) and defect detection (D. Liu et al. 2021). However, its use in dimensional quality assessment, particularly in deviation, remains limited without the incorporation of accurate as-built data sources. This model-based checking facilitates the early identification of deviations and non-conformities.

Laser scanning is a reality capture method that use laser beams to measure spatial coordinates and produce dense point clouds (M. K. Kim et al. 2020; Rausch & Haas 2021). It can capture millions of data points in seconds, making it suitable for verifying geometric accuracy in construction, especially for complex geometries. Studies demonstrate that laser scanning can attain millimeter-level accuracy under controlled conditions. Point cloud data can be compared to the design BIM model to identify inconsistencies. It provides comprehensive geometric data for the development of accurate real-site conditions (Anil et al. 2012; Becker et al. 2019; C. Kim et al. 2013; Perez & Tah, 2023; B. Wang et al. 2024; Q. Wang et al. 2016, 2018; Zabin et al. 2020).

Automated rule-based systems offer a scalable method for identifying dimensional accuracy utilizing an algorithm. These systems utilize established tolerances to compare actual measurements to design specifications, such as misalignment, displacement, etc. For instance, a study by (Polat & Ali 2023) outlines best practices emphasizing the importance of BIM and 3D laser scanning for reliable deviation assessment. While laser scanning ensures dimensional accuracy, its full potential for automated quality control is achieved only when integrated with rule-based verification in the BIM environment. However, this study utilized a manual method to identify the deviation. Therefore, it is necessary to innovate automation rule-based methods to identify deviations in optimizing the processes and minimize errors.

INTEGRATED BIM AND LASER SCANNING FRAMEWORK

The conceptual framework proposed in this study is to integrate BIM, 3D laser scanning and rule-based processes into a unified system for automated dimensional quality assessment in construction. This framework encompasses the complete workflow, from data collection to deviation identification.

The conceptual model represented in Figure 1, was initially developed through a synthesis of previous research on scan-to-BIM and BIM-enabled dimensional quality control operations. A comprehensive evaluation of peer-reviewed studies established the theoretical basis to produce a preliminary set of potential variables and empirical evidence for defining the modules of the framework. Each phase was systematically mapped with authoritative references that highlight best practices and technical limitations. Ultimately, expert validation was conducted to enhance the operational definitions and the validation of inter-dependencies among the variables. These processes collectively assured that each variable in the framework is empirically grounded and suitable for practical application, establishing a transparent methodological foundation for the conceptual model and enhancing its applicability for real-world automated dimensional quality assessment.

Variables represented in Figure 1, emerged directly from theoretical discussions in the reviewed literature and empirical evidence. The procedure commences with the acquisition of real site conditions by high-accuracy laser scanning technology, producing dense point cloud data that accurately reflects the geometry. The data are subsequently processed and registered to generate a spatially accurate representation appropriate for comparison with the design model, where individual scans are cleaned, aligned, and merged into a cohesive 3D representation. Upon processing, the point cloud data is integrated and aligned within the modeling environment. The core of the quality control process is the utilization of rule-based digital tools to assess the deviations. The rules are defined following industry standards or project-specific tolerance limits. The results are presented and communicated to the user, typically an engineer or quality control engineer/manager, through model annotations. Based on the detected deviations, the user conducts an engineering evaluation regarding safety, functioning, and compliance. The entire loop ensures a systematic, traceable, and model-driven approach to quality control in construction.

To strengthen the transparency and reproducibility of the conceptual framework, it is essential to explicitly map each variable in Figure 1 with the relevant body of literature. Table 1 fulfills the objective by associating each module of the framework with the specific variables it encompasses, the operational definitions, and the representative studies that justify their inclusion. This mapping demonstrates how the framework translates theoretical constructs into quantifiable, practice-oriented characteristics. The table facilitates clear traceability from literature evidence to framework variables, enabling researchers and practitioners to validate, replicate, or adapt the proposed model for various construction contexts while ensuring methodological rigor and alignment with established standards and best practices.

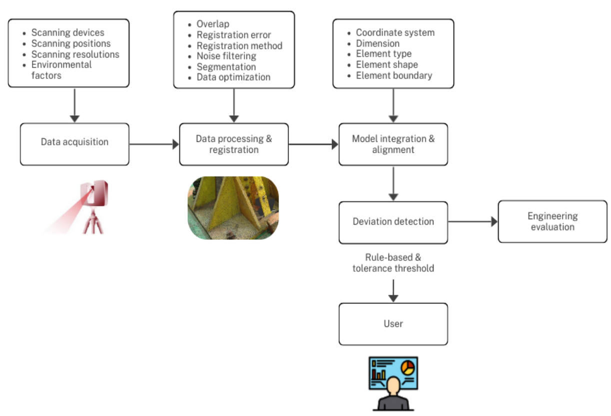

FIGURE 1. Conceptual framework for dimensional quality assessment

TABLE 1. Mapping of conceptual framework variables

Module	Variable	Definition	Representative prior work
Data acquisition	Scanning devices	Range, accuracy, and mobility affect raw point cloud quality	(Biswas et al. 2015; Valero et al. 2022; Q. Wang et al. 2018)
	Scanning positions	Line-of-sight, occlusion, and coverage area	(General Services Administration, 2009; Sanhudo et al. 2020; Soudarissanane et al. 2011)
	Scanning resolutions	Number of data points collected and distance between points	(Ghazali et al. 2011; Mognon et al. 2022; Sui et al. 2025; Syafuan et al. 2025; Tahar, 2015)
	Environmental factors	Reflectivity and stability	(Guo et al. 2010; Kuschnerus et al. 2021)
Data processing & registration	Overlap	Common area between the two scanning positions	(Chen et al. 2025; Q. Zhang et al. 2024)
	Registration error	Metric governing the model accuracy	(Yang et al. 2018; Q. Zhang et al. 2024)
	Registration method	Automatic, target-based, feature-based, or cloud-to-cloud options	(Cox, 2015; Huang et al. 2022; X. Liu et al. 2025; Syafuan et al. 2025; Tu et al. 2025; C. Wang & Zha, 2023)
	Noise filtering	Elimination of erroneous or unwanted points	(Kuschnerus et al. 2021; Soudarissanane et al. 2011)
	Segmentation	Filtering by geometry or region to strengthen matching	(Einizinab et al. 2023; Rao et al. 2022; Rocha & Mateus, 2024)
	Data optimization	Down-sampling to balance speed and fidelity	(Syafuan et al. 2025)
Model integration & alignment	Coordinate system	Standardize the positions of the data points	(H. Li et al. 2020; Sui et al. 2025)
	Dimension	Length, width, height, and thickness	(Huang et al. 2022)
	Element type	Column, beam, plate, etc	(General Services Administration, 2009)
	Element shape	Plane, cylinder, etc	(Stefańska et al. 2024; Valero et al. 2022)
	Element boundary	Geometric edge within an element	(Q. Zhang et al. 2024)
Deviation detection	Rule-based & tolerance threshold	Code or project limits encoded	(M. K. Kim et al. 2020; Seghier et al. 2024)

SPATIAL DATA ACQUISITION USING 3D LASER SCANNING

The first module in the proposed framework involves the acquisition of spatial data that reflects the real site conditions. This is accomplished using 3D laser scanning devices that can capture high-resolution spatial information as dense point cloud data as utilized by (Syed Abdullah & Mohd Yusof, 2022). All structural elements such as columns, beams, braces and their corresponding connections, are targeted during scanning to facilitate accurate dimensional assessment.

Figure 2 illustrates the four (4) key parameters that affect the quality and accuracy of 3D laser scanning in construction environments. The first parameter, 'scanning devices', emphasizes the influence of hardware selection on scan quality, as various devices offer differing levels of range, accuracy, and mobility (Biswas et al. 2015; Q. Wang et al. 2018; Valero et al. 2022). The second parameter, 'scanning positions', emphasizes the significance of scanner positioning in achieving comprehensive spatial coverage, as multiple viewpoints mitigate occlusions and blind spots (General Services Administration 2009; Soudarissanane et al. 2011; Sanhudo et al. 2020). The third parameter, 'scanning resolutions', refers to the density of point cloud data (Ghazali et al. 2011; Tahar 2015; Mognon et al. 2022; Sui et al. 2025; Syafuan et al. 2025); higher resolutions enhance measurement accuracy but require more computational resources. Lastly, 'environmental factors' include lighting, fog, and airborne particles can adversely affect data acquisition, highlighting the necessity for optimal settings during scanning (Guo et al. 2010; Kuschnerus et al. 2021).

FIGURE 2. Parameters affecting 3D laser scanning accuracy

Empirical investigations consistently show that the accuracy and efficiency of 3D laser scanning are linked to scanner resolution. Research on slope mapping in Cameron Highlands, Malaysia, demonstrated that finer resolution produces more accurate slope-class delineation and enhanced dimensional fidelity, although with longer times and considerably larger datasets (Tahar 2015). In contrast, coarse resolution reduces acquisition time and data volume but risks smoothing micro-topographic gradients, compromising analytical accuracy. In addition to the terrain-focused findings, an evaluation of a pedestrian steel bridge utilizing a Faro Focus laser scanner indicated that reducing the scan resolution from 1/5 to 1/10 resulted in approximately a 32% decrease in acquisition time and does not significantly affect the accuracy of the point cloud comparison analysis (Mognon et al. 2022). This research confirms that, for element-level quality control and design verification, moderate reductions in resolution significantly enhance operational efficiency.

POINT CLOUD PROCESSING AND REGISTRATION

Following data acquisition, the raw point cloud data is subjected to processing to improve accuracy. Challenges such as misalignment between multiple scans, noise and outlier points might compromise data quality. Recent studies highlight that careful adjustment of processing parameters ranging from data alignment to filtering is essential for achieving high fidelity and usability of the resulting 3D model (Z. Liu et al. 2024). In particular, a well-chosen combination of point cloud registration, sampling and filtering algorithms can significantly enhance processing efficiency while maintaining accuracy and completeness.

Figure 3 illustrates the parameters for point cloud processing and registration for ensuring the accuracy of 3D laser scan data. The parameters encompass overlap, which ensures adequate common area between scans for proper alignment. When overlaps are insufficiently sized, alignment algorithms have difficulties in identifying accurate matches, resulting in misalignment (Q. Zhang et al. 2024; Chen et al. 2025). For registration error, it generally measures the extent to which points deviate between the aligned datasets. The registration error directly affects the overall accuracy of the integrated point cloud model; reduced errors lead to improved alignment and a more accurate 3D reconstruction of the components (Yang et al. 2018; Q. Zhang et al. 2024).

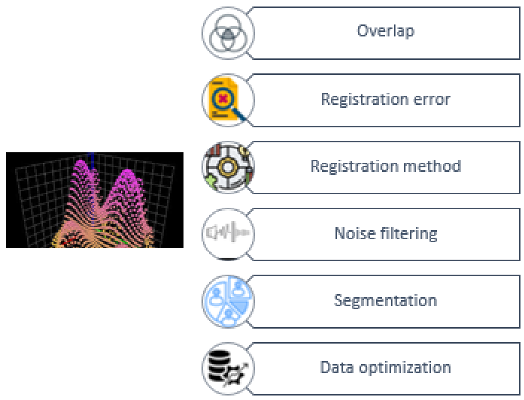

FIGURE 3. Parameters for point cloud data processing and registration

Furthermore, type of method employed also influences the point cloud accuracy, such as automatic, target-based (Cox 2015; C. Wang & Zha 2023), feature-based (Tu et al. 2025) or cloud-to-cloud (Huang et al. 2022; X. Liu et al. 2025; Syafuan et al. 2025). Target-based registration depends on the utilization of reference objects, which are physically positioned within the scanning area. The targets are identified in each point cloud, and their established geometrical positions are utilized to calculate the transformation matrices that align the scans. Feature-based registration, on the other hand, utilizes natural geometric features within the environment, such as edges, corners, and planes. These features are then matched between scans to estimate the transformation for alignment. Cloud-to-cloud registration is the most automated method and is widely used in large-scale environments. This method directly aligns complete point clouds without requiring markers or a specific feature/object. This method iteratively aligns points from overlapping scans by minimizing the distance between them to refine the alignment.

Noise filtering is employed to eliminate erroneous data points resulting from reflecting surfaces, ambient interference, or scanning artifacts. These noisy points can lead to errors in registration and model reconstruction (Soudarissanane et al. 2011; Kuschnerus et al. 2021). The aim is to retain only reliable and dense data points, which results in a cleaner and more stable dataset for further processing. Next, segmentation involves dividing the point cloud into regions based on geometric or spatial criteria (Einizinab et al. 2023). This step is essential for separating specific features or objects of interest within a scene, such as walls, floors, columns, beams, etc. Segmentation enhances the robustness of feature extraction and registration by focusing alignment efforts on significant sections rather than the full dataset. Accurate segmentation improves registration efficacy, by reducing the impact of irrelevant or redundant data. Lastly, data optimization aims to enhance the efficiency and manageability of the point cloud while preserving its essential geometric information. Point clouds can be extensive, frequently comprising millions of points, which makes processing computationally intensive. This step is necessary for managing many scans for registration, as it optimizes processing speed.

Recent empirical studies illustrated the transformative impact of 3D laser scanning and 3D point cloud data in construction quality and monitoring, achieving millimeter accuracy. Point cloud registration with the Iterative Closest Point ICP) algorithm, achieved alignment errors of less than 1 mm. The empirical findings were compelling in comparison to the traditional method, where the dimensional errors were reduced by 0.37mm, indicating measurable improvements in accuracy and efficiency (Z. Liu et al. 2025), while (X. Zhang & Ming, 2023) enhanced the efficiency and accuracy by 60-70% and 5-20% respectively, utilizing target-based methods.

MODEL INTEGRATION AND ALIGNMENT

In this module, the processed point cloud data is imported into the digital modeling environment and spatially aligned with the design model (M. K. Kim et al. 2020). This module is essential for facilitating direct comparison between the constructed and designed representations. Alignment is accomplished by utilizing control points, grid lines or any references present in both datasets.

Upon alignment, the point cloud is segmented to isolate relevant components such as walls, floors, columns, beams, etc., either manually or semi-automated. The model integration module ensures that both the design and the constructed geometries exist within the same spatial framework, facilitating a rule-based detection of dimensional accuracy in the following module.

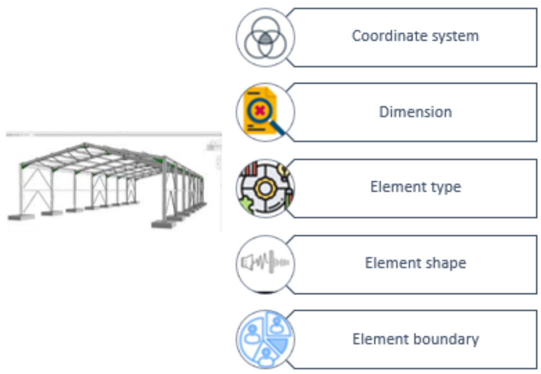

FIGURE 4. Parameters for modeling integration in BIM environment

Figure 4 illustrates parameters involved in the BIM environment for the generation of an as-built model. First, a uniform coordinate system (Sui et al. 2025) is essential to transform the datasets into a cohesive spatial reference using control points, grid lines, or corner references. Secondly, dimension is important in verifying the conformity of constructed elements (Huang et al. 2022). Dimension attributes, including length, width, height, and thickness, define the physical reality of building components. Third, accurate element type (General Services Administration, 2009) classification is facilitated by a segmentation method that has been established in the previous module, while the fourth element is shape (Valero et al. 2022) recognition involving planes, cylinders, etc. Lastly, defining element boundaries (Q. Zhang et al. 2024), including intersections and connectivity, is essential for overlaying and validating the constructed geometry.

DEVIATION DETECTION

The core of the dimensional quality assessment process is the utilization of rule-based to identify and measure geometric deviations between the constructed point cloud and the design model. This module systematically employs established rules and tolerance thresholds to assess if components align with their designated placement and dimensions. These rules are based on relevant industry standards, or project-specific quality requirements.

Deviation metrics are expressed using quantitative indicator such as displacement vectors, deviation magnitudes and comparison ratios. These are determined by examining the geometric deviations between corresponding elements in the point cloud and the design model. The outcomes are subsequently displayed as annotated models that emphasize non-conforming elements, deviation color coded heat-maps that illustrate error distribution or tabulated reports that summarize compliance status. Such outputs provide clear, traceable and actionable information for engineers and quality control engineers/managers for decision-making and rectification. Recent studies such as (M. K. Kim et al. 2020; Seghier et al. 2024) have demonstrated the efficacy of rule-based detection in achieving high-accuracy assessments of construction deviations, hence supporting the adoption of such tools in digital quality control workflows.

The strength of the rule-based detection lies in its objective, repeatability and adaptability to varying project specifications. This also allows for the early detection of construction defects, hence reducing the risk of cumulative errors, facilitating prompt corrective measures, and enhancing construction quality requirements.

Evidence from pipe and structural laboratory experiments by (B. Wang et al. 2021) confirmed the high dimensional fidelity achievable with a 3D laser scanner and point cloud reconstruction. In this study, 91.3% of the components were accurately modeled, with the reconstructed pipe radius demonstrating a root-mean-square error (RMSE) of 2.45 mm and a relative error of 1.86% in relation to the specified radius. Deviation detection indicated that point cloud data differed on average by about 0.03 m, less than 0.15% of the room span from the reconstructed model, demonstrating a high overlap rate between scan stations and excellent dimensional accuracy. Complementary testing on reinforced concrete specimens with shear keys by (Q. Wang et al. 2015) illustrated these findings: the average distance between as-built and as-designed corner points was merely 0.95 mm, with a maximum of 2.95 mm. In contrast, comparisons of overall edge dimensions revealed an average discrepancy of 0.59 mm, with approximately 2.8% and a maximum of 3.4 mm, with approximately 7.2%. The empirical results collectively demonstrate that point cloud data from a 3D laser scanner can consistently capture fine dimensional details and accurately quantify deviations for both discrete points and continuous edges in complex structures.

IMPLEMENTATION CHALLENGES OF BIM AND LASER SCANNING-BASED QUALITY CONTROL

The proposed conceptual framework provides a systematic approach for incorporating BIM, 3D laser scanning, and rule-based quality control. However, its implementation in actual construction environments encounters several technical and practical challenges. These challenges offer opportunities for further investigation and enhancement.

Highlighting the implementation challenges ensures that the proposed framework is technically robust, economically and operationally viable for real-world construction projects, to validate the external applicability of the framework. It further guides future research and industrial pilot studies by highlighting the necessity to refine and optimize the workflow. Furthermore, it offers essential insight for decision-makers by clarifying resource needs, implementation costs, and potential risks before extensive deployment. This reflective assessment enhances the practical significance of the study and ensures that the framework can be adopted across various construction contexts.

SCAN DATA QUALITY AND ENVIRONMENTAL LIMITATIONS

Although 3D laser scanning is widely recognized for its high accuracy in capturing spatial data, its application in construction environments is not without limitations. One of the primary challenges lies in the quality of the scan data, which can be compromised by various environmental and contextual factors. Noise, data gaps, and occlusions frequently occur during the scanning process, often due to reflective or transparent surfaces (e.g., glass, polished metal), poor lighting conditions, and complex architectural geometries that obstruct the scanner's line of sight.

In dense construction sites, structural elements such as scaffolding, machinery, or temporary works may block critical views, resulting in incomplete or distorted data. These occlusions create voids in the point cloud, which reduce the reliability of subsequent dimensional assessments and hinder automated processing.

Furthermore, the variability in surface textures and materials can introduce inaccuracies in laser returns, leading to noisy datasets that require significant post-processing efforts to filter and clean. The complexity of processing such data, particularly aligning, registering, and integrating multiple scans increases the time and expertise required, often making it a labor-intensive phase of the workflow.

Thus, while laser scanning remains a powerful tool for reality capture, achieving high-quality and usable scan data in dynamic, cluttered, and uncontrolled environments remains a technical challenge. These limitations must be addressed through improved scanning protocols, advanced noise filtering algorithms, strategic scanner placement, and potentially the integration of complementary sensing technologies to enhance data completeness and accuracy.

PROCESSING EFFICIENCY AND COMPUTATIONAL CONSTRAINTS

High accuracy point cloud data, often generated from laser scanning, can consist of millions or even billions of points representing detailed spatial information. While this granularity is essential for precise dimensional analysis and modeling, it introduces substantial computational challenges. The large data volume requires significant memory allocation, storage capacity, and processing power, especially when working with multiple scans or large-scale construction environments.

The transformation of raw point clouds into usable geometric models such as meshed surfaces or segmented building components adds another layer of computational complexity. Processes such as point cloud registration, noise filtering, segmentation, and object recognition are computationally intensive and time-consuming. These tasks can significantly slow down the workflow, particularly when using standard computing resources or attempting to process data in real time.

Moreover, as the dataset size increases, so does the difficulty in maintaining responsiveness and usability within digital modeling environments. Lagging software performance, slow loading times, and crashes can disrupt project timelines and reduce productivity. These issues are further compounded in collaborative settings, where multiple stakeholders may need to access, review, and process the same dataset across different platforms.

To address these limitations, there is a need for optimized algorithms, parallel processing techniques, and scalable cloud-based solutions that can handle large datasets efficiently. Additionally, implementing data reduction strategies such as down sampling or region-of-interest filtering can help balance processing speed with accuracy, without compromising the quality of the analysis. Future developments should focus on improving the computational scalability of point cloud processing workflows to support seamless integration into real-time construction quality control systems.

INTEROPERABILITY AND WORKFLOW INTEGRATION

A major challenge in implementing BIM-integrated quality control systems lies in the interoperability between native scan data, BIM models, and quality control (QC) platforms. In practice, these systems often operate using different data formats and proprietary file structures, which hampers seamless data exchange and integration. For instance, point cloud data generated by laser scanners may not be natively compatible with BIM software, requiring complex conversions or third-party plugins that can lead to data loss, misalignment, or inefficiencies.

This lack of standardization results in fragmented workflows where data must be manually transferred or reformatted between systems, increasing the risk of human error and reducing overall productivity. Moreover, limited cross-platform compatibility restricts collaboration among project stakeholders who may use different tools for scanning, modeling, and quality assessment. These issues can delay decision-making, compromise data fidelity, and undermine the accuracy of deviation analyses.

Industry studies on digital transformation in construction have consistently identified interoperability as one of the most significant barriers to adopting BIM-based quality control systems. Without a unified framework for data exchange, the integration of advanced technologies such as 3D laser scanning and rule-based detection remains inefficient and inconsistent across projects.

To overcome this, formalized data exchange protocols must be established. These should include standardized formats for point cloud data (e.g.: E57, LAS), interoperable BIM schemas (e.g.: Industry Foundation Classes (IFC)), and structured rule libraries that define tolerance thresholds and geometric verification criteria. These rule libraries should be aligned with international standards such as ISO 19650 and building SMART guidelines to ensure consistency, objectivity, and repeatability in deviation assessments.

Ultimately, enhancing interoperability is critical for enabling streamlined, end-to-end digital quality control workflows in construction. This will facilitate automation, improve accuracy, and support more effective collaboration across the project lifecycle.

COST OF IMPLEMENTATION AND ECONOMIC FEASIBILITY

One of the most significant obstacles to the widespread adoption of BIM-integrated 3D laser scanning for quality control in construction is the high initial investment required. The costs encompass not only the purchase of advanced laser scanning equipment, often priced in the tens of thousands of dollars, but also the supporting hardware and software infrastructure needed to process and analyze large point cloud datasets. These include high-performance computing systems, licensed BIM software, and specialized data processing tools, all of which contribute to substantial upfront capital expenditure.

In addition to equipment, there are costs associated with skilled manpower. Operating laser scanners, managing BIM environments, processing point cloud data, and implementing rule-based quality control systems require specialized expertise. This increases labor costs, training requirements, and in many cases, creates dependency on external consultants or technology providers.

The financial burden is particularly pronounced in developing countries, where construction firms may operate with tighter margins and limited access to high-end technology. In such contexts, the high cost of acquisition and implementation presents a major barrier, despite the long-term operational benefits these technologies can offer.

To justify the investment, it is essential to demonstrate tangible returns, such as reductions in construction rework, faster inspection cycles, enhanced compliance tracking, and improved decision-making. However, these benefits are often realized over time and may not be immediately visible, making it difficult for organizations to allocate resources toward such digital transformation efforts.

Future research should therefore focus on developing robust economic models that account for lifecycle cost savings associated with smart quality control technologies. These models should incorporate metrics such as return on investment (ROI), payback periods, cost avoidance due to reduced errors, and gains in productivity. Furthermore, scalable and modular implementation strategies could help lower entry barriers by allowing firms to adopt the technology in phases, starting with critical or high-risk components before expanding across entire projects.

Addressing cost-related challenges is crucial for enabling broader adoption of BIM and laser scanning technologies in construction, especially in resource-constrained environments.

THEORETICAL AND PRACTICAL CONTRIBUTIONS OF THE PROPOSED FRAMEWORK

This section aims to clearly demonstrate how the study enhances both academic research and professional application. It connects conceptual development with practical implementation, confirming that the framework is not only a theoretical model but a transformative solution for construction quality in the era of digital and smart construction, and directly supports the research objectives. By clarifying the theoretical innovation and practical applicability of the proposed framework, the study established both academic contribution and a viable solution ready to guide future research, industry integration, and the formulation of digital construction guidelines or policies. This presents the framework as an essential element of the digital transition in construction, facilitating IR 4.0 and fostering innovation in automated quality control.

THEORETICAL CONTRIBUTIONS

The proposed framework makes a significant theoretical contribution to the evolving discourse on digital construction quality control by introducing a systematic, rule-based approach for dimensional assessment that integrates digital design models with empirical as-built data. Unlike traditional methods that treat quality control as a fragmented or reactive process, this framework reconceptualizes it as a continuous, model-driven operation grounded in real-time, verifiable data.

At its core, the framework strengthens the theoretical foundation of the model-driven lifecycle, where a centralized and authoritative Building Information Model (BIM) becomes the reference point against which real-world conditions are consistently evaluated. This integration sets the stage for the development of a digital twin in construction an emerging paradigm where the physical and digital representations of a building are maintained in dynamic alignment throughout the project lifecycle. This shift from static documentation to an intelligent, interconnected system represents a meaningful theoretical advancement.

Moreover, the formalization of rule-based quality assessment contributes to the academic understanding of how automated logic can be applied to identify, interpret, and validate deviations. By embedding standardized rules or project-specific tolerances into the quality control process, the framework enables the transformation of deviation detection from a subjective or manual task into a structured, repeatable, and data-driven procedure. This contributes to the literature by aligning quality control practices with computational design theory and digital decision-making models.

The framework also opens new avenues for theoretical exploration into performance-based design compliance, offering insights into how automated model checking and deviation analysis can support design intent validation. It encourages future studies to investigate how rule libraries, enriched with semantic data, can support more adaptive and intelligent systems capable of not only detecting but also interpreting the significance of deviations in terms of structural safety, usability, and regulatory compliance.

Overall, this framework provides a foundation for bridging gaps between theory and practice in digital construction, promoting a proactive, intelligent, and integrated approach to quality control that aligns with broader trends in automation, digital twins, and smart construction environments.

PRACTICAL CONTRIBUTIONS

The proposed framework offers immediate and tangible benefits for construction professionals involved in the execution, supervision, and quality assurance of building projects. By integrating BIM, 3D laser scanning, and rule-based verification into a unified workflow, the framework introduces a replicable and scalable digital solution for automating inspection and dimensional quality assessment. This significantly reduces the industry's longstanding reliance on manual measurements, subjective judgment, and labor-intensive verification methods, which are often prone to inconsistencies and errors.

Through its rule-based comparison between as-built point cloud data and design models, the framework enables precise and objective detection of deviations such as misalignments, overbuilds, and undersized components. This level of precision ensures that non-conformities are identified early and consistently across various project stages, thereby improving the overall reliability of quality control evaluations. In fast-paced construction environments, where timely decisions are critical, such automation accelerates the feedback loop between on-site conditions and design verification, enabling proactive resolution of discrepancies before they escalate into costly errors or rework.

Additionally, the framework enhances data transparency and communication through the generation of digital documentation, color-coded deviation heat maps, and traceable annotations within the BIM environment. These outputs not only facilitate real-time decision-making by project teams but also serve as verifiable records for regulatory compliance, stakeholder reporting, and long-term asset management. By maintaining an auditable history of construction quality, the framework supports improved accountability and facilitates smoother project handovers.

The system's scalability makes it suitable for application across different project sizes and types—from individual structural components to full-scale buildings making it a versatile tool for construction quality management. Its modular structure also allows for gradual implementation, accommodating varying levels of technological readiness within organizations. Overall, the framework represents a significant step toward digital transformation in construction practice, aligning on-site processes with Industry 4.0 principles and smart construction strategies.

CONCLUSION

This paper has introduced a thorough conceptual framework that combines BIM, 3D laser scanning and rule-based detection to automated dimensional quality assessment in construction. The framework encompasses essential modules by framing quality control as an integrated, digital, and data-driven process. The framework signifies a significant progression in model-based construction management methodologies. In addition, the proposed framework offers a unique and original contribution to the growing body of digital construction.

By formalizing how point cloud acquisition, model integration, and automated model-based verification are performed, this study enhances digital twin theory and strengthens the scientific basis. It effectively bridges a key gap between theoretical digital-twin models and practical building quality systems suitable for field deployment. This novel integration of design-intent, as-built data, and computational rule-based establishes a new benchmark for future research and practice in automated quality control, establishing the framework as a fundamental reference for the next generation of smart construction projects.

In addressing the challenges to digital quality control, the proposed framework offers an integrated rule-based solution that is both technically and economically viable. The framework organized modules with a scalable, phased implementation strategy, that directly mitigate adoption challenges. By methodically addressing these technical, organizational, and economic challenges, the framework enhances its practical significance and establishes itself as a resilient, industry-ready solution for automated, data-driven quality control in digital construction.

Future research will focus on implementing this framework by creating standardized rule libraries that are compliant with relevant design codes and adaptable to various project requirements. Moreover, empirical validation through case studies in active construction is essential to assess the framework's resilience, usability, and influence on project outcomes. Future studies should focus on converting the proposed indicators, such as operational efficiency, cost efficiency, data quality, and sustainability impact, into comprehensive validation protocols applicable to various project types and environmental conditions. Specifically, field testing will be performed on active construction sites of diverse scales to thoroughly evaluate the framework's accuracy, resilience, and operational efficacy under various environmental conditions. Furthermore, future work will focus on incorporating predictive analytics and artificial intelligence to facilitate automated decision-making and to enhance early identification of anomalies through predictive maintenance capabilities.

Ultimately, by addressing these future directions, the framework has the potential to serve as a fundamental element in the digital transformation of quality control processing within structural engineering and construction. The findings from these implementation studies will provide substantial evidence for enhancing the framework and for guiding industry standards and public-sector digital construction guidelines or policies.

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DECLARATION OF COMPETING INTEREST

None.

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