

Systematic Review of Integrating 3D Laser Scanner and Building Information Modeling in Dimensional Quality Assessment of As-built Structures

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ABSTRACT

Ensuring the dimensional accuracy of constructed structures is crucial for quality control purposes in assessing whether the elements align with the design dimensions and tolerances and also to identify inconsistencies and deformations to prevent subsequent construction complications. This paper explores the integration of 3D laser scanner and Building Information Modeling (BIM) as an automated validation system for assessing dimensional quality. This method employs 3D laser scanner, point cloud registration and processing and scan-to-BIM techniques to facilitate dimensional deviation/tolerances analysis and verification. The paper presents a review of existing research on the automated dimensional quality assessment by using scientometric analysis and critical reviews. Firstly, three (3) key research themes are recognized and described based on the findings of scientometric analysis: a) reality capture to information integration, highlighting the transition from raw point cloud acquisition and registration to semantically enhanced BIM representations, b) dimensional conformance, which implements tolerance-aware comparisons between as-built data and design models to ensure traceability and compliance, and c) automation to site domain, which integrates the workflows into field application via automated system, machine learning, and deep learning to facilitate inspection, monitoring, and decision-making. Subsequently, existing assessment methodologies were evaluated and contrasted via critical review. The gaps between existing methodologies and actual needs are summarized. Finally, future directions in the field are anticipated correspondingly. Overall, this paper contributes to future research and applications concerning dimensional quality assessment through BIM application.

Article History

Received: 17 April 2025

Received in revised form: 19 September 2025

Accepted: 06 May 2025

Published Online: 31 December 2025

Keywords:

Dimensional Quality, Laser Scanner, Building Information Modeling, As-built

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DOI: 10.11113/ijbes.v13.n1.1568

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1. Introduction

Quality control (QC) constitutes a fundamental component of construction projects, ensuring that the resulting outputs conform to established standards and specifications while meeting criteria

for safety, functionality and durability. Efficient QC practices mitigate risks of defects (C. Kim et al., 2013) and structural failures, lower expenses linked to rework (Choi et al., 2024), and enhance confidence among stakeholders. Neglect of QC in construction projects can lead to loss of money, delays and legal

issues. Projects that do not have proper quality control processes can also face reputational damage, as stakeholders may lose trust in contractor's ability to provide quality outcomes. Furthermore, a lack of QC can make it hard to meet sustainability goals, as inefficient practices lead to excessive resources and harm the environment.

Geometric (Mirzaei et al., 2023) or dimensional quality assessment is a critical procedure in construction that verifies structural components adhere to design criteria for dimensions, tolerances (Pevzner et al., 2020) and geometry. This procedure is important to ensure correct alignment, operation and structural integrity (Özkan et al., 2024). Dimensional discrepancies frequently occur due to multiple reasons throughout the design, production, installation and construction processes. Deficiencies in design documentation or misreading of specifications may lead to components that do not conform as intended. Fabrication problems, including defective equipment or inaccurate measurements, can result in dimensional differences. During installation, factors such as improper alignment procedures or environmental factors including temperature and humidity might lead to the error.

This paper examines the integration of 3D laser scanner and Building Information Modeling (BIM), emphasizing their theoretical foundations and applications for the construction industry in improving the accuracy, efficiency, and reliability of automated dimensional quality assessment processes of as-built structures.

2. Background

2.1 Problem Statement

Traditional quality control techniques frequently exhibit inefficiencies, inaccuracies (De Angelis et al., 2015), manual measurements using tape measures (Truong-Hong et al., 2020) or calipers that are prone to errors (Q. Wang et al., 2015) and insufficient interoperability. While these have served the construction industry for a number of decades, they face significant challenges that often compromise both efficiency and accuracy. Traditional QC introduces human dependency, which brings inconsistencies, as inspections and assessments are subject to judgement and expertise of an individual. Traditional methods are also time-consuming (Jung et al., 2014; Özkan et al., 2024), require substantial labor (Xiong et al., 2013) and often lead to delays in the resolution of quality issues. Another limitation is the lack of accuracy, which may not be able to identify small imperfections or misalignments (Kalasapudi et al., 2015) that can eventually become costly repairs or safety risks. Further, reliance on paper-based records poses challenges in managing data, hence making project monitoring and regulatory compliance difficult. Poor QC can also jeopardize structural safety (Özkan et al., 2024), creating potential hazards for occupants and workers and reputational damage to contractors and firms.

Advances in technology, particularly the integration of BIM and laser scanners are reshaping traditional practices and offer promising solutions to these problems. BIM serves as a centralized

platform for data management, collaboration (Zeng et al., 2024) and visualization (Choi et al., 2024), whereas laser scanner delivers detailed geometric data (C. Wang et al., 2015) for the development of precise as-built models. Their integration improves accuracy, automates quality assessment procedures and enables instantaneous decision-making (Volk et al., 2018). Additionally, it simplifies compliance checks and documentation, optimizing a historically burdensome task. The impact of automation on construction quality control goes beyond just efficiency. Automated systems encourage sustainability by maximizing the use of resources and minimizing waste generated. They enhance collaboration through centralized data platforms, where stakeholders can make informed decisions quickly. Automation further ensures making it very easy to maintain consistent quality standards on large and complex projects. Overcoming the weaknesses of traditional methods of quality control, and automation poses the way for a new standard in reliability, safety and sustainability in the construction industry.

2.2 Research Objectives

This paper focuses on the dimensional quality assessment and attempts to address the following research questions through a comprehensive review of automated dimensional quality assessment: a) What are the key research themes in the field? b) How have the key research themes been developed? c) What are the characteristics of the methodologies employed in each theme and gaps exist between them? d) How will the field develop in the future?

3. Methodology

This paper combines the scientometric analysis with a critical review to deliver a comprehensive review of existing research findings. The research methodology is illustrated in Figure 1.

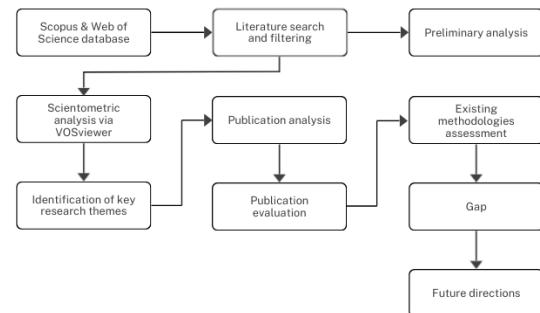


Figure 1 Schematic representation of research methodology

For a comprehensive literature review, literature retrieval is a crucial step. In this study, a pilot search was conducted in Scopus and Web of Science databases and compared. As a result, Scopus database was selected as the main literature database because it also covered the results from Web of Science. Articles were collected up to 2024. PRISMA (Preferred Reporting Items for

Systematic reviews and Meta-Analyses) method was adopted for the systematic review, to support the precise flow, reporting of information, and strengthen transparency.

3.1 Literature Retrieval and Preliminary Analysis

The search formula was conducted as follows: TITLE-ABS-KEY ("laser scan") OR TITLE-ABS-KEY ("laser scanner") AND (TITLE-ABS-KEY ("building information modeling") OR ("building information modelling") OR BIM) AND TITLE-ABS-KEY (measure* OR inspect* OR assessment* OR evaluate*) AND TITLE-ABS-KEY (quality OR geometric OR dimension* OR tolerance* OR geometry) AND TITLE-ABS-KEY (automat*).

The search yielded a total of 139 publications, and the articles were further filtered to remove the irrelevant publications. The scope of the search was limited to: a) document type: article and conference paper (yield at 134 publications), b) subject area: engineering (yield at 104 publications), c) year: until 2024 (yield at 91 publications), and d) excluded irrelevant publications, such as works without BIM linkage and non-automated process (yield at 90 publications). After filtering, 90 publications were obtained,

as shown in Table 1, which explained the main sources and publication year.

3.2 Scientometric Review

Scientometric review is a quantitative method for examining scientific literature, emphasizing the assessment of research trends, collaboration networks and the influence of scientific contribution. Utilizing statistical and computational methodologies offers insights into the evolution of a research domain, identifying influential authors, publications, journals and institutions. The primary objectives of scientometric review are to comprehend emerging research trends, evaluate the impact of scientific contributions, inform funding and policy decisions, promote collaborations and visualize the structure of knowledge domains. This method is beneficial for academics, policy makers and funding organizations aiming to identify key areas of impactful research within a designated domain. In this paper, VOSviewer was used as a tool for scientometric review, recognized for its user-friendly interface and capacity to generate interactive visualizations. The key research themes were identified by scientometric review, followed by the identification of relevant publications for each theme through the examination of their abstract.

Table 1 Primary source data and number of publications

Source of publications	Publication year				Total
	Before and in 2010	2011 – 2015	2016 – 2020	2021 – 2024	
Automation in Construction		5	9	9	23
Journal of Computing in Civil Engineering			2	2	4
Lecture Notes in Civil Engineering		1		3	4
Journal of Building Engineering				3	3
Avn Allgemeine Vermessungs Nachrichten		1		1	2
Engineering, Construction and Architectural Management			1	1	2
ISPRS Journal of Photogrammetry and Remote Sensing			1	1	2
Nanotechnologies in Construction				2	2
Procedia Engineering	2				2
Proceedings of SPIE the International Society for Optical Engineering				2	2
Advances in Computational Design			1		1
Applied Energy			1		1
Applied Geomatics				1	1
Applied Sciences Switzerland			1		1
Bauingenieur	1				1

Buildings		1	1
Computer Aided Civil and Infrastructure Engineering	1		1
Congress on Computing in Civil Engineering Proceedings	1		1
Dyna Colombia	1		1
Energy and Buildings	1		1
Engineering Structures		1	1
Fib Symposium	1		1
Frontiers in Built Environment		1	1
IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems		1	1
IEEE Transactions on Instrumentation and Measurement		1	1
International Journal of Architectural Heritage		1	1
International Journal of Building Pathology and Adaptation		1	1
International Journal of Sustainable Building Technology and Urban Development		1	1
Measurement Journal of the International Measurement Confederation	1		1
Ocean Engineering Sensors		1	1
Structural Control and Health Monitoring		1	1
Structural Survey	1		1
Structure and Infrastructure Engineering		1	1
Others	10	7	3
Total	2	20	39
			90

3.3 Critical Review

The critical review in this paper consisted of two (2) primary phases. Firstly, a comprehensive reading and analysis of the publications was conducted, focusing primarily on the key research themes associated with the papers and their content. Secondly, analyzing and assessing the publications, focusing mainly on the methods used in each publication. The two (2) phases offer a comprehensive understanding of advancements in automated dimensional quality assessment.

4. Results

In this section, a scientometric review was carried out to identify the main themes associated with the 90 publications obtained

from the search and filtration process. Subsequently, to enhance the critical review of the publications, the main themes were modified based on the distribution of the papers to derive the essential key research themes

4.1 Scientometric Review and Identification of Main Theme

Scientometric review was conducted on the 90 publications obtained from the search and filtering process. VOSviewer was employed to examine the co-occurrence of keywords that were collected from the title and abstract fields. The frequency threshold for keywords was established at one (1) time, while keywords with minimal relevant information such as a) energy efficiency, interior finishing robot, and solar systems: not

dimensional quality assessment, b) laser-doppler-vibrometry: different domain, c) case study and construction: generic term, and d) South Africa: geography application, were excluded. Similar terms such as terrestrial laser scanner, laser scanning, terrestrial laser scanning, and terrestrial 3D laser scanning were combined.

The results indicated that 71 keywords were identified which were subsequently categorized and analyzed into five (5) clusters. Table 2 displays the content of each cluster, while Figure 2 illustrates the analysis results and Figure 3 presents the average publication year of each keyword.

The five (5) clusters obtained as shown in Figure 2 were examined. Cluster 1 included mainly terms "data acquisition", "laser scanner", "point cloud", and "terrestrial laser scanner", indicating that this cluster focused on how dimensional information is captured in the field and aligned into a meaningful dataset. The literature treats laser scanners and terrestrial laser scanners as instruments to capture physical structure information. The raw point cloud is subsequently aligned via registration, followed by point cloud segmentation and clustering. Cluster 2 included mainly terms "bim", "digitalization", "reverse engineering", "scan-to-bim", and "visualization", indicating that this cluster focused on modeling. This cluster encompasses the

conversion of geometry into information and visualization. The integration of reverse engineering underscores the production of parametric elements that preserve design semantics. The BIM node's equal centrality to the point cloud indicates that research is increasingly evaluated based on its effectiveness in bridging raw geometry and structured models. Cluster 3 included "accuracy", "as-built", "automated dimensional measurement", "automated quality control", "dimensional measurement", "geometric quality assessment", "quality control", and "tolerance", indicating that this cluster focused on dimensional quality and tolerance assessment. This cluster operationalizes as-built versus design by converting measurements for automated comparisons. Cluster 4 included "automation", "augmented reality", "deep learning", "machine learning", and "virtual reality", indicating that this cluster focused on automation and Artificial Intelligence (AI). The automation seeks to minimize manual involvement and enhance scalability. Cluster 5 included "bridge", "building", "façade", "finite element", "infrastructure", "manufacturing", "mep", "precast concrete", "precast pier", "steel", "steel girder", "steel portal frame", "timber", and "wall" indicating that this cluster focused on application that categorized within the types. The application encompasses erection alignment, installation, and precast fit-up assessment.

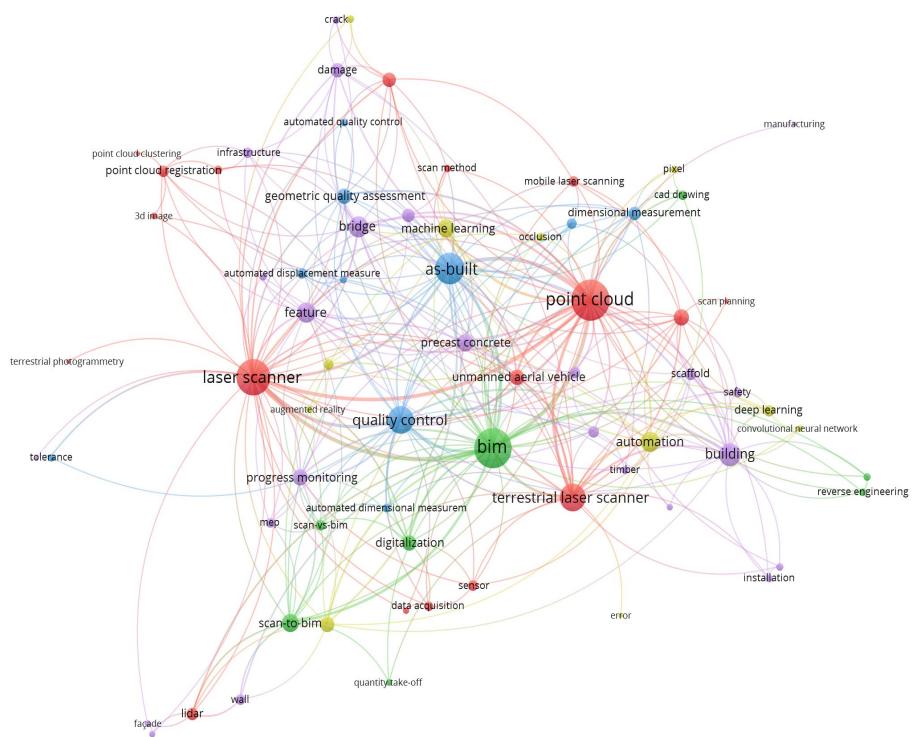


Figure 2 Keyword co-occurrences (network visualization, five (5) clusters)

Table 2 Keyword and occurrence in each cluster

No.	Keyword	Occurrences	No.	Keywords	Occurrences			
Cluster 1 (18 items, red)								
1	3d image	1	1	augmented reality	1			
2	data acquisition	2	2	automation	7			
3	laser scanner	26	3	convolutional	1			
				neural network				
4	lidar	3	4	deep learning	2			
5	mobile laser scanning	2	5	error	1			
6	mobile lidar	1	6	machine learning	7			
7	point cloud	31	7	object detection	5			
8	point cloud clustering	1	8	occlusion	1			
9	point cloud processing	3	9	pixel	1			
10	point cloud quality	1	10	texture	1			
11	point cloud registration	3	11	virtual reality	2			
12	point cloud segmentation	5	Cluster 5 (24 items, purple)					
13	scan method	1	1	bridge	7			
14	scan planning	1	2	building	10			
15	sensor	3	3	crack	1			
16	terrestrial laser scanner	16	4	damage	5			
17	terrestrial photogrammetry	1	5	façade	1			
18	unmanned aerial vehicle	4	6	feasibility	1			
Cluster 2 (8 items, green)								
1	bim	31	7	feature	7			
2	cad drawing	2	8	finite element	2			
3	digitalization	4	9	infrastructure	2			
4	quantity take-off	1	10	installation	1			
5	reverse engineering	1	11	manufacturing	1			
6	scan-to-bim	6	12	mep	1			
7	scan-vs-bim	2	13	precast concrete	7			
8	visualization	1	14	precast pier	1			
			15	progress monitoring	5			
Cluster 3 (10 items, blue)								
1	accuracy	2	16	retrofit	1			
2	as-built	19	17	safety	1			
3	automated dimensional measurement	2	18	scaffold	2			
4	automated displacement measurement	2	19	steel	3			
5	automated quality control	1	20	steel girder	2			
6	dimensional measurement	3	21	steel portal frame	1			
7	displacement measurement	1	22	tank	1			
8	geometric quality assessment	6	23	timber	1			
9	quality control tolerance	15	24	wall	2			
10		2						

According to Table 2, high occurrences of terms "laser scanner", "terrestrial laser scanner", and "point cloud" establish a theme of data acquisition of the physical structure. It involves

raw data registration, processing, clustering, and segmentation. The inclusion of scan planning and scan method indicates a methodical focus on coverage, incidence angle, and noise.

Collectively, Cluster 1 establishes a strong data foundation, where the focus of research has transitioned from acquiring dense point clouds to ensuring their quality, which preserves characteristics essential for subsequent modeling. In Cluster 2, the BIM term predominates, indicating the formalization of collected geometry within information-dense models. It demonstrates an effort to automate the conversion from point clouds into parametric elements. In Cluster 3, high occurrences of terms as-built and quality control, signify that the field has shifted from capture to the auditable performance of constructed reality to design intent. Within this distribution, dimensional, displacement, and tolerance are foundational criteria, where dimension validates the geometric accuracy of constructed elements that influence rigidity and strength, displacement measures the structure's reaction, such as misalignment, settlement, and rotation, while tolerance provides the established criteria that transforms measurement into requirement determination. In Cluster 4, the themes focus on automation, indicating a transition from traditional methods to actual on-site integration. However, deep learning is comparatively limited, suggesting that this method selection is not significant. In Cluster 5, the terminology significantly aligns with application domains. The predominant setting is a building and followed closely by a bridge. Two (2) operational concerns, which are damage and progress monitoring, indicate that actual condition assessment and construction-phase oversight are significant, where damage is crucial as it links geometry or dimension to structural integrity, functionality, and lifecycle cost, while progress monitoring is essential as it transforms observations into time-stamped evidence of output, which

influences scheduling, cash flow and adherence to contractual obligations.

In addition, according to Figure 3, the inferences regarding research trends can be drawn. During the initial phase (2016 to 2018), the research focused on the essentials of geometric acquisition and preprocessing utilizing a laser scanner, point cloud registration, segmentation, and building modeling, establishing measurement reliability and reproducible capture methodologies. The second phase (2019 to 2020) transitions the field from scan-to-BIM to verifiable as-built information, closely linking quality control, dimensional measurement, and progress monitoring, indicating the rise of model-centric assessment and verification. The subsequent phase (2021 to 2022) is characterized by automation, facilitating semantic recognition of elements. In the most recent period (2023 to 2024), deep learning and reverse engineering are closely integrated with BIM, demonstrating comprehensive and data-driven approaches that transmit dimensional uncertainties into decision support and lifecycle updates, effectively aligning with digital twin practices.

Based on the results of the analysis, five (5) themes were mainly identified in conjunction with scientometric analysis. The themes included the data acquisition (Cluster 1), modeling and digitalization (Cluster 2), dimensional assessment (Cluster 3), automation (Cluster 4) and application (Cluster 5).

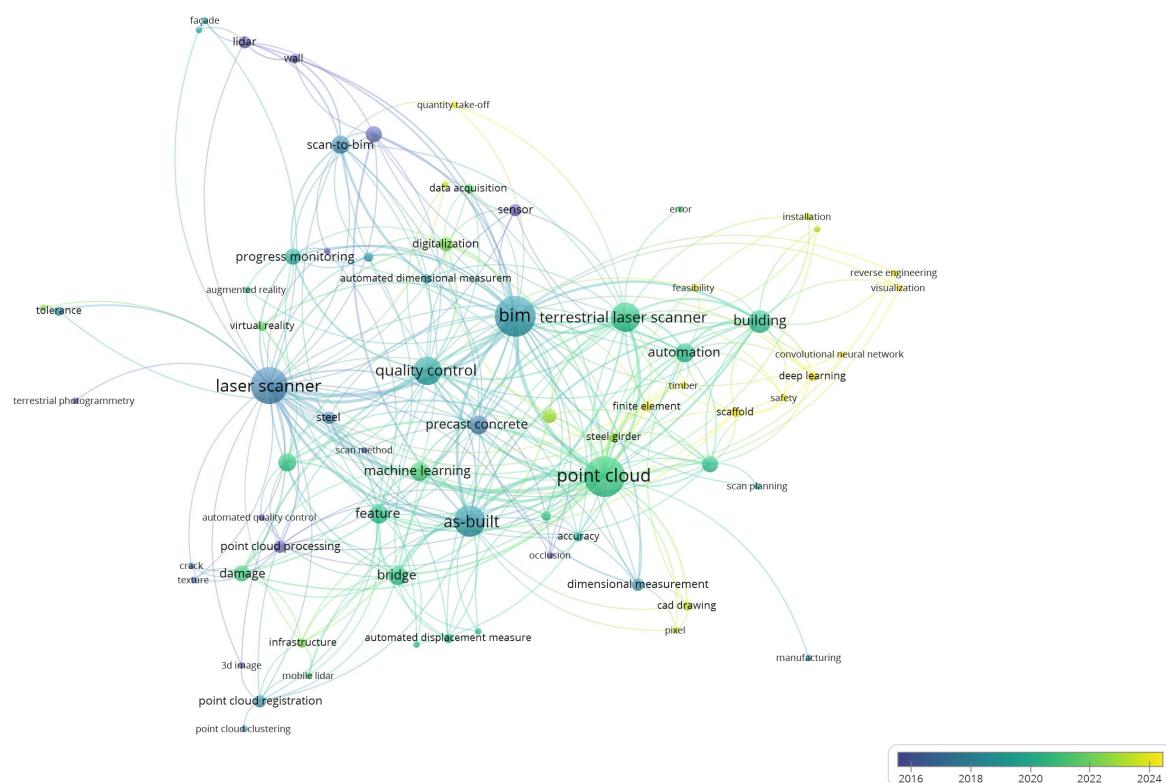


Figure 3 Keyword co-occurrences (average publication year)

4.2 Identification of Key Research Themes

Abstracts of 90 publications were examined, to identify the articles relevant to specific themes, and then determined to modify the primary themes based on the distributions of the associated papers to enhance the critical review of the publication. The clusters identified before were data-driven groupings from a co-occurrence network, while the themes constitute a theory-informed synthesis, aligned to the workflow of scan-to-BIM research.

Utilizing scientometric map, the findings were restructured into three (3) research themes that align with the field and preserve all cluster content. Theme 1 – Reality Capture to Information Integration consolidated Clusters 1 and 2, illustrating the seamless workflow from data acquisition, registration, clustering, and segmentation to semantics-rich modeling and digitalization. Theme 2 – Dimensional Conformance preserves Cluster 3, acknowledging its methodological essence: transforming measurement into verifiable conclusions via dimensional, displacement, and tolerance, while explicitly addressing traceability. Theme 3 – Automation to Site Domain integrates Clusters 4 and 5, wherein machine learning and virtual reality are applied in specific domains such as buildings, bridges, precast elements, and steel structures to provide damage detection, progress tracking, and decision-ready outputs.

4.2.1 Reality Capture to Information Integration

Laser scanners have evolved from a documentation instrument into the foundation of continuously updated, data-rich as-built models. Progressive scans across the project life-cycle effectively facilitate the creation of accurate and comprehensive as-is-BIM. The practice of reality capture (Ali et al., 2020; Arayici, 2008; Chen et al., 2019) has matured from unstructured scanning to a systematic specification-oriented acquisition process, wherein scan objectives, instrument setup (Sing et al., 2024), and control networks are explicitly organized to facilitate subsequent information utilization.

The workflow initiates with data acquisition aimed to provide an accurate 3D representation of the constructed environment (Macher et al., 2017; Q. Wang, Cheng, et al., 2016), utilizing a 3D laser scanner, including a Terrestrial Laser Scanner (TLS). The choice of scan method depends on target scale (Q. Wang et al., 2015), accessibility, obstructions, and accuracy requirements, while scan planning (Biswas et al., 2015; Frías et al., 2022; Han et al., 2023; Sing et al., 2024; Son & Han, 2023; Tang & Alaswad, 2012; C. Xu et al., 2024), including station configuration and incidence angles (Anil et al., 2012; Han et al., 2024; O'Donnell et al., 2019), ensures measurement reliability.

Raw capture undergoes systematic point cloud processing. Initially, multi-station data is subjected to point cloud registration (Brandstatter et al., 2024; G. Cheng et al., 2023; Dong et al., 2018; P. Kim et al., 2018; Lin et al., 2021; Nahangi et al., 2015; Romanschek et al., 2020) utilizing target-based methodologies, with a specific focus on the quality of the

point cloud, considering factors such as overlap (Hamdan et al., 2021), noise (Anil et al., 2012; Gao et al., 2012; Han et al., 2024; Sing et al., 2024; B. Wang et al., 2024; Q. Wang et al., 2015; Xiong et al., 2013; Zeng et al., 2024; J. Zhao et al., 2024), ranging error, and resolution (Hamdan et al., 2021; C. Kim et al., 2013; B. Wang et al., 2024). Subsequently, point cloud clustering (Jiang et al., 2020b) and segmentation (B. Wang et al., 2024; C. Wang & Cho, 2014) isolate elements (example columns, beams, and plates) and distinguish construction from different materials, facilitating analysis rather than visualization. Throughout, outlier management and resolution harmonization (Shan et al., 2023), ensure that models derive justifiable accuracy from the registered point cloud data.

Information enrichment occurs when geometry is converted into computable representations that facilitate design verification and decision-making. Scan-to-BIM procedures recreate parametric elements using reverse engineering, whereas comparisons assess conformity between the constructed state and design intent. In instances where complete parametricization is not required, authoritative CAD drawing (M. Kim & Lee, 2023) extractions provide deliverables for detailing and coordination.

Reality Capture is also maturing from points and pixels to integrated, analysis-ready representations (Echeverría-Valiente et al., 2017). Multi-sensor register infrared thermography with point cloud technology produces orthothermograms that identify thermal anomalies and measure heat loss, making it valuable for envelope diagnostics. However, this approach remains inconsistent in terms of resolution, field of view, and perspective during registration as noted by (González-Aguilera et al., 2012). Therefore, recent work from (C. Kim et al., 2013) has addressed the resolution and shadow effects of thermography by mapping corrected thermal images onto 3D geometry, thereby enhancing subsequent energy simulation and defect detection. The advantage lies in the superior decision-quality thermal-geometric data, while the weakness remains sensitivity to capture conditions and preprocessing selections.

On the geometric side, automated transformation of unstructured point clouds into semantically enriched, minimizes manual effort, proving in speed and repeatability, but its effectiveness still depends on the regularity of the scene and the segmentation robustness (Zabin et al., 2020). Upstream planning is progressively optimized, including scan planning associates quality and accuracy criteria, as studied by (Frías et al., 2022; B. Wang et al., 2024), with scanner configuration and positioning beneficial for coverage under occlusion, although it relies on dependable models and specifications.

Ultimately, integration facilitates project-level value. Model-linked visualization conveys discrepancies to site teams, facilitates automatic quantity take-off (Sing et al., 2024) and supports audit trails for acceptance. This comprehensive workflow enhances digitalization by transforming field data into reliable information assets.

Established that Scan-to-BIM workflow may provide analysis-ready models when the quality of scan planning, registration, and processing are managed. Fails when capture, registration or processing are sensitive and when clustering and segmentation encounters irregular geometrics or occlusions.

4.2.2 Dimensional Conformance

Dimensional conformance determines if the constructed geometry meets the specified tolerance requirements of the project (Kalasapudi et al., 2015), hence supporting contractual approval and structural integrity. In the scan-to-BIM context, dimensional quality assessment advances from a metrically reliable point cloud data to a design-referenced model, where discrepancies are calculated and identified. The primary need is accuracy (Kong et al., 2023) and traceable control, ensuring that any reported deviations reflect the work.

With these foundations, dimensional measurement assesses the size, positions, and orientation of elements such as offsets and levels in relation to design intent. Contemporary workflows increasingly utilize automated dimensional assessment, deriving primitives and features from point clouds while calculating distances and angles (Peansupap & Theint, 2024). The outcome is a concentrated deviation field refined into actionable metrics in relation to defined tolerance categories.

Related to dimensionality, (Anil et al., 2012) quantified the reliability of identifying steel sections from a 3D laser scanner. The investigation employing the manual method revealed a low identification accuracy. The primary causes included scan occlusion due to unrelated objects, mixed pixels at the edges, and noisy data. Complementing this, (Frías et al., 2022; B. Wang et al., 2024) demonstrated proactive scan planning, enhancing station configuration, incidence angles, resolution, and overlap, which improves dimensional accuracy by minimizing occlusions and noise. Collectively, these results justify the implementation of statistical methods, such as those implemented by (Razali et al., 2023) or machine learning methods, such as DINOv2 (B. Wang et al., 2024), SVM (Xiong et al., 2013; J. Zhao et al., 2024) which may enhance identification and establish the dataset and findings as a baseline for recognition algorithms. This method was also proposed by (Anil et al., 2012) for future work.

In addition to size, positions, and orientation assessments, displacement measurement (D. Kim et al., 2020) evaluates movement and functionality such as deflection and settlement. This distinction is crucial, where dimensional non-conformance indicates a production or installation/erection error (Li et al., 2023), while displacement beyond limitations denotes load-path or restraint issues. Dimensional and displacement studies collectively offer a comprehensive perspective on performance throughout the erection and handover phases.

The ultimate objective is a quality control process that is evidence-based and efficient. The framework establishes tolerance criteria, assesses constructed elements accordingly, and highlights discrepancies via model-associated reports. When

linked to BIM data, the prompts trigger targeted rework, informed approval, or engineering justification, completing the cycle from measurement and assessment to decision-making. In summary, a thorough integration of accuracy, dimensional and displacement assessment, and rule-based dimensional quality assessment for modern projects, enhances assurance while reducing inspection burden (Nena et al., 2024).

Determines that automated dimensional assessments transform point-cloud features into tolerance-based metrics appropriate for approval determinations. Fails occur when occlusion or noise degrade identification and when orientation or position errors propagate from the capture process.

4.2.3 Automation to Site Domain

Translating automation into the site domain involves converting models into consistent field operations for inspection (González-Aguilera et al., 2012), acceptance, and handover. Field acquisition plans must emphasize feasibility (Shan et al., 2023), establishing explicit objectives such as installation or erection inspection for precast concrete (Jiang et al., 2020b, 2020a; M.-K. Kim et al., 2015, 2019; Q. Wang et al., 2015, 2017, 2018; Q. Wang, Cheng, et al., 2016; Q. Wang, Kim, et al., 2016; Y. Xu et al., 2022), steel structures (Anil et al., 2012; G. Cheng et al., 2023; Laefer & Truong-Hong, 2017; Yan & Hajjar, 2021a, 2021b), walls (Adán et al., 2011; Choi et al., 2024; Zabin et al., 2020), tunnels (Vierhub-Lorenz, Werner, von Olshausen, et al., 2023; Vierhub-Lorenz, Werner, Weiher, et al., 2023), and timber (Özkan et al., 2024) components. BIM establishes the contractual foundation, such as manufacturer requirements and installation or erection tolerances, to ensure that each automated operation produces traceable documentation instead of visuals.

Automation (Adán & de la Rubia, 2019; Balado et al., 2017; Bosché et al., 2015; W. Cheng et al., 2019; Forth et al., 2024; Garwood et al., 2018; Jung et al., 2014; Liu et al., 2021; Lorenzo et al., 2012; Razali et al., 2023; Schleinkofer & Rank, 2009; Tang & Akinci, 2012; Zhu et al., 2023) also expedites progress monitoring (Love et al., 2019; Prieto et al., 2020; Rada, Kuznetsov, Akulov, et al., 2023; Rada, Kuznetsov, Zverev, et al., 2023) and condition assessment, by automatic identification of cracks (Turkan et al., 2018) and damage (H. Kim et al., 2021) on the building façade and envelope. In safety critical tasks, dimensional outputs inform a coupled finite element analysis (Yan & Hajjar, 2024), seismic risk assessment (X. Wang et al., 2023), and assessing the structural impact (Özkan et al., 2024) of detected misalignment, so integrating dimensional quality with engineering performance.

On-site interpretation is driven by machine learning (Hake et al., 2023; Hu & Hu, 2024) or deep learning (J. Kim et al., 2024) methods that operate at the pixel and texture level (Zabin et al., 2020) to extract robust features from images (Guldur & Hajjar, 2017; Rankohi & Waugh, 2015) and point clouds. Object detection and semantic segmentation utilizing neural networks accurately identify components and relationships.

The advantages include scalability and consistency (Frías et al., 2022; Xiong et al., 2013), particularly in automatic segmentation (B. Wang et al., 2024; C. Wang & Cho, 2014), defect or damage detection, and guided capture, reducing cycle time and operator reliance, facilitating near real-time, fit-for-purpose insights, as the algorithms run repeatably. However, automation is fragile under occlusion (Gao et al., 2012) and noisy point cloud data acquisition, requires high computation for large scan data (J. Zhao et al., 2024), robust fitting (Q. Wang et al., 2015; Zeng et al., 2024) of imperfect as-built dimensions, interoperability with BIM or other tools (Love et al., 2019), and can be confused by the geometry of thin/curved members (Xiong et al., 2013), such as angles, plates, rebars, and cables. In practice, this high-reliability deployment integrates automation, which remains useful for decision-making on projects, replacing traditional methods whose reliability has declined.

Implements scalable automation for progress and defect detection, along with guided capture. Fails in the presence of occlusion or noisy data, or curved elements, and when faced with interoperability or computational constraints.

5. Discussions

Guided by the research objectives, a synthesis of 90 papers indicates that the current scan-to-BIM literature is most accurately seen as a dependency chain for reality capture and information integration that supports verifiable dimensional conformance, which subsequently facilitates automation on site. The advancements are consistent, as recent automation studies consider scan planning and scan parameters to address inadequate failure modes such as occlusion and incidence angle. This framework explains both the successes in the literature in achieving the first and second objectives, and the trends observed that meet the needs and requirements in real projects.

Across themes, characteristic methods are evident, which are data capture, dimensional fitting, clustering and segmentation, tolerance-aware deviation assessment, and BIM integration. However, discontinuities persist, especially in studies that transmit errors from capture decisions to acceptance determinations, lack statistical metrics, and interoperability among tools. To bridge the gaps, there are several contributions to address this review for future: a) treat the workflow as a unified system from data capture to dimensional conformance that is regulated by defined requirements and specifications, where predefined scan planning mitigation is to be included, b) statistical metrics for the dimensional assessment when comparing against traditional method, c) translating project specifications or tolerance rules machine-readable as parameterized checks, d) to close the loop inside BIM such as visualization of quality results by color map, and e) link the acceptable elements to downstream such as structural analysis to ensure structural evaluations are conducted on the actual construction rather than on idealized geometry.

6. Contribution to the Theoretical and Practical Dimension

This research contributes to the theoretical basis of automated dimensional quality assessment by establishing a novel integration between 3D laser scanner and Building Information Modeling (BIM). This study enhances theoretical understanding by exploring point-cloud data processing and linking as-built geometry for dimensional assessment, creating a data-driven feedback loop between construction accuracy and engineering design validation.

Theoretically, this study introduces a hybrid verification paradigm that transition quality control assessment from traditional to dynamic, model-based verification systems. It strengthens the utilization of Scan-to-BIM workflows not only for documentation purpose but also for structural performance analysis, thereby expanding the scope of BIM beyond coordination to structural integrity evaluation.

This study also offers significant practical contributions to the field of construction quality control and structural verification, by providing a systematic, technology-based framework for stakeholders such as contractors and client to autonomously verify the dimensional quality control and actual structural performance of as-built structures, when third-party consultants are unavailable or impractical due to cost or time constraints. Practically, the workflow allows experts to document as-built conditions using 3D laser scanner and translate this data into BIM-compatible formats for precise comparison with design models. By utilizing this workflow, users can identify dimensional deviations, simulate real-world load conditions and assess whether the deviations compromise structural integrity. This reduces expensive rework, prevents structural failures and ensures greater compliance to engineering standards and safety codes.

7. Conclusions

This paper provides a thorough and methodical assessment of automated dimensional quality techniques. Initially, 139 publications were obtained from the Scopus database and further filtered, with the total number of publications involved being 90. Subsequently, three (3) key research themes were identified through scientometric analysis: a) reality capture to information integration, b) dimensional conformance, and c) automation to site domain. Due to high accuracy requirements for the dimensional quality assessment in as-built structures, 3D laser scanners are currently employed for the assessment, achieving millimetric standard deviation/tolerance requirements. This paper evaluated and assessed prior research, revealing that the integration of 3D laser scanners and BIM offers a revolutionary method for automated dimensional quality assessment, where the processes enable stakeholders to analyze dimensional deviation/tolerance, ensuring enhanced accuracy, efficiency, and automation in quality control. The implementation significantly reduces dependence on human verification and improves data-informed decision-making in construction. In conclusion, this paper is significant for future research and

applications in automated quality dimensional assessment of as-built structures.

Acknowledgements

The authors would like to express sincere appreciation to all individuals who provided constructive feedback and support throughout the development of this paper. Their insight has contributed meaningfully to the refinement of the ideas presented in this paper. This work was supported by the Research Grant Hi-Tech (F4+), Q.J130000.4622.00Q65.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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