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Review

Structural Equation Modeling in Technology Adoption and Use in the Construction Industry: A Scientometric Analysis and Qualitative Review

Chuyou Fu [1], Jun Wang [2,*], Ziyi Qu [2], Martin Skitmore [3], Jiaxin Yi [4], Zhengjie Sun [5] and Jianli Chen [6]

1 School of Public Administration and Humanities, Dalian Maritime University, Dalian 116026, China
2 School of Management Engineering, Qingdao University of Technology, Qingdao 266520, China
3 Faculty of Society and Design, Bond University, Robina, QLD 4226, Australia
4 Yishui Campus, Linyi University, Linyi 276400, China
5 School of Accounting, Southwestern University of Finance and Economics, Chengdu 611130, China
6 Department of Civil Engineering, University of Utah, Salt Lake City, UT 84112, USA
* Correspondence: wangjun.gt@gmail.com

Abstract: Considering the emergence and adoption of various innovative technologies, the construction industry has undergone transformation into a more secure, highly efficient, and ecologically sustainable landscape. An increasing number of studies uses the structural equation modeling (SEM) method to explore the dynamics of technology adoption and use within the construction sector. Previous studies have mainly focused on qualitative analysis using the SEM method to analyze technology adoption and usage in the construction industry. This study, however, distinguishes itself from previous research by focusing on the SEM method itself and conducting a systematic analysis using scientometric methods. Based on a total of 140 relevant journal articles, this study adopts a scientometric analysis approach to conduct a holistic review encompassing sources, researchers, keywords, and highly cited documents. The research findings are as follows: (1) the primary focus of the current research topics is on BIM technology; (2) most studies employ cross-sectional SEM instead of longitudinal SEM; (3) there is a deficiency in the theoretical foundation for designing SEM in current research; and (4) the selection of either reflective or formative measures lacks sufficient rigor. Qualitative analysis is used to examine prevailing issues in research design and address the intricate technicalities and potential challenges inherent in the SEM method. Three research gaps and future directions are presented: diversifying regions of study and research topics, incorporating theoretical support for research design, and carefully choosing reflective or formative measures. The findings provide a comprehensive roadmap and valuable reference for future research in this field.

Keywords: construction industry; emerging technologies; technology adoption; structural equation modeling (SEM); scientometric analysis; innovative technologies

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1. Introduction

The construction industry, as a key pillar industry of a country or region, faces numerous pressures and challenges in the modern era. Such frequent issues as severe resource waste, low production efficiency, environmental contamination, and occupational safety incidents have jeopardized the construction industry's long-term development [1]. Emerging technologies (tools, modifications, or equipment that can help construction practitioners achieve certain goals, carry out specific tasks, or overcome new obstacles) have thus been regularly incorporated into design and construction practices [2,3]. Both promote the construction industry's healthy and sustainable development [4,5] and help practitioners improve.

Significant research has been conducted to date on adopting and using various technologies in the construction sector to create a safer, more productive, and more sustainable working environment. Wearing sensing devices, for example, can significantly improve the safety of front-line construction workers [6]. Promoting the use of social media [7] and building information modeling (BIM) [8] can boost construction productivity significantly. In the road construction industry, intelligent compaction (IC) or ground penetrating radar (GPR) applications can help quality managers improve job efficiency and quality [9]. Adopting green building technology (GBTS) is an important step toward long-term environmental, economic, and social sustainability in the construction industry [10]. Three-dimensional printing [11] and cloud computing [12] technology can reduce costs, preserve resources, develop industry production processes, and eliminate over-reliance on labor.

Structural equation modeling (SEM) has been used in an increasing number of studies due to its greater ability to estimate effects. Compared to other methods, SEM is a useful technique for assessing complex theoretical relationships among multiple variables [13], widely applied in the field of construction for technology adoption. Ahmed et al. use partial least squares (PLS)—SEM in analyzing questionnaires distributed to 1200 construction companies to study the impact of interoperability-related factors, determinants, and barriers in adopting BIM technology in Malaysia's construction industry [14]. PLS-SEM is used by Al-Hashmy et al. to investigate the impact of a computerized accounting information system (CAIS) on construction firm performance, finding that most of it is mediated by innovation [15]. Etemadi et al. investigate the factors influencing architecture professionals' use of social media for work-related knowledge sharing using covariance-based (CB)—SEM [7].

SEM has the advantage of not requiring all variables to be observable and not assuming that all variables are error-free measurements [16,17]. It can model and estimate the complex relationship between multiple dependent variables and independent variables at the same time, use multiple indicators to indirectly measure the unobservable concepts under consideration, and account for the estimation relationship and measurement errors of observed variables (OVs) [17,18]. When dealing with structures and investigating mediating and regulating effects, SEM is frequently superior to multiple regression [19]. Furthermore, the study of technology adoption and use is essentially social research because it involves the analysis of people's behavioral intentions [20], and dealing with the difficulty of quantifying such social science issues as human motivation, perception, and attitude is often the major advantage of using SEM [21]. This makes it a commonly chosen technique for analyzing technology adoption and use in both the private and public sectors [22].

Despite the increasing popularity of using SEM to analyze technology adoption and use in the construction sector [7,14,15,23], existing publications can be expanded or improved. Most studies use the SEM method to assess the impact of multiple variables on technology adoption in the construction field, but little attention has been paid to SEM itself, and there are many issues in the design of the model. Essential rules are sometimes violated or ignored [24,25]. For example, the principle of using 10 times the maximum number of paths for any structure in the external model [26] is not always followed. Furthermore, despite the multivariate normality of data being a required assumption for CB-SEM, some studies fail to test and report it, resulting in such problems as an inflated goodness of fit [27]. Furthermore, theories should be used to define individual constructs. All latent variables (LVs) should be present in a hypothesized model [28–31]. Some studies, however, do not provide adequate theoretical support for selecting measurement items and developing appropriate hypotheses. As a result, a comprehensive and critical review is required to summarize existing research, identify common errors, and direct future work using SEM to examine technology adoption and use in the construction industry.

Previous reviews [2,32–38] have contributed significantly to the current body of knowledge. Despite its growing popularity, they do not pay attention to SEM. Furthermore, most review articles are manual and qualitative, with only a few employing a scientometric analysis approach to conduct a systematic approach. According to recent research, humans are better at acquiring and interpreting domain knowledge when presented in graphical formats [39,40]. To bring the situation up to date, the present study employs the science mapping approach, which uses graphical representation to reveal the inherent relationships involved. Science mapping is a powerful bibliometric technique used to understand and monitor the structure and evolution of the SEM-related research field in order to identify the relationships among authors, disciplines, and studies [41]. To supplement previous qualitative work, this approach allows to conduct a quantitative analysis for discovering technology applications in the construction sector using SEM. This study offers several contributions: It aids scholars in achieving a comprehensive understanding of the literature direction concerning the use of SEM methods in the field of construction technology adoption and usage, identifies emerging and promising topics within the existing knowledge framework, and uncovers issues in current research that utilizes SEM methods, thereby facilitating improvements.

This review has the following specific research objectives, with a clear scope of focusing on studies that use the SEM approach to discover technology adoption and use in the construction industry: (1) analyzing sources, keywords, authors, and articles using a science mapping approach; (2) analyzing research works from both the research design and SEM technique perspectives; and (3) exposing existing research gaps and determining potential future research areas.

2. Research Methods

This section outlines the three-step review approach, which consists of a literature review, scientometric analysis, and a qualitative discussion. Quantitative analysis using scientometric methods quantifies the application of SEM in the field of construction technology adoption, while qualitative analysis provides current research references for relevant scholars. A comprehensive literature review assists researchers in related fields to better understand the development trends, existing issues, and future expectations of the topic. Figure 1 depicts the entire research methods procedure.

2.1. Literature Search

The literature search was carried out in three widely used academic databases (Web of Science, Scopus, and Engineering Village) using the query "(structural equation modeling) AND (construction industry) AND (technology)" to limit the topic to the use of SEM to reveal technology adoption in the construction industry. After narrowing the search criteria to journal articles published in English, a total of 2323 initial documents were identified. Duplicated documents were deleted, and the remaining article titles and abstracts were manually evaluated for further screening. This resulted in the elimination of items referring to industries other than construction (e.g., the chemical, manufacturing, shipbuilding, electrical and electronic, and automotive sectors), methods other than the SEM technique (e.g., Delphi, analytic hierarchy process, linear regression, and machine learning), and topics other than technology adoption and use (e.g., safety behavior, contractor selection, knowledge management, effective communication, and social interaction). Ultimately, 140 journal articles were chosen to form the literature sample for analysis.

2.2. Scientometric Analysis

The review's second stage includes scientometric analysis, a popular method for domain analysis and visualization [42]. This has been widely used to support systematic literature reviews in various aspects of building construction research (e.g., [43–47]). *VOSViewer* is a text-mining tool that generates network-based visualizations using distance metrics. Each node in the network can represent various data points, such as the source journal, author, organization, country, and keyword [48,49]. According to van Eck and Waltman, the proximity between nodes represents their degree of closeness, which can be quantified using various metrics such as co-authorship, shared references, and co-occurrence [50]. The 140 articles are entered into *VOSViewer* (1.6.20) to conduct the scientometric analysis, allowing the generation of results relating to the impact of journals, keywords, researchers, and articles in applying SEM to uncover technology adoption and use in the construction industry.

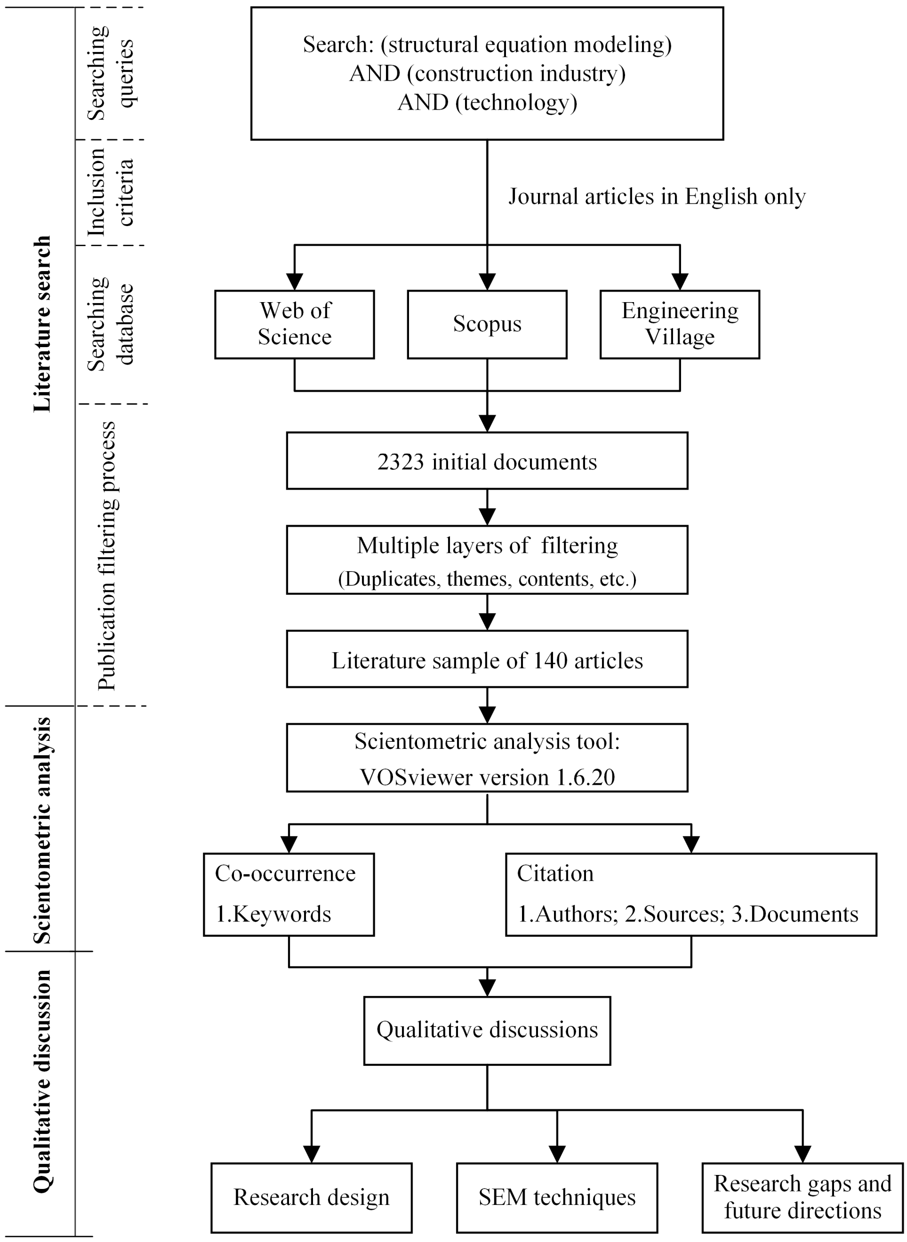

Figure 1. Workflow of the research methods.

2.3. Qualitative Discussion

Finally, a thorough qualitative discussion is held from various perspectives. The first section examines research design issues, such as the study's geographical scope and central focus, choice between cross-sectional and longitudinal study designs, and prevalent use of theoretical frameworks. The section on SEM techniques that follows discusses the technical complexities and potential pitfalls. This includes deciding between CB-SEM and PLS-SEM methodologies, distinguishing between reflective and formative measures, emphasizing the importance of theoretical foundations for both structural and measurement models, and debating mediation and moderation effects in SEMs. The final section identifies research gaps and potential directions for future research.

3. Results

This section presents the findings of science mapping based on the 140 articles which include journal analysis, researcher analysis, keyword analysis, and document analysis using *VOSViewer*.

3.1. Journal Source Analysis and Researcher Analysis

Figure 2 depicts journal sources as nodes, with the size of each node corresponding to the number of associated publications. The distance between nodes roughly reflects the extent to which they are cross-referenced [50], and the color of each node represents the clustering results, which is automatically determined by *VOSViewer* using the smart local moving average algorithm [22,49,50]. In terms of the number of articles, the visualizations show that *Engineering Construction and Architectural Management* (18 documents) as well as *Sustainability* (18 documents) make the most significant contributions, followed by the *Journal of Construction Engineering and Management* (12 documents) and *Buildings* (11 documents).

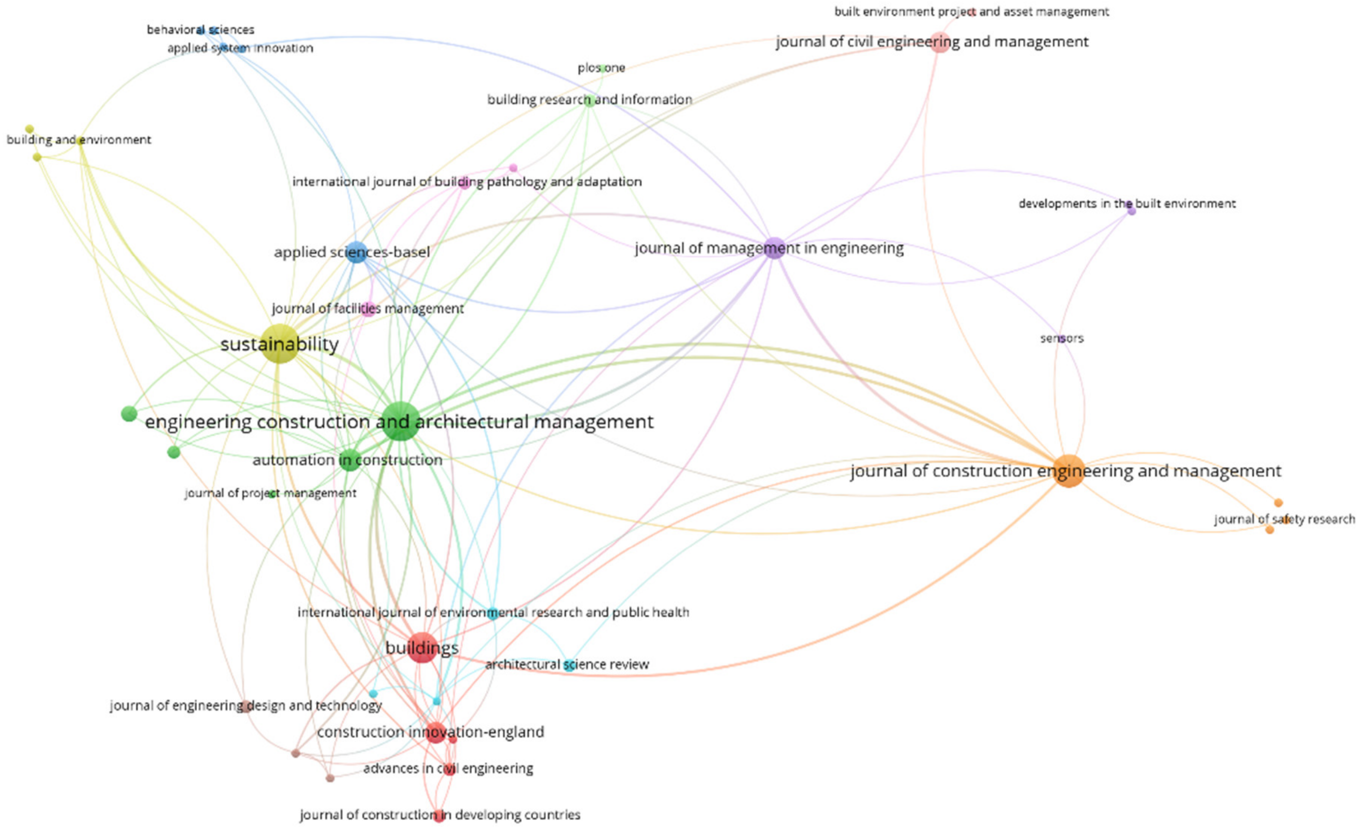

Figure 2. Visualization of journals.

Table 1 summarizes the quantitative metrics of most productive journals, highlighting the highest total citation counts for *Automation in Construction*, *Engineering Construction and Architectural Management*, *Sustainability*, *Journal of Management in Engineering*, and *Journal of Construction Engineering and Management*. A normalized citation metric is introduced to counter the potential bias of older documents receiving more citations. This is obtained by dividing a document's citation count by the average citation count of all documents using VOSViewer [48]. The recipients of the most normalized citations are *Engineering Construction and Architectural Management* and *Sustainability*.

Table 1. Quantitative metrics of most productive journals.

Journals	Number of Publications	Total Citations	Average Publication Year	Average Citations	Normalized Citations	Average Normalized Citations
Engineering Construction and Architectural Management	18	312	2021	17.33	16.90	0.94
Sustainability	18	194	2021	10.78	15.87	0.88
Journal of Construction Engineering and Management	12	112	2021	9.33	8.14	0.68
Buildings	11	24	2022	2.18	4.55	0.41
Applied Science	6	42	2021	7.00	6.62	1.10
Automation in Construction	6	511	2011	85.17	7.63	1.27
Journal of Management in Engineering	6	187	2021	31.17	8.48	1.41
Construction Innovation	5	41	2020	8.20	2.38	0.48
Journal of Civil Engineering and Management	5	50	2019	10.00	2.13	0.43
Architectural Engineering and Design Management	3	26	2021	8.67	2.17	0.72
Journal of Facilities Management	3	25	2022	8.33	5.91	1.97

Researchers are producers of knowledge, and a thorough analysis of researchers' collaborative network relationships as well as countries can help explore their related research efforts to capture the application domains of SEM in the construction field, especially in recent dominant areas.

Figure 3 depicts the number of articles ($\geq$2) published by individual researchers. Each researcher is represented as a node in this diagram, with the node's size corresponding to the number of citations the researcher has received. The distance between nodes represents the number of times two researchers have cited each other. This visual representation identifies the researchers who have received the most citations, including Seulki Lee (4 documents, 240 citations), Jungho Yu (4 documents, 240 citations), Changwan Kim (2 documents, 231 citations), Hyojoo Son (2 documents, 231 citations), and Nicholas Chileshe (3 documents, 194 citations). Table 2 summarizes the quantitative metrics of the highly cited researchers, with Nicholas Chileshe and Ahmed Kineber emerging as the top normalized citation recipients.

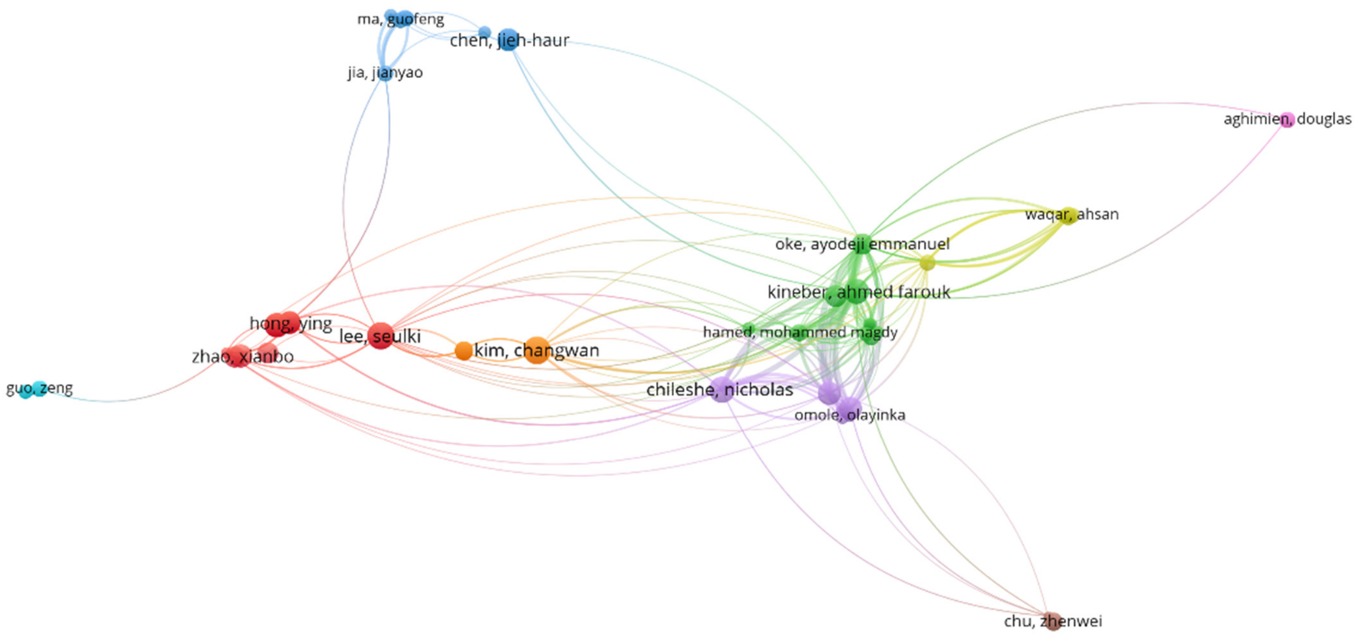

Figure 3. Visualization of researchers.

Table 2. Quantitative metrics of the highly cited researchers.

Researcher Name	Number of Publications	Total Citations	Average Publication Year	Average Citations	Normalized Citations	Average Normalized Citations
Lee, Seulki	4	240	2017	60.00	3.54	0.89
Yu, Jungho	4	240	2017	60.00	3.54	0.89
Kim, Changwan	2	231	2013	115.50	2.92	1.46
Son, Hyojoo	2	231	2013	115.50	2.92	1.46
Chileshe, Nicholas	3	194	2019	64.67	16.59	5.53
Kineber, Ahmed	15	164	2022	10.93	30.10	2.01
Jeong, David	1	154	2015	154.00	2.03	2.03
Aibinu, Ajibade A.	1	145	2010	145.00	2.00	2.00
Al-Lawati, Ahmed Murtadha	1	145	2010	145.00	2.00	2.00
Lee, Sungwook	1	124	2016	124.00	1.63	1.63

Figure 4 illustrates the collaboration network among researchers from different geographical regions, where each region is represented by a node, and the connections between nodes reflect the collaboration relationships between regions. The thickness of the connections between nodes reflects the strength of collaboration between the corresponding publications. In terms of productivity and impact, Australia (26 documents, 869 citations), China (51 documents, 640 citations), and South Korea (11 documents, 591 citations) are the top-producing regions. This indicates their significant contributions to enriching and advancing the application of SEM in the adoption of technology in the construction field. In terms of collaboration strength, researchers from Malaysia, Nigeria, and Saudi Arabia have the strongest collaboration relationships with researchers from other geographical regions.

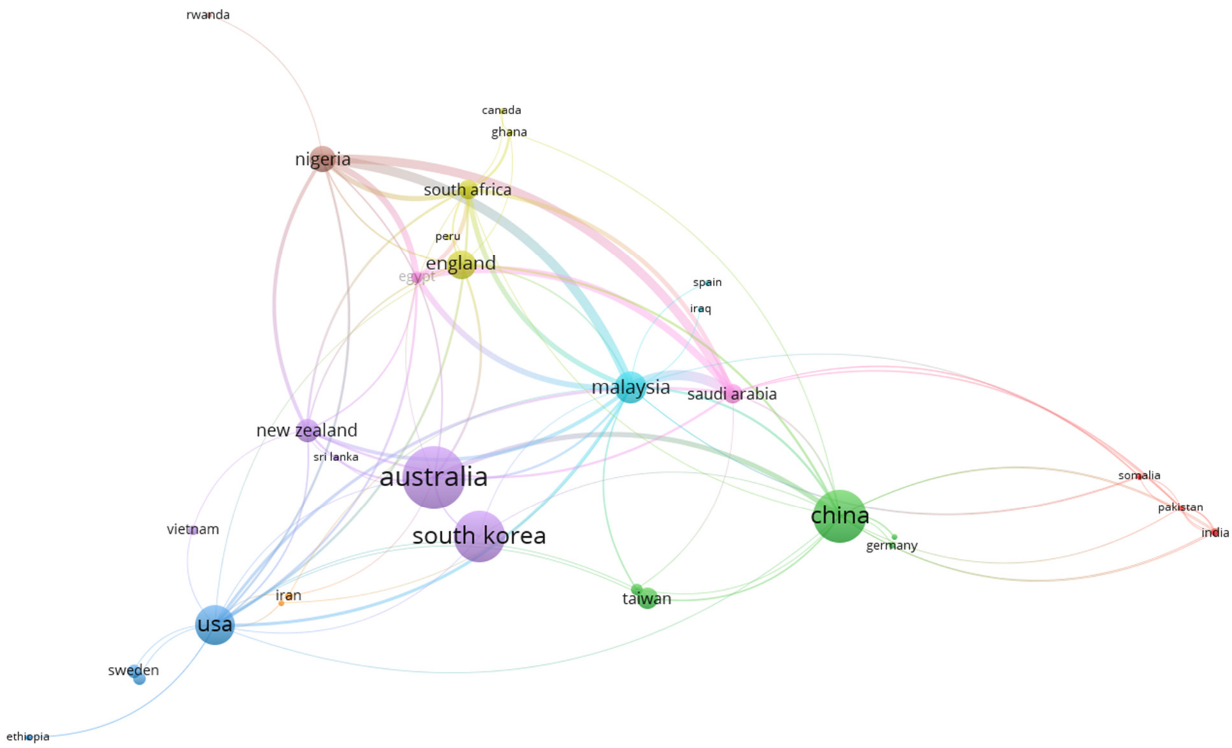

Figure 4. Visualization of co-authorship network for geographical regions.

3.2. Researchers, Keywords, and Document Analysis

Keywords are short phrases that represent the core content of the article. Keyword analysis is crucial because scientific publications contain valuable textual information that can represent the primary interests and hotspots of specific fields [51]. This analysis takes into account both Author Keywords (keywords that are manually entered by authors) and Keywords Plus (keywords that are automatically suggested by programs). To ensure consistency, manual text data preprocessing is used to standardize the writing formats of various semantically similar expressions. For example, terms such as 'building information modeling (BIM)', 'BIM', and 'building information modeling' are all treated as synonymous with 'BIM'.

Following the establishment of a minimum keyword occurrence threshold of three in *VOSViewer*, 120 out of 711 keywords are chosen and visualized in Figure 5. Nodes with bigger sizes signify keywords that appear more frequently. As indicated in the timeline legend, the average year of occurrence is represented by the node color, and the distance between nodes generally reflects how frequently two terms appear together. Notably, the top 10 most frequently occurring keywords are 'bim' (44), 'adoption' (38), 'structural equation modeling' (38), 'technology' (36), 'management' (36), 'construction industry' (29), 'pls-sem' (27), 'implementation' (26), 'construction' (22), 'user acceptance' (21), 'barriers' (21), and 'information technology' (18). The number of times each keyword appears is indicated in parentheses.

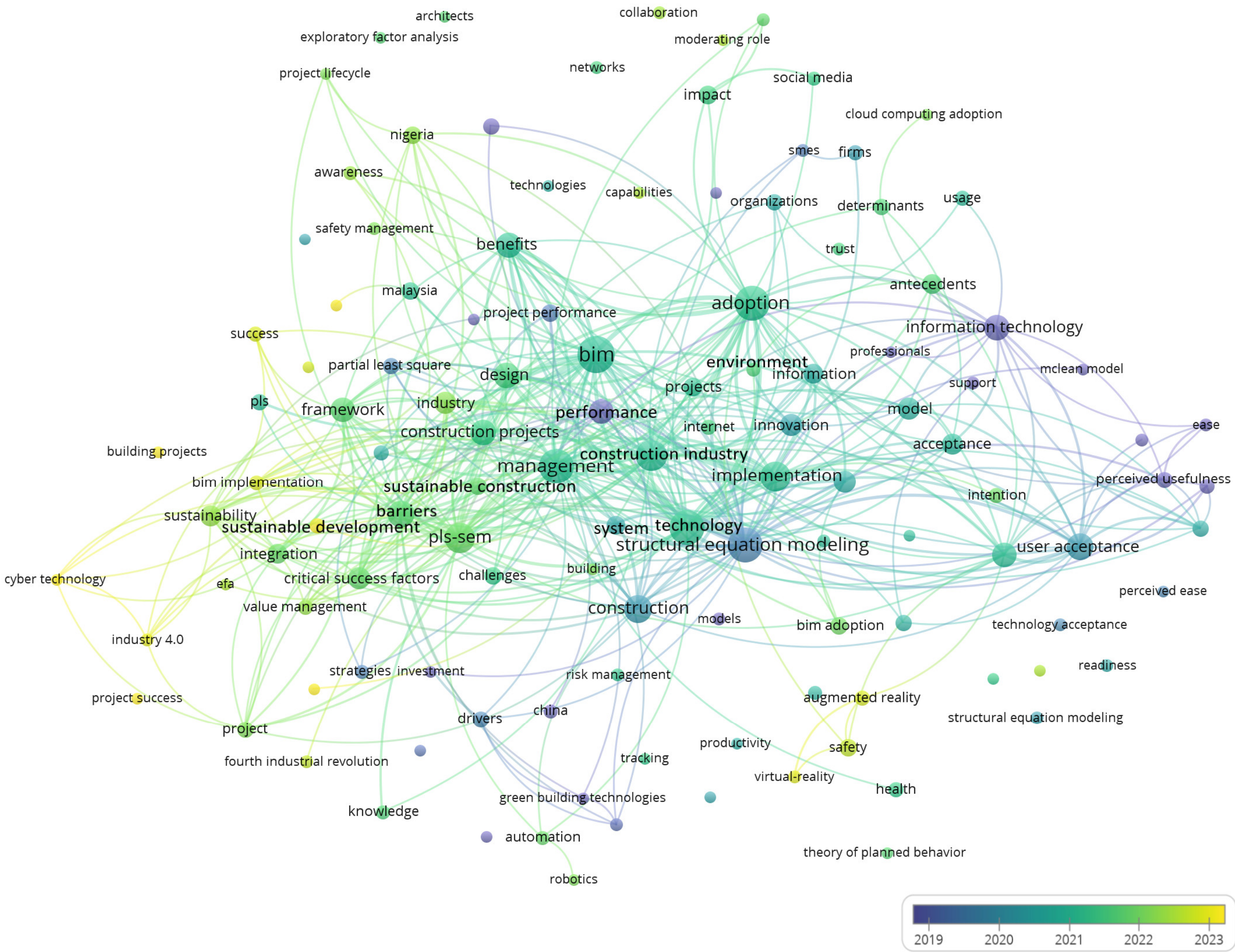

Figure 5. Visualization of keywords.

Finally, the articles are used to analyze the literature sample. Figure 6 depicts the 71 documents obtained via *VOSViewer*, with at least five citations per article. Each node in this representation stands for a specific article, and the size of the node reflects the overall number of citations that article has received. The closer the nodes are, the more related they are, with the distance between them roughly reflecting the frequency at which they cite each other.

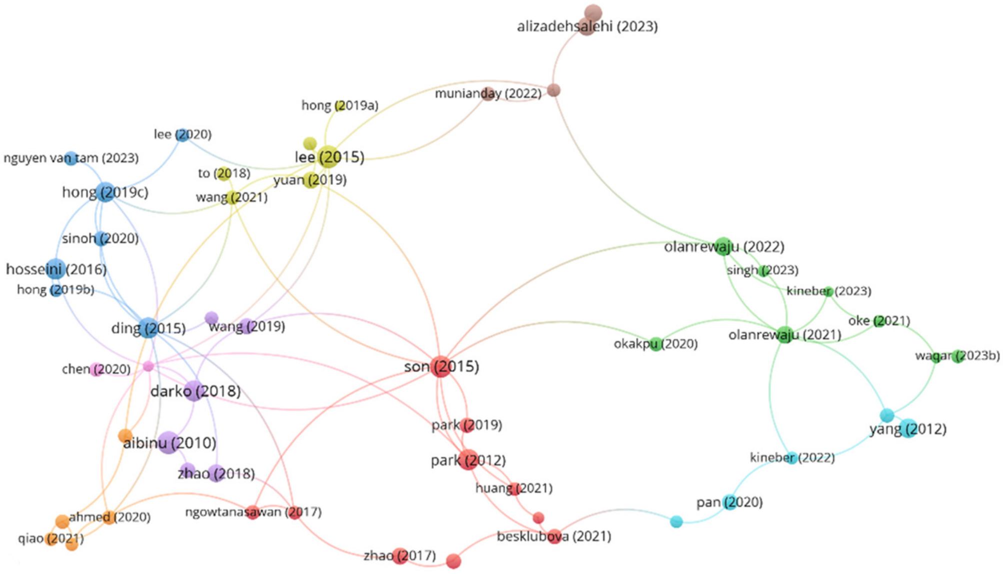

Figure 6. Visualization of documents.

Table 3 shows the titles and citation counts for the 20 most-referenced documents, arranged in descending order by citation number. The frequency of citations underscores the enduring popularity of BIM in using SEM [52–63].

Table 3. Twenty most-referenced articles in the literature sample.

Article	Title	Total Citations	Normalized Citations
Lee et al. [52]	BIM Acceptance Model in Construction Organizations	154	2.03
Aibinu et al. [64]	Using the PLS-SEM technique to model construction organizations' willingness to participate in e-bidding	145	2.00
Son et al. [53]	What drives the adoption of building information modeling in design organizations? An empirical investigation of the antecedents affecting architects' behavioral intentions	124	1.63
Darko et al. [65]	Influence of barriers, drivers, and promotion strategies on green building technologies adoption in developing countries: The Ghanaian case	111	3.56
Park et al. [66]	Investigating the determinants of construction professionals' acceptance of web-based training: An extension of the technology acceptance model	107	1.28
Ding et al. [54]	Key factors for the BIM adoption by architects: a China study	102	1.34
Hosseini et al. [55]	BIM adoption within Australian Small and Medium-sized Enterprises (SMEs): an innovation diffusion model	96	2.77
Hong et al. [60]	BIM adoption model for small and medium construction organizations in Australia	80	3.02
Yang et al. [67]	Assessing impacts of information technology on project success through knowledge management practice	72	0.86
Lee et al. [68]	Success model of project management information system in construction	71	0.85
Olanrewaju et al. [63]	Modelling the relationship between Building Information Modeling (BIM) implementation barriers, usage, and awareness on building project lifecycle	55	10.76

Table 3. *Cont.*

Article	Title	Total Citations	Normalized Citations
Alizadehsalehi and Yitmen [69]	Digital twin-based progress monitoring management model through reality capture to extended reality technologies (DRX)	53	15.09
Zhao et al. [59]	Risk paths in BIM adoption: empirical study of China	48	1.54
Olanrewaju et al. [62]	Modelling the Impact of Building Information Modelling (BIM) Implementation Drivers and Awareness on Project Lifecycle	43	3.06
AlizadeSalehi et al. [58]	Modelling and analysis of the impact of BIM-based field data capturing technologies on automated construction progress monitoring	39	1.25
Yuan et al. [61]	Promoting Owners' BIM Adoption Behaviors to Achieve Sustainable Project Management	35	1.32
Zhao et al. [57]	Modelling paths of risks associated with BIM implementation in architectural, engineering and construction projects	35	1.75
Wong et al. [70]	Exploring the acceptance of PPE by construction workers: An extension of the technology acceptance model with safety management practices and safety consciousness	30	2.13
Hosseini et al. [56]	Sustainability by Information and Communication Technology: A paradigm shift for construction projects in Iran	26	2.77
Pan and Pan. [71]	Understanding the Determinants of Construction Robot Adoption: Perspective of Building Contractors	25	1.67

4. Qualitative Discussion

This section offers a thorough qualitative assessment of research design perspectives, SEM techniques, research gaps and future directions, which comes after the scientometric analysis and outcomes in Section 3.

4.1. Research Design

4.1.1. Regions of Study

When surveys and questionnaires are the primary means of data collection for SEM, the region frequently plays a pivotal role in influencing social research outcomes. Among the 140 articles in the sample, 138 explicitly stated the regions from which their data were gathered, with the vast majority (134 articles) focusing on a single region. Within this subset of 134 articles focused on specific regions, China (42 articles) received the most attention, followed by Nigeria (20), Malaysia (14), Australia (9), South Korea (7), Ghana (5), Hong Kong (4), India (3), Iran (3), and South Africa (3). Only 4 of the 140 articles [57,68,71,72] contained research conducted across multiple regions.

Several highly cited studies explicitly stated that their research findings should be interpreted within the specific regions where the data were collected, emphasizing the difficulty in generalizing their findings due to the research's region-specific nature [52,55–57,59,61–63,65,70,71].

4.1.2. Research Topics

BIM has become a focal point of study due to its increasing popularity and widespread use throughout the project life cycle. Of the 140 articles reviewed, 64 are primarily concerned with BIM from two perspectives: investigating the major factors, barriers, and drivers influencing BIM adoption among various stakeholders (e.g., owners, architects, engineers, contractors) at various organizational levels (e.g., large, medium, or small) and across diverse regions; and evaluating the impact of BIM usage on such emerging areas as sustainable building construction [73–77], project performance [78,79], and the construction supply chain [80,81]. The remaining frequently studied topics are digitalization (9 articles), information communication technologies (ICT) (8), social media (6), robotic automation (5), blockchain (4), cloud technology (4), 3D printing (3), cyber technology (3), green building technology (3), internet of things (IoT) (3), virtual reality or augmented reality (VR/AR) (3), and web-based training or management systems (WBTMS) (3).

In the construction industry, the adoption of various technologies—including BIM, 3D printing, and IoT—is driven by the need to enhance productivity and efficiency, improve quality, and meet market demands. Scholars frequently utilize SEM methods to investigate the factors influencing the adoption of these technologies and to assess the beneficial impacts of SEM methods on the adoption practices across construction projects of varying scales. This growing application of SEM methods in the construction sector underscores their relevance and utility. Nevertheless, numerous studies still face significant challenges in designing SEM methods effectively.

4.1.3. Cross-Sectional vs. Longitudinal Studies

Cross-sectional SEM is used to examine data collected at a single point in time, focusing on the relationships between variables at that time [82], while longitudinal SEM analyses data collected over multiple time points—most commonly to investigate how variables evolve or to evaluate causal relationships that may emerge over time [83]. While cross-sectional studies can establish associations between variables, it is difficult to determine whether these associations reflect true causal relationships. In such cases, incorporating time lags into the research design becomes critical, indicating the need for a longitudinal component [24]. Only 2 of the 140 articles were longitudinal studies. In comparison, 23 of the remaining 138 articles acknowledged their cross-sectional nature's limitations. These recognize the importance of future research incorporating longitudinal studies to further expose the causal relationships between variables in their models.

4.1.4. Theoretical Frameworks and Key Constructs

Many theories and models have been developed to help understand the rationale for accepting or rejecting new technology in various industries, including construction. Within the literature sample, five theoretical models stand out: the Technology Acceptance Model (TAM) [84], Technology–Organization–Environment (TOE) [85] theory, Theory of Planned Behavior (TPB) [86], Innovation Diffusion Theory (IDT) [87], and Unified Theory of Acceptance and Use of Technology (UTAUT) [88], utilized in thirty-one, eight, seven, five, and five articles, respectively. These theoretical frameworks have aided researchers in identifying key constructs and developing causality hypotheses, thereby advancing the evolution of information system theories and behavioral sciences, particularly through the construction industry lens. Table 4 summarizes the main concepts and descriptions of each commonly used theory.

Table 4. Frequently used theories and their key constructs with descriptions.

Theory	Key Constructs	Description
TAM	1. Perceived usefulness 2. Perceived ease of use	1. "The degree to which a person believes that using a particular system would enhance their job performance" [89] 2. "The degree to which a person believes that using a particular system would be free of effort" [89]
TOE	1. Technological context 2. Organizational context 3. Environmental context	1. "All of the technologies (both already in use and available in the marketplace) that are relevant to the firm" [90] 2. "Characteristics and resources of the firm, including linking structures between employees, intra-firm communication processes, firm size, and the amount of slack resources" [90] 3. "The structure of the industry, the presence or absence of technology service providers, and the regulatory environment" [90]
TPB	1. Attitude toward behavior 2. Subjective norm 3. Perceived behavioral control	1. "The degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question" [91] 2. "The perceived social pressure to perform or not to perform the behavior" [91] 3. "The perceived ease or difficulty of performing the behavior" [91]

Table 4. *Cont.*

Theory	Key Constructs	Description
IDT	1. Relative advantage 2. Compatibility 3. Complexity 4. Trialability 5. Observability	1. "The degree to which an innovation is perceived as being better than the idea it supersedes" [92] 2. "The degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential" [92] 3. "The degree to which an innovation is perceived as relatively difficult to understand and use" [92] 4. "The degree to which an innovation may be experimented with on a limited basis" [92] 5. "The degree to which the results of an innovation are visible to others" [92]
UTAUT	1. Effort expectancy 2. Performance expectancy 3. Social influence 4. Facilitating conditions	1. "The degree of ease associated with the use of the system" [88] 2. "The degree to which an individual believes that using the system will help them to attain gains in job performance" [88] 3. "The degree to which an individual perceives that important-others believe they should use the new system." [88] 4. "The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system." [88]

4.2. SEM Techniques

SEM uses diverse model types to delineate relationships between observed variables, aiming to quantitatively test theoretical hypotheses. Fundamentally, SEM combines features of path models with confirmatory factor models, enabling the simultaneous inclusion of both latent and observed variables. SEMs are categorized into two types: the structural model, which focuses on relationships between latent variables, and the measurement models, which relate latent variables to their observed indicators [93].

4.2.1. CB-SEM vs. PLS-SEM

Two types of SEMs are commonly used in construction-related research: CB-SEM and PLS-SEM. These are complementary but differ in estimation methodology, data distribution assumptions, and research objectives. CB-SEM, for example, uses methods such as maximum likelihood to estimate model parameters based on OV covariance matrices [94]. As a result, CB-SEM necessarily assumes that data follow a multivariate normal distribution. On the other hand, PLS-SEM employs the partial least squares technique to estimate model parameters by maximizing the OVs' explained variance [17], which is less sensitive to data distribution assumptions and provides greater robustness [95]. Furthermore, CB-SEM is better suited for confirmatory analysis aimed at testing theories, while PLS-SEM is more suited to exploratory analysis, especially when dealing with smaller sample sizes [95].

Figure 7 depicts the timeline-based choice between CB-SEM and PLS-SEM in the reviewed literature. Only 1 of the 140 articles in the sample failed to specify the method. The graph shows a growing trend of using SEM, while PLS-SEM is shown to be more popular than CB-SEM, especially in 2022 and 2023.

In total, 23 of the 140 articles did not specify the software programs used to build SEM. The following software tools were frequently used in the remaining 117 articles: for CB-SEM, AMOS [96] in 46 articles and LISREL [97] in 5; and for PLS-SEM, SmartPLS [98] in 62 articles, with PLS Graph and Warp PLS each used in 2 articles. PLS-SEM was preferred over CB-SEM for a variety of reasons, the most common of which is its ability to handle non-normally distributed data (mentioned 28 times), suitability for exploratory studies (26 times), better handling of small sample sizes (19 times), ability to accommodate formative constructs (5 times), and superior predictive capabilities (3 times). It is worth noting that even though CB-SEM requires data to conform to multivariate normality, only 10 of the 59 CB-SEM studies disclosed that they conducted a normality test on their collected data. Most of these studies either omitted or provided insufficient disclosure about these tests, although failing to satisfy this assumption can lead to overestimating the model's goodness of fit [27].

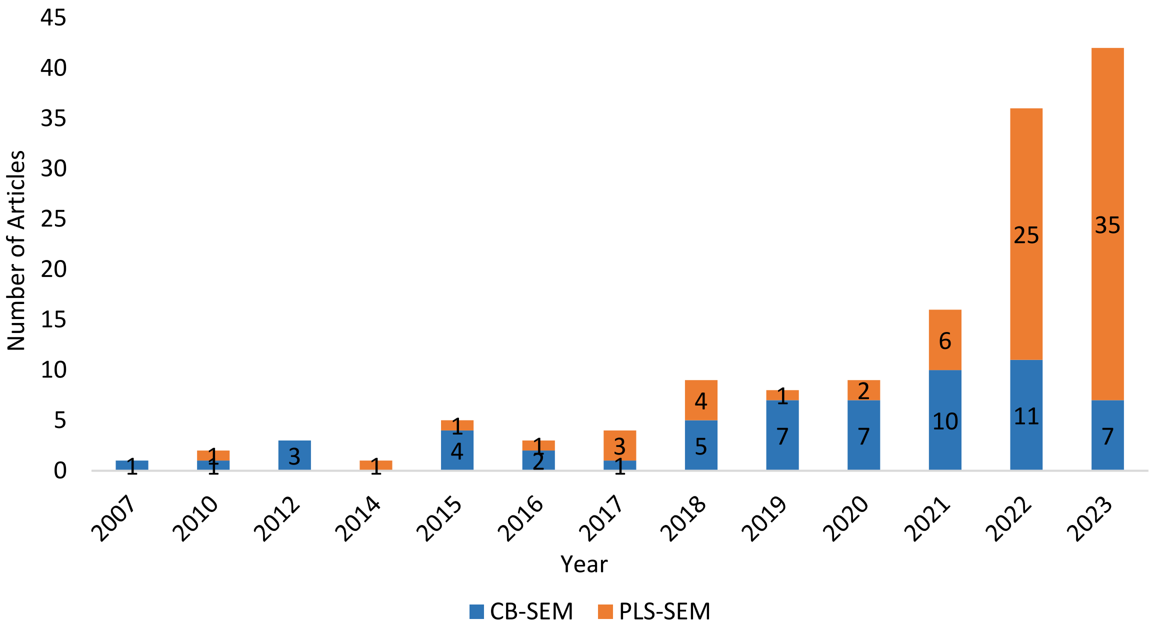

Figure 7. Timeline-based choice between CB-SEM and PLS-SEM.

4.2.2. Reflective vs. Formative Measures

Within the measurement model, two potential relationships exist between the OVs and the LV: reflective and formative. Variations in the LV cause covariance among OVs in reflective measures, establishing a causal direction from the LV to the Ovs [99]. As a result, because they all manifest the same latent construct, OVs are expected to have correlations. Evaluating the construct validity of reflective measures, including reliability assessments, convergent validity, and discriminant validity [100], is often critical. On the other hand, formative measures contend that OVs collectively influence changes in the LV, thereby establishing a causal pathway from the OVs to the latent construct [99]. In contrast to reflective measures, the expectation for correlations among OVs in formative models is less stringent because they may or may not be correlated. In addition, multicollinearity among OVs can pose a significant challenge and should therefore be tested with such measures as the variance inflation factor [25]. Figure 8 depicts a graphical representation of both reflective and formative measures.

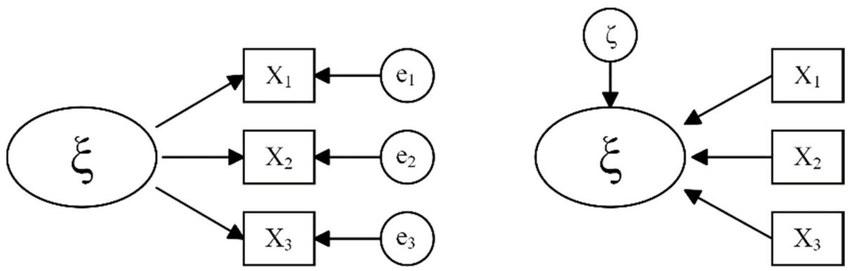

Figure 8. Reflective (on the left) and formative (on the right) measures illustration.

A total of 3 of the 140 articles reviewed built first-order formative measurement models. Furthermore, six articles used first-order reflective models but second-order formative measurement models. The remaining 131 articles only built reflective measures. However, in all the remaining cases, the assumption that the relationships between LVs and OVs are inherently reflective raises concerns. Some articles, for example, developed a reflective measure that linked job satisfaction (the LV) to various OVs, such as job security, ability development, income level, and worker safety. However, whether a formative measure is more appropriate is debatable because each OV captures different aspects or attributes of job satisfaction. As a result, they are not always related. The true causal relationship between OVs and LVs needs to be carefully considered because the choice of reflective versus formative measures has significant implications for overall goodness of fit in the context of measurement model misspecification [98]. Although traditional CB-SEM is well known for its compatibility with reflective measures [24], it is also important to note that formative measures can be integrated into CB-SEM [101]. In addition, given the emergence and growing popularity of PLS-SEM, researchers should feel more encouraged to include formative measures in their future work. Table 5 summarizes the differences between reflective and formative measures.

Table 5. Differences between reflective and formative measures.

	KEY Constructs	Description
LV-OV relationship	OVs are manifested by the LV	OVs jointly define the LV
Causality direction	From LV to OVs	From OVs to LV
Interchangeability	OVs are interchangeable	OVs need not be interchangeable
Intercorrelation	OVs are expected to be intercorrelated	OVs can have any pattern of intercorrelation
Multicollinearity	Multicollinearity is a virtue	Multicollinearity should be ruled out

4.2.3. Theories for Structural and Measurement Models

Theories at the structural and measurement model levels should be used as the primary foundation in SEMs to hypothesize causal relationships and define individual constructs [28–31]. A causal relationship in hypotheses that lack proper justification or theoretical foundations can be undermined [102]. As a result, hypothesized causal relationships in structural models need to be articulated transparently, based on theoretical support, previous research, scientific knowledge, logical reasoning, or other empirical evidence [103]. Furthermore, using factor analysis, whether exploratory or confirmatory, within LV measurement models requires a solid theoretical foundation that reveals prior knowledge about the OVs associated with LVs [104]. Without this theoretical underpinning, factor analysis risks becoming nothing more than a dimensionality reduction tool. To ensure accurate interpretation of LVs, SEM requires measurement models to be grounded in prior knowledge. Based on established theories, studies should also examine the relationships between OVs and LVs [105,106].

Following the literature review, it was clear that 30 of the 59 CB-SEM articles lack adequate theoretical support for their measurement models, and 28 lack the necessary theoretical foundations for their structural models. Similarly, 24 of the 80 PLS-SEM articles lack theoretical support for their measurement models, and 43 face a similar shortfall in theoretical support for their structural models. In summary, 38% of the reviewed articles need more theoretical support for their measurement models, while 51% need more theoretical support for their structural models.

Furthermore, 54 of the 140 articles in the sample contain models with an OV:LV ratio of less than three. This is significant because Kline's three-variable principle recommends a minimum of three OVs to adequately identify a measurement model. Models with single-indicator constructs representing a single LV with only one OV are included in five articles [82]. However, single-indicator constructs are only considered appropriate when the OV perfectly represents the LV [24]. Using such constructs is typically risky because they perform less effectively than multi-item constructs in most scenarios [107].

Finally, because CB-SEM is frequently associated with theory testing and confirmation tasks, it is critical to summarize, delineate, and effectively integrate pre-existing theories concisely. Although PLS-SEM is particularly useful for promoting theory development, it is still useful to encapsulate theories that can provide partial support for the hypotheses within the structural model and aid in selecting measurement items, thereby contributing to the provision of theoretical support.

4.2.4. Mediation and Moderation Effects

Path analysis was created to quantify the relationships between multiple variables and effectively test and develop structural hypotheses of mediation and moderation effects [31]. In SEM, the mediation effect assumes that an LV can influence another LV directly and indirectly through a third LV (the mediator) [103]. In contrast, the moderation effect investigates how a third LV (the moderator) influences the relationship between two LVs, typically through interaction [108]. Mediators and moderators are frequently used in research design, especially when dealing with complex and unresolved issues in theory development [24]. Identifying and quantifying mediation and moderation effects can significantly contribute to the existing body of knowledge, making these variables focal points in research design across a wide range of scenarios [109]. Furthermore, as situations become more complex, the need to understand mediated moderation and moderated mediation effects becomes more apparent [108].

Only four articles in the sample examined and discussed the moderation effect. For example, Yang et al. find that team relationships moderate the relationship between knowledge management and project success [67]. According to Jia et al., formal knowledge governance moderates the relationship between learning inertia and BIM integration intention [110]. Furthermore, Yang and Huang find that the platform type (traditional vs. cloud-based) moderates the relationship between information platform usage and construction capability [111]. Furthermore, Jiang et al. find that team member support moderates the relationship between the connective use of mobile information and communication technology (MICT) and the technology–work conflict [112].

In terms of mediation effects, a larger subset of 19 out of 61 articles in the sample that included mediation effects in their structural models conducts tests and discusses these mediation effects.

4.3. Research Gaps and Future Directions

While using SEM methods to investigate technology adoption and usage in the construction industry is becoming more popular, it is critical to recognize and address several limitations. This recognition of limitations can aid in identifying research gaps and defining future research directions.

4.3.1. Diversifying Region of Study and Research Topic

A sizable portion of existing research focuses on developing regions, with China alone accounting for 30% of all reviewed articles. Surprisingly, fewer studies relate to developed regions than those of China. As a result, there is a clear need for future research to delve into the adoption and utilization of technology in other prominent construction markets, such as the United States, India, Japan, Indonesia, and Australia, especially given the difficulty in generalizing findings from region-specific studies to other contexts. Furthermore, researchers are encouraged to conduct more comprehensive multi-region studies, allowing for a more robust comparison of technology adoption and usage patterns across different regions.

In terms of research topics, BIM has taken the lead, accounting for 45% of all articles reviewed. This is largely due to its growing popularity and proven benefits, which have attracted the interest of researchers and industry professionals. Given the construction industry's increasing digitization, researchers are encouraged to investigate other emerging and underutilized technology categories such as drones, digital twins, IoT, blockchain, 3D printing, and AR/VR. This encouragement is especially important because many of these technologies can be integrated with BIM to improve the design and construction processes further.

4.3.2. Incorporating Theoretical Support for Research Design

Even though numerous theories have been developed to analyze the adoption and utilization of technology across various industries, construction industry research continues to face significant challenges. This stems from the lack of well-founded theories at both the structural and measurement model levels. To ensure the trustworthiness and interpretability of research findings, it is critical that hypothesized causal relationships be firmly rooted in theoretical underpinnings and measurement models anchored in existing knowledge when using SEM in research. However, 51% of the reviewed articles lacked adequate theoretical support to establish structural models, and 38% lacked the necessary theoretical foundation for their measurement models. As a result, researchers are strongly encouraged to review and incorporate existing theories to aid in formulating hypothetical causal relationships and selecting appropriate measurement indicators, particularly when employing the CB-SEM method, which well-established theoretical frameworks should ideally support. A thorough examination and appropriate incorporation of existing theories may also aid in avoiding the use of single-indicator constructs.

4.3.3. Carefully Choosing Reflective or Formative Measures

Because each type of measure is subject to different rationalities and statistical tests, the choice between reflective and formative measures should be based primarily on the causal relationships between LVs and OVs. Incorrectly configuring the measurement model can significantly impact the overall model's goodness of fit. Currently, the vast majority of studies use reflective measures. Nevertheless, upon a comprehensive examination of these reflective studies, situations emerge where formative measures might be more suitable when each OV captures distinct LV attributes. As a result, these OVs are not necessarily intercorrelated. Given the PLS-SEM method's growing popularity, researchers should feel less hesitant about incorporating formative measures. In essence, they should carefully deliberate on the relationships between the LV and its OVs, recognizing that formative measures may be more appropriate in some contexts.

5. Conclusions

This study adopts a three-stage approach, systematically reviewing 140 journal articles that utilize SEM to investigate technology adoption and usage in the construction industry, employing scientometric and qualitative analysis methods. The scientometric analysis includes co-authorship analysis, citation analysis, keyword analysis, and literature theme analysis. The results reveal that (1) there is a noticeable growth trend in research over the past two years, with a preference for using PLS-SEM over CB-SEM; (2) in terms of the number of published articles, leading contributors include *Engineering Construction and Architectural Management*, *Sustainability*, *Journal of Construction Engineering and Management*, and *Buildings*; (3) Ahmed Kineber is the most prolific researcher, having published the highest number of articles in this field, while Seulki Lee, Jungho Yu, Changwan Kim, Hyojoo Son, and Nicholas Chileshe have received the highest number of citations; (4) a visualization of keyword chronological analysis identifies and discusses the most frequently cited articles, providing insights into their significance and impact; (5) current research topics primarily focus on BIM, with most studies utilizing cross-sectional SEM and overlooking longitudinal SEM. The analysis results can assist scholars in familiarizing themselves with SEM-related literature and guide researchers in addressing existing issues for improvement.

A detailed qualitative discussion covers research design scopes, SEM technical intricacies, research gaps, and future research directions. In terms of research design, the current body of research focuses primarily on the application of BIM in developing regions. As a result, there is a noticeable lack of studies investigating other emerging technologies, more developed regions, and multiple regions. Furthermore, most studies in this field are cross-sectional. Longitudinal studies, on the other hand, cover a longer time span and may provide valuable insights into causal relationships. It is critical to recognize that the feasibility of both longitudinal and multi-regional studies is frequently dependent on the availability of relevant data. TAM, TOE, TPB, IDT, and UTAUT are examples of theoretical frameworks that originated in other domains and have been primarily used to discover technology adoption and usage in the construction industry.

In terms of the SEM technique, there is a growing trend favoring the use of PLS-SEM over CB-SEM, particularly in the last two years. Reflective measures continue to dominate SEM constructs, emphasizing the importance of researchers taking into account the relationships between LVs and their OVs in future research, especially since the increasingly popular PLS-SEM technique is better suited for formative measures. Notably, many articles lack the theoretical underpinning required for developing causal hypotheses at the structural model level and selecting appropriate indicators at the measurement model level. Furthermore, only a few articles delve into discussions concerning mediation and moderation effects, which are critical aspects of SEM that should be considered to make valuable contributions to the existing body of knowledge. Several research gaps and future directions are identified based on the review findings, including diversifying study areas and research topics, incorporating theoretical support for research design, and carefully selecting reflective or formative measures.

This review-based study combines an innovative scientometric analysis method with traditional qualitative discussion to provide a comprehensive overview of research investigating technology adoption and utilization in the construction industry via SEM. It adds to the existing body of knowledge by (1) using a science mapping approach to visualize and investigate the intricate relationships among journal sources, keywords, authors, and documents in the literature sample; (2) examining and discussing existing research by outlining research design issues and addressing the technical complexities and potential challenges associated with SEM techniques; and (3) identifying current research gaps and highlighting prospective avenues for future research, thereby providing valuable insights for both researchers and practitioners.

It should be noted that the current study has some limitations. First, the literature sample only includes English-language journal articles obtained from the Web of Science, Scopus, and Engineering Village databases. Second, the analysis of relevant literature on the adoption of SEM in the construction field is conducted solely based on the titles, author keywords, and abstracts without examining the core content. Finally, for VOSviewer, the outputs of the analysis may fluctuate slightly when using different processing thresholds. Future research would benefit from broadening the inclusion criteria to encompass other publication sources such as conference articles and books, as well as articles published in languages other than English, and exploring additional databases to provide additional valuable insights.

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Abbreviations

BIM	Building information modeling
CAIS	Computerized accounting information system
CB	Covariance-based
GBTS	Green building technology
GPR	Ground penetrating radar

IC	Intelligent compaction
ICT	Information communication technologies
IDT	Innovation diffusion theory
IoT	Internet of things
LVs	Latent variables
MICT	Mobile information and communication technology
OVs	Observed variables
PLS	Partial least squares
SEM	Structural equation modeling
TAM	Technology acceptance model
TOE	Technology–organization–environment
TPB	Theory of planned behavior
UTAUT	Unified theory of acceptance and use of technology
VR/AR	Virtual reality or augmented reality
WBTMS	Web-based training or management systems

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