



Artificial Intelligence, Building Information Modeling, and Digital Twins in Smart Cities: A Systematic Bibliometric and Thematic Review of Research Trends and Integration Maturity

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ABSTRACT

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The convergence of artificial intelligence (AI), building information modeling (BIM), and digital twin (DT) is increasingly shaping data-driven smart city development, yet the literature remains fragmented across disciplinary and application domains. This study conducts a hybrid review combining Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-based systematic screening, bibliometric mapping, and thematic synthesis to examine research trends, intellectual structures, integration maturity, and future directions. Searches of Scopus, Web of Science, and IEEE Xplore for publications from 2020 to 2025 yielded 342 records; after duplicate removal and eligibility screening, 44 studies were retained. Bibliometric analysis using VOSviewer identified four major keyword clusters spanning digital technologies, smart city planning, sustainability and energy, and computational methods. Thematic synthesis further identified five recurring domains: data-driven decision-making and real-time monitoring, sustainable urban development and energy efficiency, interoperability and technology integration, smart infrastructure management, and visualization and simulation. An integration-maturity analysis showed that conceptual studies dominated the literature (52%), followed by one-way data-flow studies (23%) and bidirectional synchronization (18%), while only 7% reported closed-loop, AI-driven DTs. Publication activity increased sharply in 2024–2025, indicating growing interest but limited operational maturity. The review synthesizes these findings into a conceptual framework and research agenda focused on interoperability, data standardization, privacy, scalable urban deployment, and empirically validated AI-enabled feedback loops for future smart city DTs.

1. INTRODUCTION

The idea of smart cities has emerged as a transformative approach to tackle the issues brought about by rapid urban growth. Central to this development is the merging of artificial intelligence (AI), building information modeling (BIM), and digital twin (DT) technologies. This collaborative integration is reshaping urban environments, making cities more efficient, sustainable, and attuned to the needs of their residents. The combination of such technologies is being considered critical to improving urban management and sustainability [1, 2]. The combination of systematic, bibliometric, and thematic reviews as a methodological approach chosen in the given paper is strong, as it represents the strategy of mirroring used in different fields to trace knowledge structures, determine research trends, and summarize the findings [3, 4]. The integration of AI, BIM, and DT is changing the architecture, engineering, and construction (AEC) sector and allowing the development of so-called smart cities where information technology can enhance and optimize the performance of cities and make them more sustainable [5]. The transformation is an answer to important problems of complex urban

ecosystems that are subject to fast development and multilateral problems [2]. The central point of this paradigm shift is DTs, the virtual copies of real objects or systems that provide city managers with increased opportunities [1]. They are deeply integrated with the help of machine learning (ML) for predictive analysis and the Internet of Things (IoT) to collect data in real time, which is a significant contribution to the development of smart cities [6]. BIM is a data-centric approach to project management powered by both digital building information and a digital backbone of the AEC industry [7]. It has also become a revolutionary technology, especially in civil infrastructure works [8]. The connection between BIM and AI methods is essential, as AI is used to automate and process huge volumes of information in unpredictable and dynamic settings [9]. As an example, AI-based applications can suggest BIM elements to improve the efficiency of designs, despite the problems related to vast element libraries [10]. Rather than replacing BIM, DTs build upon it: BIM supplies the static, geometric, and semantic model of an asset, while a DT extends this model with live sensor data and bidirectional synchronization to provide a dynamic, real-time reflection of the physical asset [11]. To

avoid conflating these technologies, this review treats BIM as a data source, AI as the analytical layer, and DT as the integrative construct that combines both with real-time measurement; a study is treated as addressing genuine three-way integration only where all three elements are jointly present, rather than where BIM or AI is discussed in isolation or only two of the three technologies interact [11]. It enables two-way communication between a physical object and a digital object, and this makes them able to make informed decisions [12]. DTs have the ability to combine both the BIM data and real-time sensor data of IoT devices and AI-based analytics to monitor, predict, and optimize infrastructure performance, which increases resilience to environmental, social, and operational challenges [13, 14]. DTs, which will be developed in smart cities, are inspired by AI models to provide insights into their functionality and performance [15]. AI is the analytical core of smart city projects, providing computational intelligence to deal with vast amounts of city data. It aids in predictive maintenance, traffic optimization, and improving the safety of people by making data-driven decisions. The BIM software supplements AI by enabling the creation of intricate computerized models of the constructed environment, which enhances cooperation and the accuracy of the design, construction, and maintenance processes [16]. DT technology develops dynamic virtual representations of tangible assets and systems that allow city managers to simulate scenarios, predict the results, and optimize the work in real-time. Although the merging of AI, BIM, and DT has the potential for transformation, the discipline of research is divided as shown in Figure 1. The existing body of literature tends to discuss these technologies individually or in small disciplinary contexts, resulting in a disjointed view of the overall

possibilities they hold. The consequences of this fragmentation include considerable gaps in knowledge, including the lack of quantitative mapping of the interdisciplinary research space, the lack of any systematic thematic synthesis between technical and social aspects, and the absence of integrated structures to inform further research and practice.

To address these gaps, this paper will attempt to systematically identify and map the scientific literature on the intersection of AI, BIM, and DTs on smart cities, perform a bibliometric analysis to reveal publication patterns and collaboration relationships, conduct a thematic analysis to determine some of the central research topics and issues, and come up with a synthesized framework of how future research can be undertaken. Consistent with the journal's emphasis on computational methods and experimental measurement, this review pays particular attention to the computational-measurement loop that underlies urban DTs: the static, geometric parameters supplied by BIM, the real-time measurements captured through IoT sensors or laser scanning, the computational (AI-based) processing of these combined data streams, and the validation of resulting predictions against observed conditions [16]. Where the reviewed literature reports this loop explicitly, it is highlighted in the thematic and bibliometric findings that follow. The originality of this review is that it has a hybrid approach, an extensive intellectual mapping, and a research agenda. The study presents a comprehensive perspective of the field by using a combination of systematic, bibliometric, and thematic analysis, provides a synthesized framework of the AI–BIM–DT convergence, and can be utilized by the researchers, urban planners, and policymakers in developing smart cities.

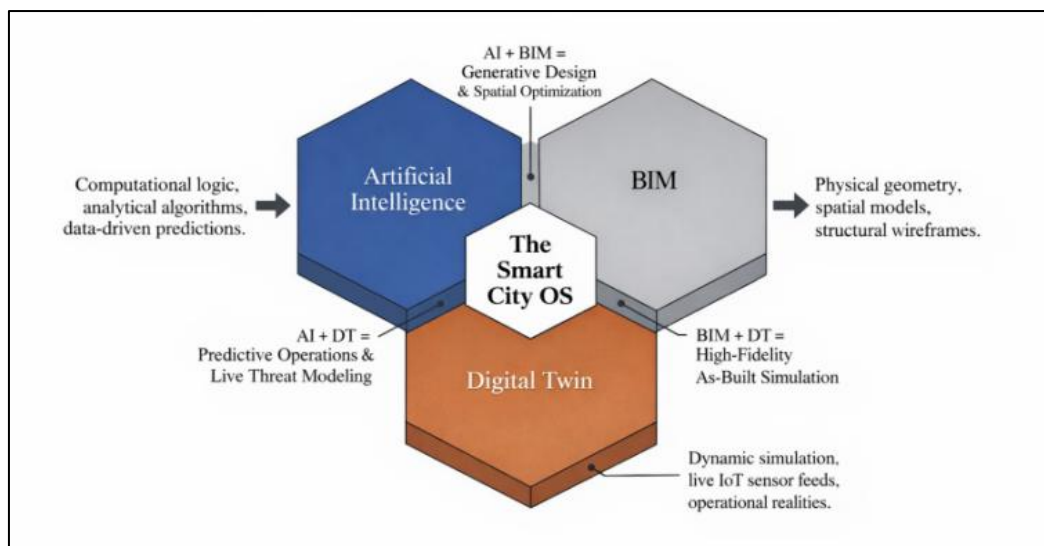


Figure 1. Integration of artificial intelligence (AI), building information modeling (BIM), and digital twin (DT) technologies for a unified smart city operating system

2. METHODOLOGY

The methodology employed for this review paper on the integration of AI–BIM–DT in smart cities is a combination of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-based systematic review, bibliometric analysis, and thematic synthesis. This multifaceted method is used to ensure an organized and clear mechanism for the

identification, screening, and inclusion of relevant studies. The literature search and selection process are based on the systematic review, which uses the PRISMA protocol. The next step would then be bibliometric analysis, which is used to quantitatively evaluate patterns of publication, citation networks, and trends of research in the field to get the information about how the research changes and what impacts it has over the years. Lastly, thematic synthesis will be applied

to qualitatively analyze and synthesize the contents of a set of chosen studies to determine essential themes, concepts, and relationships. Such a combined approach enables a comprehensive understanding of the research advancement in AI, BIM, and DT technologies applied to smart cities, which encompasses both the quantitative and qualitative aspects of the existing literature.

As shown in Figure 2, the hybrid review workflow proceeds through four linked stages: a PRISMA-guided systematic search and screening of the literature, a bibliometric mapping of publication and citation patterns, a thematic synthesis of the

screened studies, and the consolidation of findings into a conceptual framework. This staged workflow allows the quantitative mapping of the AI–BIM–DT research landscape (bibliometric analysis) to be interpreted alongside a qualitative understanding of how these technologies are applied (thematic analysis), with each stage building on the inclusion criteria established by the PRISMA process. However, as with any literature-based synthesis, the approach remains subject to data-integration, privacy, and standardization limitations that are discussed further in the Conclusion.

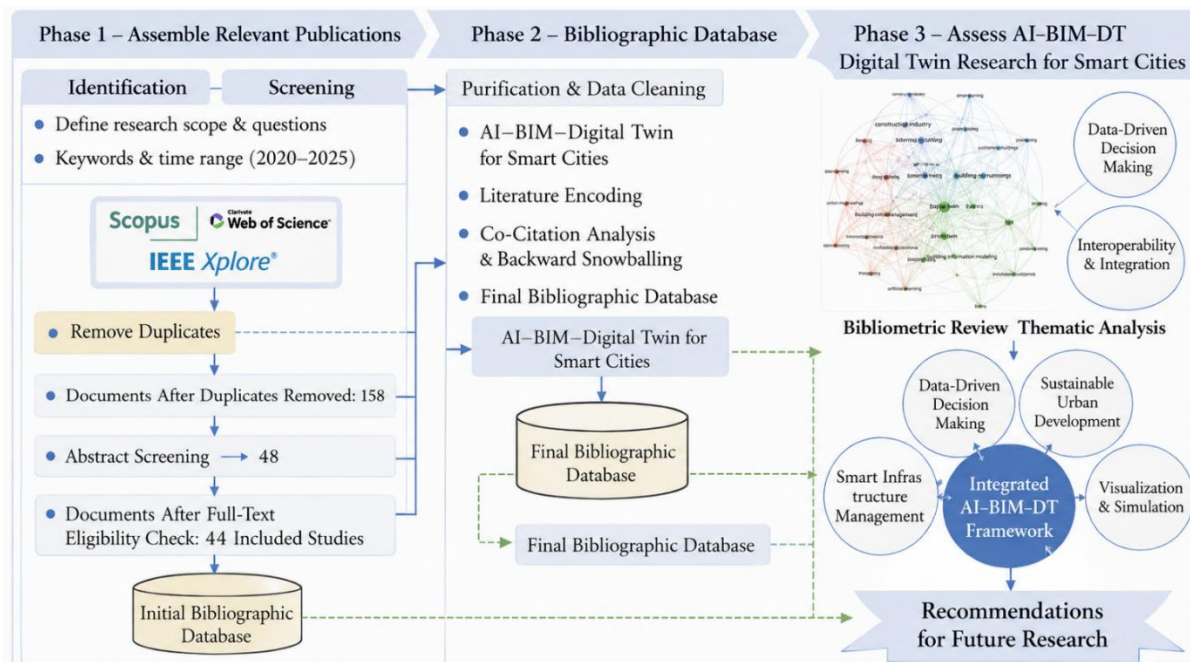


Figure 2. Workflow of hybrid systematic review and analysis for artificial intelligence (AI)–building information modeling (BIM)–digital twin (DT) integration

2.1 PRISMA systematic review

This review's focus is on the integration of AI–BIM–DT in smart cities and its applicability, and on identifying how far the current research has achieved its goal, to draw a research agenda that can lead future research on the integration of AI–BIM–DT in smart cities. Thus, the search was performed on papers that addressed the AI–BIM–DT on a city scale in three major search engines, which are among the largest databases for multidisciplinary research: Scopus, Web of Science, and IEEE Xplore. Thus, the search strings were widened to include built environment, urban environment, and district. Using the topic filter in Web of Science, which leads to finding data in Title, Abstract, and Keywords, the search strings for Scopus, Web of Science, and IEEE Xplore were identical. Therefore, we utilized the same string that could generate as many outputs as possible that were related to our main topic. As a result, 342 published article outputs were generated. The search covered the publication period from 2020 to 2025 and was restricted to the Title, Abstract, and Keywords fields (or the closest equivalent field available in each database); the exact search-execution date is not restated here but will be confirmed in the search-methods documentation to be supplied during revision.

2.1.1 Inclusion and exclusion criteria

The inclusion criteria were: (i) peer-reviewed journal

articles; (ii) published in English; (iii) reporting empirical studies, systematic reviews, or frameworks addressing the integration of AI, BIM, and DT for a smart city or urban digital context. The exclusion criteria were: (i) editorials, conference papers, and preprints; (ii) non-English-language publications; (iii) purely theoretical work without empirical or applied validation; (iv) studies that addressed the development of an AI–BIM–DT solution for a single building or a small infrastructure project in isolation, rather than at a smart city or urban digital scale. These criteria were applied consistently across Scopus, Web of Science, and IEEE Xplore. The systematic literature search was conducted through the University's electronic library/discovery platform, covering the period 2020–2025. The following Boolean search string was consistently applied across the databases as shown in Table 1, with minor syntax adjustments where required by the respective database: ("Digital Twin" OR "Digital Twins") AND ("BIM" OR "Building Information Modeling") AND ("AI" OR "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Smart City" OR "Smart Cities" OR "Urban Digital"). Searches were performed within the Title, Abstract, and Keywords fields, or the nearest equivalent fields available in each database. The filtering functions available within the university library platform were subsequently applied to refine the search results according to publication year, subject area, document type, language,

source type, and publication stage, where applicable. Records retrieved from the three databases were consolidated, and duplicate publications arising from overlapping database coverage were identified by comparing bibliographic information and removed manually, with only one instance of each publication retained; this removed 184 of the 342 records, leaving 158 unique records. Following deduplication, a two-stage manual screening procedure was performed: title/abstract screening against the eligibility criteria, followed by full-text examination of potentially relevant articles. The title/abstract and full-text screening was conducted by one reviewer using the predefined eligibility criteria; consequently, procedures for resolving disagreements between multiple reviewers were not applicable, and this single-reviewer design is acknowledged as a limitation of the review process. During title/abstract screening, 110 of the 158 records were excluded: 58 were conference papers, editorials, or preprints; 29 focused exclusively on a single building or small infrastructure project; 18 were purely theoretical studies without validation; and 5 were non-English-language publications. This left 48 articles for full-text assessment, during which 4 further studies were excluded: 2 were purely theoretical studies without validation, and 2 were limited to single-building or small-scale infrastructure applications. This review includes papers that integrate all three technologies (AI, BIM, and DT) within the context of smart cities, while excluding those that address only two of the three technologies (e.g., AI with BIM, or BIM with DT). Ultimately, 44 studies satisfied the eligibility requirements and were included in the final qualitative and quantitative synthesis, as shown in Figure 3.

Table 1. Data collection and search keywords

Database	Search Queries	Outputs
Scopus	Keywords (("Digital Twin" OR "Digital Twins") AND ("BIM" OR "Building Information Modeling") AND ("AI" OR "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Smart City" OR "Smart Cities" OR "Urban Digital"))	206
Web of Science	Keywords (("Digital Twin" OR "Digital Twins") AND ("BIM" OR "Building Information Modeling") AND ("AI" OR "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Smart City" OR "Smart Cities" OR "Urban Digital"))	95
IEEE Xplore	Keywords (("Digital Twin" OR "Digital Twins") AND ("BIM" OR "Building Information Modeling") AND ("AI" OR "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Smart City" OR "Smart Cities" OR "Urban Digital"))	41
	Total Searched Articles	342
Final articles selected for review	after eliminating duplicates and irrelevant Articles	44

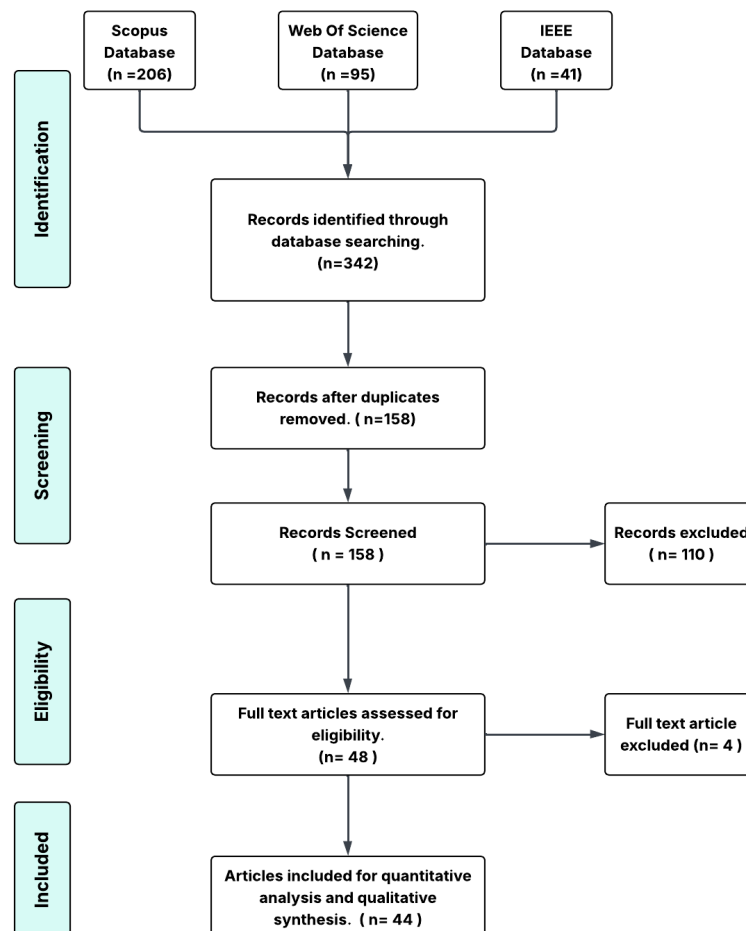


Figure 3. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram illustrating identification, screening, eligibility, and inclusion stages

Table 2. Summary of reviewed studies on artificial intelligence (AI), building information modeling (BIM), and digital twin (DT) integration, classified by integration tier and primary data source

Ref.	Application Focus	Integration Tier	Primary Data Source
[1]	DTs in smart cities (macro-scale bibliometric mapping)	Conceptual discussion	Bibliometric/citation records
[2]	Urban DT integration, challenges and directions	Conceptual discussion	Literature corpus
[5]	AI-BIM relationship for sustainable building	Conceptual discussion	Literature corpus
[6]	Consumer electronics in smart cities	Bidirectional synchronization	IoT/device sensor data
[7]	BIM+AI integration in AEC/FM industry	Conceptual discussion	Literature corpus
[8]	BIM applications in civil infrastructure	Conceptual discussion	Bibliometric/citation records
[9]	BIM + AI for smart construction management	Conceptual discussion	Literature corpus
[10]	Generative AI for energy systems/buildings	Conceptual discussion	Literature corpus
[11]	BIM and DT technologies in construction	Conceptual discussion	Literature corpus
[12]	Vision-based construction progress monitoring	One-way data flow	Site imagery/vision data
[13]	DT + AI for infrastructure resilience	Conceptual discussion	Literature corpus
[14]	3D interactive building operations (BIM + IoT + AI + MR)	Bidirectional synchronization	BIM model + IoT sensors
[15]	AI in DT models for stormwater infrastructure	Bidirectional synchronization	Sensor/hydrological data
[16]	Geospatial data management research	Conceptual discussion	Geospatial/GIS literature
[17]	DTs in built environment – definitions/applications/challenges	Conceptual discussion	Literature corpus
[18]	Automated BIM generation via deep learning	One-way data flow	Point-cloud/scan data
[19]	AI + BIM in construction	Conceptual discussion	Literature corpus
[20]	DTs in built environments (characteristics/applications)	Conceptual discussion	Literature corpus
[21]	Synergies between digital construction technologies for smart buildings/cities	Bidirectional synchronization	Multi-source building/city data
[22]	City DT technologies for sustainable smart city design	Conceptual discussion	Bibliometric/citation records
[23]	DTs in construction industry – concept/creation/services	Conceptual discussion	Literature corpus
[24]	Applied AI in smart buildings/cities	Conceptual discussion	Literature corpus
[25]	Differentiating DT from Digital Shadow	Conceptual discussion	Literature/conceptual
[26]	Smart Parks / Park Information Modeling	One-way data flow	GIS/park design data
[27]	CIM – data perspective	One-way data flow	Urban/geospatial datasets
[28]	Urban dynamics through DTs	Bidirectional synchronization	Urban/geospatial data
[29]	DTs of buildings – data-driven energy modeling	Bidirectional synchronization	Building energy/IoT data
[30]	Air quality modeling in DTs for green cities	One-way data flow	Air-quality sensor data
[31]	AI-enabled cognitive predictive maintenance of urban assets (CIM)	Full twin with AI-driven feedback	CIM + sensor data
[32]	Strategic approach to smart city development	Conceptual discussion	Policy/literature
[33]	IoT-enabled predictive analytics for smart city logistics (cybernetic feedback)	Full twin with AI-driven feedback	IoT logistics/sensor data
[34]	DT framework for built environment	Conceptual discussion	Literature corpus
[35]	DTs, BIM and AI in structural engineering	Conceptual discussion	Literature corpus
[36]	BIM + drone flyover data for building energy efficiency	One-way data flow	BIM model + drone/UAV data
[37]	Smart city technologies for real estate development	Conceptual discussion	Literature corpus
[38]	Data-driven net-zero carbon monitoring (GIS + BIM + remote sensing)	One-way data flow	GIS + remote-sensing data
[39]	Deep learning for predicting indoor temperatures (toward DT HVAC)	One-way data flow	Indoor sensor/temperature data
[40]	XR for smart building O&M	Conceptual discussion	Literature corpus
[41]	Sustainable design and BIM for construction project management (circular economy)	One-way data flow	BIM model data
[42]	DT publications in construction 2017–2023	Conceptual discussion	Bibliometric/citation records
[43]	DTs in supply chain operations using AI	Bidirectional synchronization	Supply-chain operational data
[44]	Urban DTs for smart cities – Herrenberg case study	Bidirectional synchronization	3D city model + citizen participation data
[45]	Web-based weather data into BIM via robotic process automation	One-way data flow	Web/weather API data
[46]	Integration of AI and DTs – simulation to autonomy	Full twin with AI-driven feedback	Literature corpus/simulation data

Note: AI = artificial intelligence, BIM = building information modeling, DT = digital twin, ML = machine learning, IoT = Internet of Things, HVAC = heating, ventilation, and air conditioning, CIM = City Information Modeling, GIS = geographic information system, XR = extended reality.

Table 2 synthesizes 44 studies drawn from the reviewed corpus and classifies each according to the depth of AI–BIM–DT data integration it reports, using a four-level integration tier taxonomy: (i) conceptual discussion, where AI, BIM, or DT concepts are discussed narratively without an operational data pipeline (ii) one-way data flow, where a single data source (e.g., a BIM model, point cloud, or geographic information system (GIS) layer) feeds a downstream process without feedback (iii) bidirectional synchronization, where the

physical asset and its digital representation exchange data continuously in both directions and (iv) full twin with AI-driven feedback, the most advanced tier, in which an AI/ML layer closes the loop by generating predictive or prescriptive actions back onto the physical system.

In terms of primary data sources, the corpus is dominated by literature-corpus and bibliometric/citation-record sources (consistent with the high share of conceptual-discussion papers), followed by a smaller but technically important

cluster of sensor- and IoT-derived sources (building energy, air quality, indoor temperature, and hydrological sensors) and geospatial sources (GIS, remote sensing, and point-cloud/UAV data) that underpin the one-way and bidirectional tiers. This pattern suggests a maturity gradient in the field: geospatial and BIM-based inputs are comparatively well established as one-way feeds into DTs, whereas real-time, bidirectionally synchronized sensor networks and especially AI-driven feedback loops remain comparatively nascent, pointing to a clear direction for future empirical work in this review.

2.2 Bibliometric analysis

In this quantitative bibliometric analysis, 44 articles have been selected for analysis, as illustrated in Table 1, and were chosen based on the PRISMA inclusion criteria after the filtering process. In this analysis, the high citation publication trend, the top ten authors, and the highly cited journals have been explained. With AI–BIM–DT technology for smart cities, the year-wise publication trend graph of articles from 2020 to 2025 has also been presented. Within the 2020–2025 search window and inclusion criteria applied here, no articles meeting the full AI–BIM–DT integration criterion were retrieved before 2020; earlier conceptual work relevant to individual components of this convergence exists but falls outside the defined search period and inclusion criteria, so its absence from the 44-paper sample reflects the review’s scope rather than an absence of prior research. After 2020, several papers were published, though with more limitations and research gaps, which are addressed in this review.

The bibliometric analysis was performed using VOSviewer (version 1.6.20). Bibliographic records exported from the combined Scopus, Web of Science, and IEEE Xplore search results were used as the citation database. Author keywords were selected as the unit of analysis for a co-occurrence

analysis, applying a minimum occurrence threshold of 3, full counting, and association-strength normalization; the clustering resolution was left at the VOSviewer default (1.00), and no thesaurus file was applied to merge synonymous or variant terms. Figure 4 presents the resulting keyword co-occurrence network, showing four thematic clusters (digital technologies; smart city/urban planning; sustainability/energy; and computational methods). The interpretation of these clusters, and of the citation and authorship patterns in Figure 5, is presented in Section 3 (Bibliometric Findings) rather than repeated here, to keep this subsection focused on methods.

An interconnected research landscape encompassing smart cities, digital technologies, and sustainable urban development has been presented through the bibliometric analysis. Four major thematic clusters have been identified in the VOSviewer visualization, each represented by distinct colors as shown in Figure 4. The blue cluster is identified as the largest and most central, based on research concerning digital technologies like DT, IoT, 3D modeling, and BIM, which have been highlighted as afforded by its contribution to data-driven urban systems. Smart cities, urban planning, and GIS have been related to the green cluster; practical applications and strategic development have been mentioned. Sustainability, energy conservation, life cycle management, and decision-making have been targeted in the red cluster based on long-term and environmental planning. The yellow cluster has been associated with new ways of computing and analysis, implying that they are becoming more and more used in the urban development processes. Close connections between these clusters, especially those related to DT, smart city, and BIM, have been witnessed, and these connections show the interdisciplinary character of this research field. The relative node sizes have also denoted the core role of DT, smart city, and BIM, representing a change to more integrated and technology-focused solutions to the challenges of complex city life.

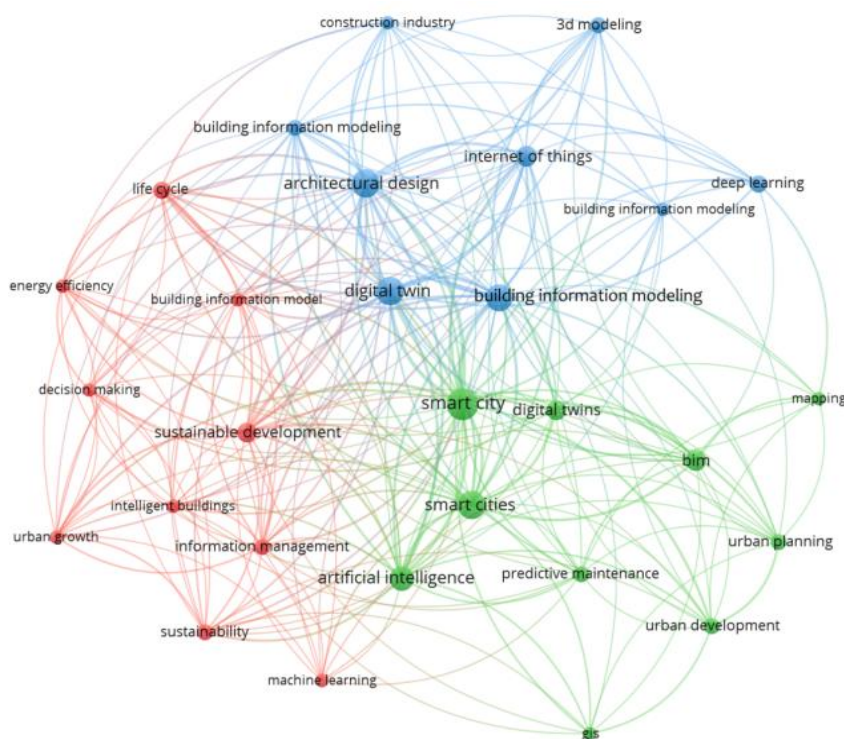
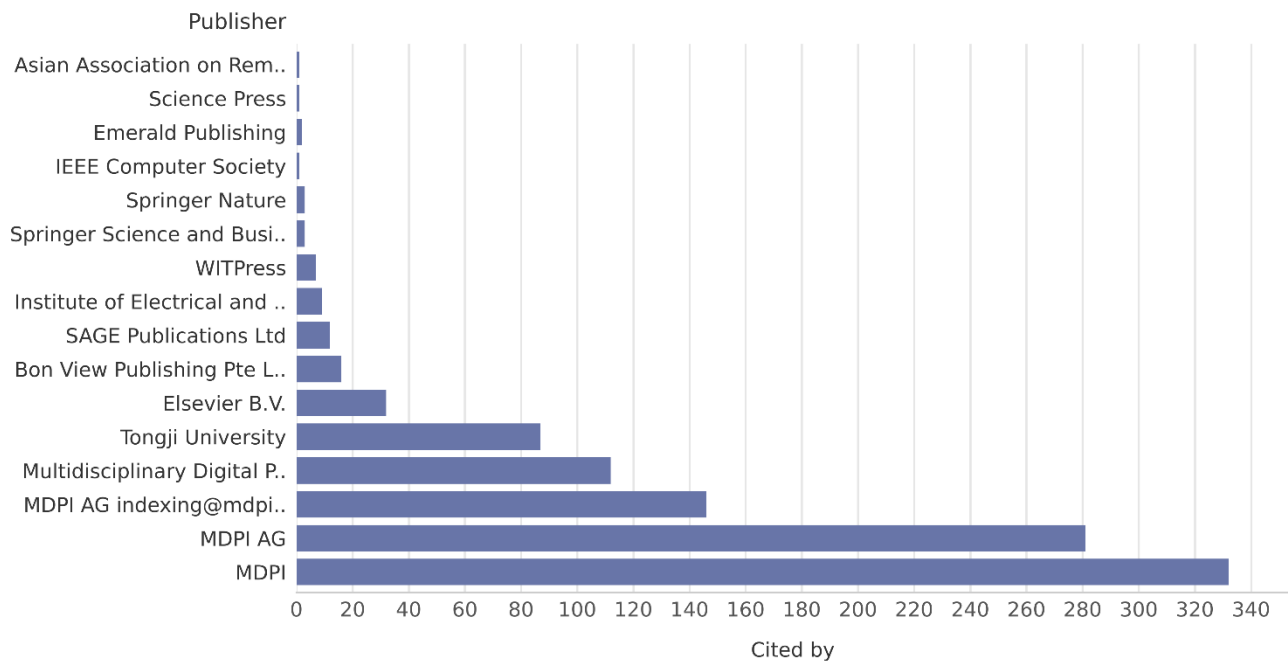
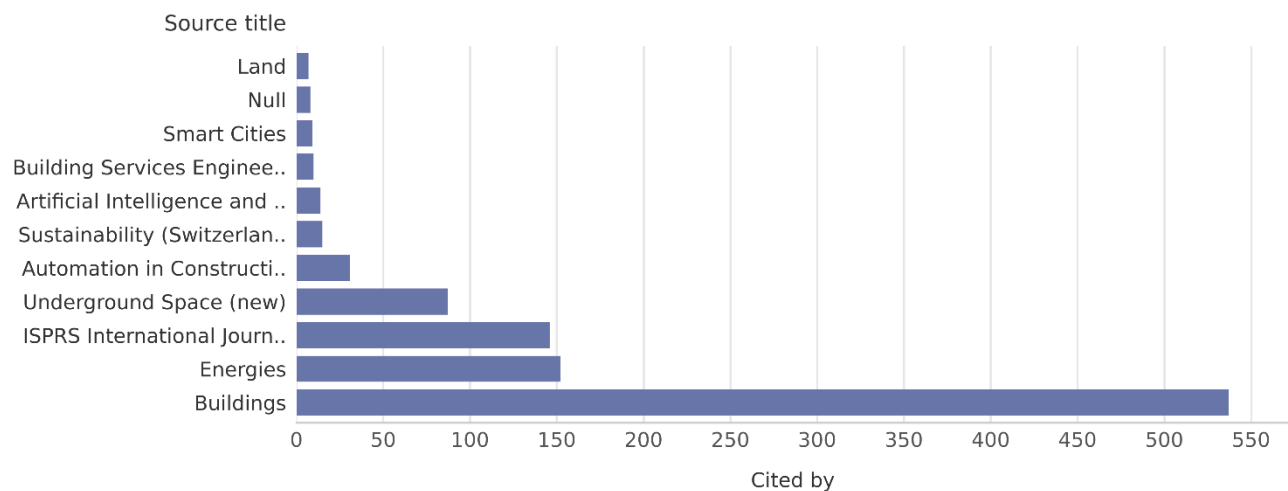


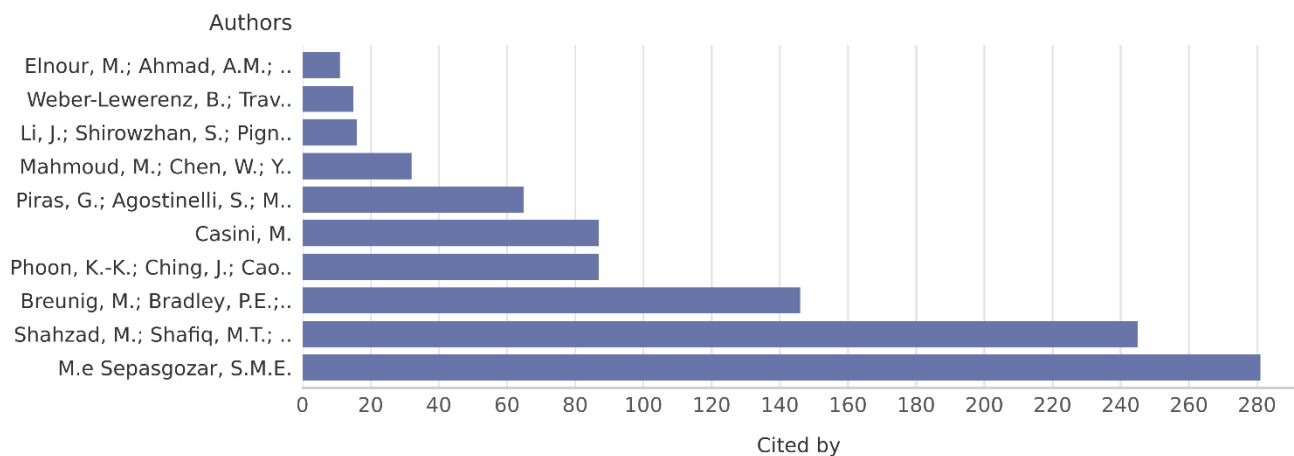
Figure 4. Keyword co-occurrence network map showing thematic clusters



(a) Publication and citation trend showing the relationship between research output and citation impact.



(b) Journal wise citation trend showing the leading publication sources in the research field.



(c) Top ten most cited authors illustrating leading contributors in this research field.

Figure 5. Bibliometric publication trend graphs

Figures 5(a)–(c) summarize the publication/citation trend, the leading journals, and the most-cited contributing authors identified in the bibliometric analysis, using the same VOSviewer export (Scopus + Web of Science + IEEE Xplore combined) described above. These results are interpreted in Section 3 rather than repeated here. As Figure 5(b) indicates, sustainability, energy efficiency, and spatial information systems are prominent topics of interest in this research community.

Figure 5 presents a comprehensive bibliometric analysis highlighting the relationship between publication output and citation impact within the research domain. The most used publishing platforms are MDPI and the publishing companies of (MDPI AG and MDPI AG) Indexing, which demonstrates its great contribution and citation influence in this sphere. A similar pattern can be observed with other publishers like Elsevier B. V., Tongji University, and Springer Nature, which also have moderate citation influence, with the highest citation numbers obtained by Buildings, Energies, and the ISPRS International Journal of Geo-Information, as illustrated in Figure 5(a). As Figure 5(b) indicates, sustainability, energy efficiency, and spatial information systems are prominent topics of interest in this research community, with the two most notable contributors being M.E. Sepasgozar and M.T. Shahzad, who will most likely contribute significantly to the field and be cited frequently in other related sources. All in all, these analyses help to understand that the research in this area

is mainly focused on open-access platforms due to several highly productive authors and journals that determine the existing picture of knowledge, as Figure 5(c) demonstrates.

2.3 Thematic analysis

The thematic analysis followed an inductive coding approach in which recurring concepts, applications, and challenges across the 44 included studies were identified through repeated reading of the full texts, grouped into provisional codes, and then consolidated into broader analytic categories. Some studies contributed evidence to more than one theme where their content spanned multiple domains. A theme-definition table (giving the inclusion rule, representative studies, and number of papers per theme) and the inter-coder verification procedure will be provided as supplementary material in the next revision. This process identified five main themes: data-driven decision-making and real-time monitoring, sustainable urban development and energy efficiency, interoperability and integration of technologies, smart infrastructure management and maintenance, and visualization and simulation of urban planning illustrated in Figure 6. The themes assist in knowing the actual and expected possibilities and use of AI–BIM–DT in smart cities, which in turn can be incorporated in a research agenda that could further contribute to the benefit of smart cities.

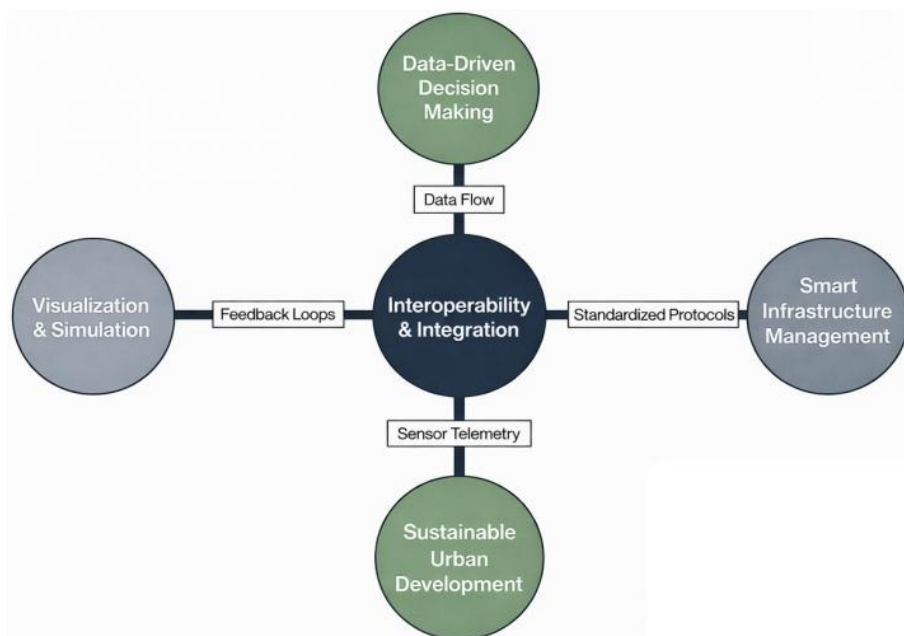


Figure 6. Key thematic relationships enabling integrated smart city development

2.3.1 Interoperability and integration of technologies

Interoperability and technology integration are significant in the smart city sphere because they will ensure the smoothness of information transfer and communication among different technological systems [16]. Such integration is critical to the development of overall and efficient smart city solutions capable of managing the city resources efficiently and enhancing the quality of life of citizens. Earlier research has touched upon the issues of incorporating various technologies like AI, BIM, DT, IoT, GIS, and cloud computing [17]. The study has paid attention to developing data interoperability frameworks and standards, middleware solutions, and open architecture to allow different systems to

communicate with each other [1, 18]. Some of the technologies and approaches include API development, semantic web technologies, ontology-based approaches, and standardized data formats [19]. Cloud computing environments have been applied to allow the integration of different smart city systems to be scalable and flexible [7, 20]. ML algorithms are used to optimize information processing and decision-making in interconnected systems [19, 20]. The new realities and agreements comprise the understanding that interoperability is the key to maximizing the value of smart city technologies. It is accepted that open standards and protocols should be used to enable integration [5, 20]. Research has indicated that effective integration results in

effective management of cities, optimization of resources and increased services to the citizens. Key contributions in this theme have involved advancement of all-inclusive smart city systems, which accommodate several technologies. DT as a framework that integrates multiple urban sources and systems of data has also been studied. Future opportunities and gaps are the necessity to have stronger security and privacy provisions in integrated systems, the need to extend the standardization of protocols in cross-domain data interchange, and discussion of some advanced AI methods of managing complex and integrated urban systems. Also, the research regarding the scalability and long-term sustainability of integrated smart city solutions should be done further.

2.3.2 Visualization and simulation for urban planning

Smart city urban planning in visualization and simulation technologies helps to give a living soul to urban planning, wherein planners get to play with dynamic virtual lives and make the best decisions that determine the future of our urban sceneries [21]. The tools provide more effective decision-making as they enable the stakeholders to envision complicated urban systems, anticipate results, and compare options [22]. This theme is discussed in earlier research on the creation of 3D modeling, virtual reality (VR), and augmented reality (AR) applications in the design of cities [8, 23]. These visualization tools have been combined with GIS and BIM to give data-rich simulations [24]. The process and interaction of urban systems have been simulated using agent-based modeling and system dynamics [25]. Newfound agreement indicates that these technologies are contributing immensely to stakeholder interaction, better spatial cognition, and that urban planning decisions become more informed [9, 25]. Such works as the city-engine platform of procedural urban modeling and the Urban-Sim project of an integrated land use and transportation simulation are notable. Nevertheless, there are still opportunities to work on the process of data integration in real-time and to make forecasting models more accurate and the interface accessible to non-expert stakeholders. Problems associated with the implementation of these visualization and simulation technologies include how to integrate data, computing needs, and adoption by the users. Data integration entails the combination of various sets of data that are sourced in different locations in a manner that guarantees that the data is interoperable, and that the data is of quality and currency. The urban simulation of large cities, which requires real-time use of high-performance computing infrastructure, can be expensive for certain municipalities. The challenge of user adoption is associated with the complexity of these tools, which cannot be used without the relevant training and professional skills.

2.3.3 Data-driven decision-making and real-time monitoring

The foundation of efficient smart city management is represented by data-driven decision-making and real-time monitoring, which allow authorities to optimize resource allocation, enhance service delivery, and increase urban resilience [26]. These strategies utilize large volumes of urban information to offer practical information in different sectors, such as transportation, energy, and citizen safety [27]. Previous research has considered the use of AI, BIM, and DT technologies to build complete urban data ecosystems [28]. These technologies collaborate with each other to gather, process, and analyze urban information in real-time in support of informed decision-making at various levels of city

governance [29]. Algorithms in AI are able to analyze complicated datasets, finding patterns and trends that are not necessarily visible to the human eye [30]. This has the advantage of making more precise predictions of urban phenomena, like traffic patterns or peaks of energy consumption. BIM gives a high level of detail of the built environment in digital form, which is a valuable source of information for urban planners and managers [10, 11, 30]. DTs, virtual models of real-world objects or systems, provide the opportunity to monitor and simulate the processes in the city in real-time, which allows the authorities to test the situation and optimize the work without interfering with the services in the field. These integrated methods have shown that they can be of great benefit. In urban design, such as in land use optimization, the technology has been shown to forecast infrastructure requirements, simulate the effect of a proposed development, and enable better management of traffic and energy use as well as response times to emergencies. Nonetheless, there are still difficulties with data standardization, compatibility of various systems or systems and assurance of privacy and security of data. Significant contributions made in this area have been made in terms of creating scalable data structures, efficient analytic algorithms, and easy to use dashboards to guide decision-makers. The opportunities of the future are connected with the improvement of predictive abilities, creating more advanced AI models of urban planning, and developing ethical guidelines of data handling in smart cities.

2.3.4 Smart infrastructure management and maintenance

Smart infrastructure management and maintenance, optimizing resources, reducing the cost, and extending the life of the infrastructure [13, 14, 31]. It combines AI, BIM, and DT technologies to monitor in real-time, predictively maintain as well as optimize assets [32]. IoT sensors have been investigated to collect data, and ML to recognize patterns in infrastructure systems [12, 33]. The most important technologies are AI-based analytics, 3D modeling with BIM, Simulations of DT, IoT sensors, and cloud computing [6, 34]. High-level data analytics tools work with huge volumes of infrastructure data. It is agreed that AI-BIM-DT systems can be used to enhance management efficiency and reduce costs. Predictive maintenance increases the service life and reduces downtime [35]. The technologies help in decision-making and allocation of resources in urban settings. Major works have developed extensive management platforms with real-time data gathering, AI analytics, and DT modeling in different infrastructural spheres [35]. Future research opportunities consist of further improvement of the matters of data integration and standardization, scalability of solutions to large urban settings, edge computing as a tool for real-time processing, and more advanced AI algorithms for predictive maintenance and risk evaluation of complex systems. Scientists are considering the use of blockchain technology to unify the safe and transparent management of data in intelligent infrastructure networks in the context of smart infrastructure. As well, it is increasingly becoming a topic of interest to come up with more sustainable and resilient infrastructure solutions capable of adapting to the effects of climate change and ensuring the sustainability of urban areas.

2.3.5 Sustainable urban development and energy efficiency

Sustainable urban development and energy efficiency are paramount in the sphere of smart cities and urban planning as

it may help solve the urgent environmental issues and make the life in the cities better [7, 14, 36]. This theme deals with the role of introducing hi-tech technologies towards sustainable urban planning, energy usage, and minimization of carbon emissions in smart cities [37]. This is a theme that has been covered in earlier research works that are focused on the application of smart grid systems, energy-efficient buildings, and integration of renewable energy in urban settings [15, 38]. It has also been studied how urban planning affects the minimization of energy consumption and sustainable transportation [39]. IoT sensors, AI, and big data analytics are some of the most popular technologies that have been utilized to track and optimize energy use in buildings and urban infrastructure [40].

There has also been the use of smart metering systems, energy management software, and building automation technologies to improve energy efficiency [41]. Novel findings and agreements involve a high possibility of energy efficiency through smart building design and retrofitting, the necessity to incorporate renewable energy sources into urban power systems, and the efficiency of data-driven solutions to optimize the use of energy in city systems [42]. Precedent works in the field have been directed toward the development of holistic systems of sustainable urban development, the effects of different energy-saving technologies on the urban landscape, and the models of predicting and controlling energy use in intelligent cities [43]. The future opportunities are in the more profound integration of AI and ML in order to make

energy systems efficient, to create more efficient energy storage models in urban settings, and to develop comprehensive methods that implement energy efficiency in relation to other attributes of sustainable urban development (water management and waste reduction).

3. BIBLIOMETRIC FINDINGS

The bibliometric analysis of the final 44 articles selected through the PRISMA process reveals a rapidly growing scholarly interest in the convergence of AI, BIM, and DT technologies for smart city development. Publication trends show that no studies combining all three technologies appeared before 2020, but a sharp rise is observed from 2020 to 2024, indicating the emergence and consolidation of this interdisciplinary research domain. The peak in publications is recorded between 2021 and 2023, influenced by global interest in digital transformation and urban resilience.

The year-wise count in Figure 7 shows a modest and irregular output between 2020 and 2023 (two, one, five, and three studies, respectively), followed by a sharp increase to eighteen studies in 2024 and fifteen in the partial 2025 window covered by the search. This confirms the sharp post-2020 rise referenced qualitatively in Section 3, while indicating that the true inflection point in the included-study sample occurs in 2024 rather than 2021–2023, a distinction that is only visible once the annual counts are plotted explicitly.

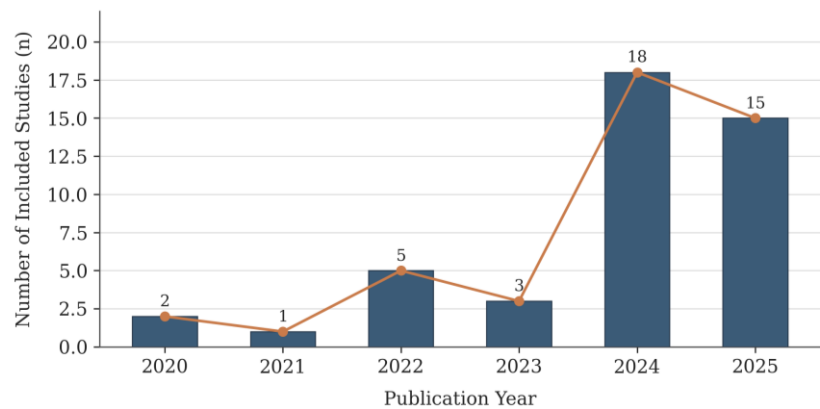


Figure 7. Year-wise distribution of the 44 included artificial intelligence (AI)-building information modeling (BIM)-digital twin (DT) studies (2020–2025)

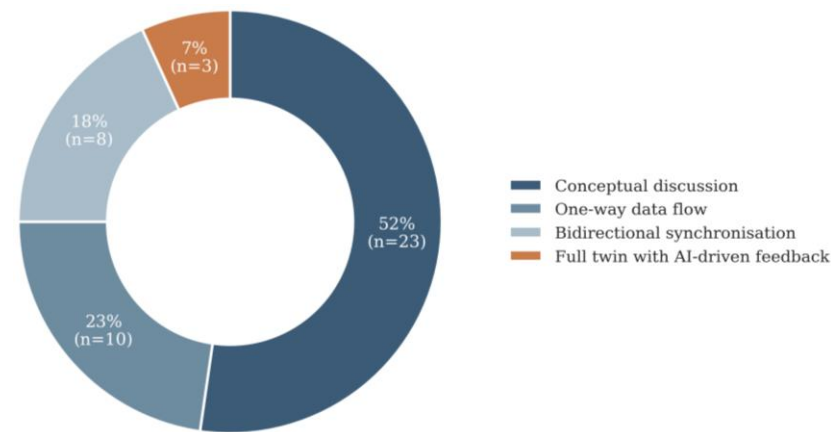


Figure 8. Distribution of reviewed studies by artificial intelligence (AI)-building information modeling (BIM)-digital twin (DT) integration tier (n = 44)

Figure 8 translates the integration tier taxonomy defined in Table 2 into proportional terms. Conceptual-discussion studies dominate the corpus (52%, $n = 23$), followed by one-way data-flow studies (23%, $n = 10$) and bidirectional-synchronization studies (18%, $n = 8$); only three studies (7%) report a full twin with closed-loop, AI-driven feedback. This distribution provides a quantitative basis for the maturity gradient discussed narratively in Section 2.2, namely, that empirically instrumented, AI-closed-loop DTs remain the least common configuration in the current literature.

The mapping of keyword co-occurrence shows four large clusters of key terms where digital technologies are found in the blue cluster, smart city and urban planning in the green cluster, sustainability and energy efficiency in the red cluster, and advanced computational methods in the yellow cluster. The close interconnections between the keywords DT, smart city, and BIM prove the tendency towards a more consolidated and multi-disciplinary character of the research area because of the cross-disciplinary cooperation between the researchers of computer science, civil engineering, and urban planning. The combination of AI, BIM, and DT is a new research direction and clearly provides extensive opportunities to researchers in the future.

4. THEMATIC SYNTHESIS

The integration of AI, BIM, and DT technologies within smart cities is a rapidly evolving field, characterized by several interconnected themes that highlight its potential and ongoing challenges, as shown in Table 3. The thematic synthesis of the literature in detail demonstrates that there are five major areas: Data-driven decision making and real-time monitoring, sustainable urban development and energy efficiency, interoperability and integration of technologies, smart

infrastructure management and maintenance, and visualization and simulation of urban planning [44, 45]. All these themes collectively lead to a sound research agenda that will add value to such convergent technologies in urban settings [46]. Data-Driven Decision Making and Real-Time Monitoring. This theme is seminal and, as such, the use of AI, BIM, and DT technology allows advanced data collection, processing, and analysis to underpin urban management and decision-making. DTs are dynamic and virtual models of real-life objects or systems, constantly recording more information from a variety of sensors, such as environmental conditions such as temperature and weather and operational indicators such as energy production [47]. This real-time information, which is frequently provided by IoT devices, is combined with static BIM models that present a very rich semantic and geometrical background. The large and heterogeneous data will be essential to process using AI algorithms, extracting insights and predicting future states, as well as finding anomalies or areas that could be improved [48]. As an example, artificial intelligence-based DTs may be used to observe urban infrastructure and predict the need to maintain it, as well as to streamline operational parameters, thus helping urban planners and managers make proactive decisions [49].

This is particularly crucial in overcoming the mayhem of rapidly expanding urban ecosystems. Future studies in this field ought to emphasize the creation of more advanced AI models that are able to process high-velocity, high-volume data streams of various urban sensors, as well as the development of robust frameworks for turning these insights into actionable urban policies and interventions [50]. BIM is a systematic data storage of building materials and their performance traits. Together with the real-time operation data of DTs and processed using AI algorithms, this data may streamline the performance of buildings and urban systems [51].

Table 3. The Summarization of the limitations, challenges, and future directions

Aspect	Limitations	Challenges	Future Scope and Opportunities
Technical	– Lack of data interoperability and semantic understanding across diverse platforms [14]. – Early developmental stage of DTs in the built environment, leading to limited functionality [17]. – Difficulty in multi-source data integration and technology interoperability [7].	– Developing standardized data exchange protocols and formats for seamless information flow between BIM, AI, and DT systems [17]. – Overcoming complexities in real-time data capture, processing, and visualization for comprehensive DTs [15]. – Ensuring accurate mirroring of physical assets in digital counterparts with bidirectional communication [48]. – Addressing the nascent state of DT applications in building operations regarding integration and visualization [14].	– Development of universal data standards and interoperability frameworks (e.g., DT Definition Language, DTDL) [17]. – Advanced sensor technologies and data-fusion techniques for higher-fidelity DTs [6]. – Research into modular and compositional analysis of cyber-physical systems [17]. – Enhanced visualization technologies, such as XR, for immersive interaction with DTs [19]. – Integration of GIS with BIM for urban-scale DTs [22].
Operational	– High computational demands for processing vast datasets from BIM, IoT, and smart city infrastructure [15]. – Scalability issues of integrated AI-BIM solutions across entire smart cities [21]. – Challenges in developing robust AI models for dynamic and uncertain urban environments due to their inherent complexity [1].	– Managing and interpreting enormous datasets generated by smart city infrastructure, including real-time metrics such as energy output, temperature, and weather conditions [15]. – Ensuring the resilience of infrastructure through continuous monitoring, prediction, and optimization under various stresses using AI and DT [21]. – Optimizing urban phenomena through sophisticated AI models that handle rapid urban growth and multifaceted issues [1].	– Development of more efficient AI algorithms and high-performance computing infrastructures for large-scale urban data processing [15]. – Creation of advanced AI models for predictive analysis and optimization across diverse urban domains, including stormwater management [15]. – Leveraging AI for automated vision-based construction progress monitoring and bridge management [7].

Implementation	– Shortage of interdisciplinary skills among the workforce (construction, IT, AI expertise) [5]. – Gaps between traditional AEC practices and advanced digital technologies [5]. – Ethical considerations and data-privacy concerns associated with collecting and processing sensitive urban data [1]. – Developing comprehensive training and education initiatives to equip professionals with the skills needed for AI–BIM–DT system design, implementation, and management [5]. – Building public trust and ensuring sustainable adoption through responsible AI use, data security, and adherence to privacy regulations [1]. – Mitigating potential biases in AI data or decision-making to ensure equitable and inclusive smart city development [1]. – Overcoming resistance to change and facilitating the digital transformation of the construction industry [52]. – Implementing AI-driven systems for urban resource management and circular-economy initiatives [23]. – DT for 3D interactive building operations, integrating BIM, IoT-enabled building automation systems, AI, big data, and mixed reality [14]. – Establishment of specialized academic programs and industry certifications for AI–BIM–DT integration [5]. – Formulation of ethical guidelines and regulatory frameworks for AI and data governance in smart cities [1]. – Research into privacy-preserving AI techniques and secure data-sharing platforms [22]. – Promotion of collaborative research between academia, industry, and government for integrated solution development [53]. – Utilization of DTs for cultural-heritage protection and structural-integrity assessment [54].
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Note: AI = artificial intelligence, BIM = building information modeling, DT = digital twin, IoT = Internet of Things, GIS = geographic information system, DTDL = digital twin definition language, AEC = architecture, engineering, and construction, XR = extended reality.

The AI models are proficient at interpreting and forecasting energy consumption trends, forecasting changes in demand, and proposing energy-saving options. They may include optimization of heating, ventilation, and air conditioning (HVAC) systems and lighting in accordance with occupancy and external conditions, or more advanced urban energy management systems [55]. Besides buildings, DTs, especially when utilized in relation to critical infrastructure, can enhance functionality and performance, resulting in more sustainable urban spaces and higher resistance to environmental-related issues. These digital technologies are also useful to the broader understanding of a circular economy in construction since the open-BIM and DTs allow integrating sustainability concepts in the form of tools such as material passports, which serve to advance the goals of countries to mitigate environmental impact and enhance energy efficiency [56].

Research directions include the following: This theme deals with the longstanding challenges and ongoing research to be able to facilitate smooth communication and data exchange between AI, BIM, and DTs. Data fragmentation and lack of standardized data exchange protocols traditionally impact the AEC industry adversely and deter any information flow [57]. DTs can be seen as a strategic attempt to bridge these gaps because the convergence of BIM and Industry 4.0 innovations like AI, IoT, big data, or extended reality (XR) has been attempted [45]. Nonetheless, the emergence of present-day DT applications in building operations supports the idea that the challenge of multi-source data integration, technological interoperability, and visualization needs to be addressed. The focus of future work is on building universal data standards and interoperability systems, including the digital twin definition language (DTDL), required to support compositional and modular analysis of complex cyber-physical systems [58].

This also implies that studies of the common data environment and semantic web technologies are required to make sure that data provided by different sources can be effectively connected and interpreted by AI systems [59]. Smart infrastructure management and maintenance. The fourth theme is concerned with the critical role of AI–BIM–

DT integration in developing the field of managing and servicing smart city infrastructure. DTs offer a moving, dynamic, real-time reflection of physical assets, which allows constant monitoring and predictive analysis of their state [60]. Using sensor data provided by IoT devices, AI algorithms can identify abnormal conditions, predict possible failures, and plan preventative maintenance, thus making urban infrastructure using a variety of sensors much more resilient and efficient. It is of great importance, especially in the management of various kinds of assets, including stormwater infrastructure systems, bridges, roads, and public buildings, where AI and DT will be able to streamline performance, increase the lifespan of assets, and avoid expensive disruptions [61].

An example is the work of AI models in automated progress monitoring of construction using vision and bridge management, increasing the accuracy and safety of infrastructure development projects. Future research in this field should consider predictive maintenance models of the future, robotic inspection with the help of DTs, and AI-based decision support systems for infrastructure resilience planning. Visualization and Simulation of Urban Planning. The last theme is the ability of integrated AI–BIM–DT to provide three-dimensional and interactive visualization and simulation environments required in the contemporary urban planning process [46]. BIM models form the basis of geometric and semantic information of urban assets, which is supplemented with real-time operational information of DTs.

AI capabilities further enhance simulation aspects, enabling complex scenario analysis, predictive modeling of urban phenomena (e.g., traffic flow, pedestrian movement, environmental impacts), and optimization of urban designs [62]. Such visualizations can be turned into immersive experiences with the help of technologies such as XR, which enables urban planners, stakeholders, and even citizens to engage with DTs, compare alternative urban designs, and predict the effects of the suggested developments [63]. This interactive 3D environment leads to better communication, collaborative planning, and, finally, better and more sustainable strategies of urban planning [64]. The five themes

discussed above would then point to the future research of urban DTs that should incorporate advanced human-computer interaction, the incorporation of generative AI in prediction of urban design alternatives, and the creation of a simulation model that can easily predict changes in social and economic aspects of urban interventions. They also define areas of critical focus in future research and technological

development, pushing the limits of urban innovation as shown in Figure 9. This is presented as a conceptual arrangement of the technological pillars identified in this review rather than a fully dynamic framework; a redesigned version illustrating information flow, model updating, and feedback into the physical system, using bridge predictive maintenance as a concrete illustrative example, is provided below as Figure 10.

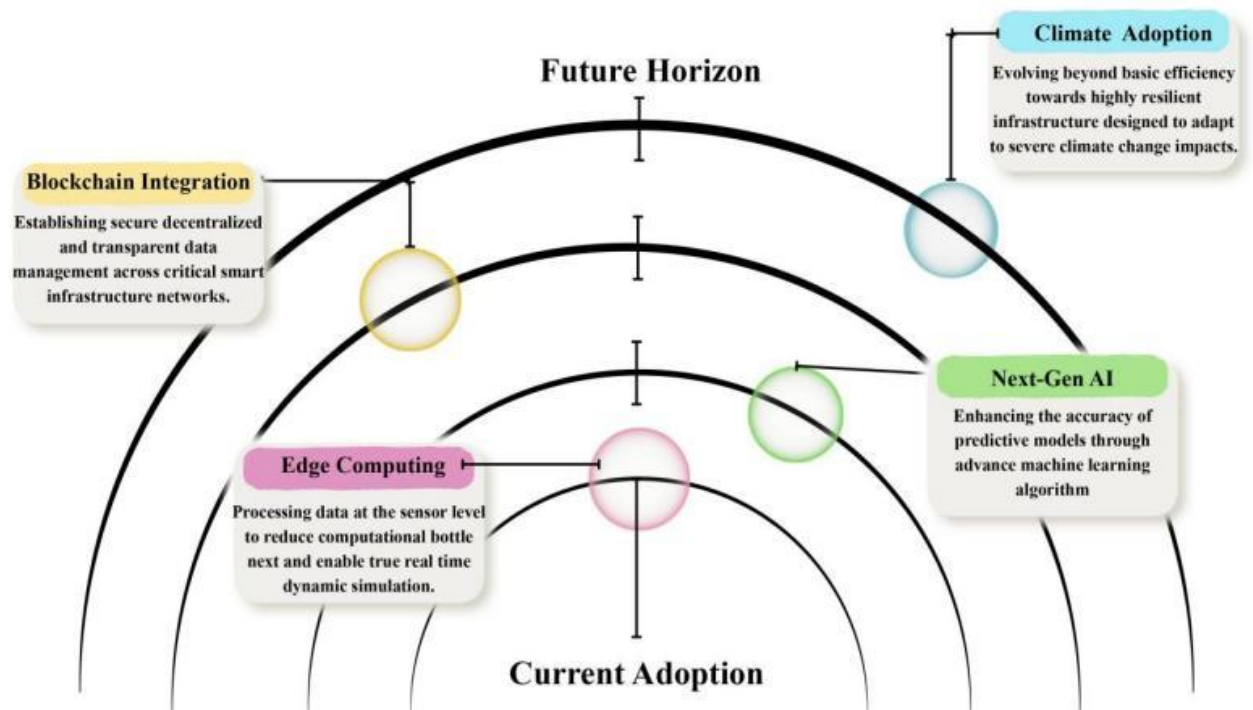


Figure 9. Key technological pillars shaping future smart infrastructure systems

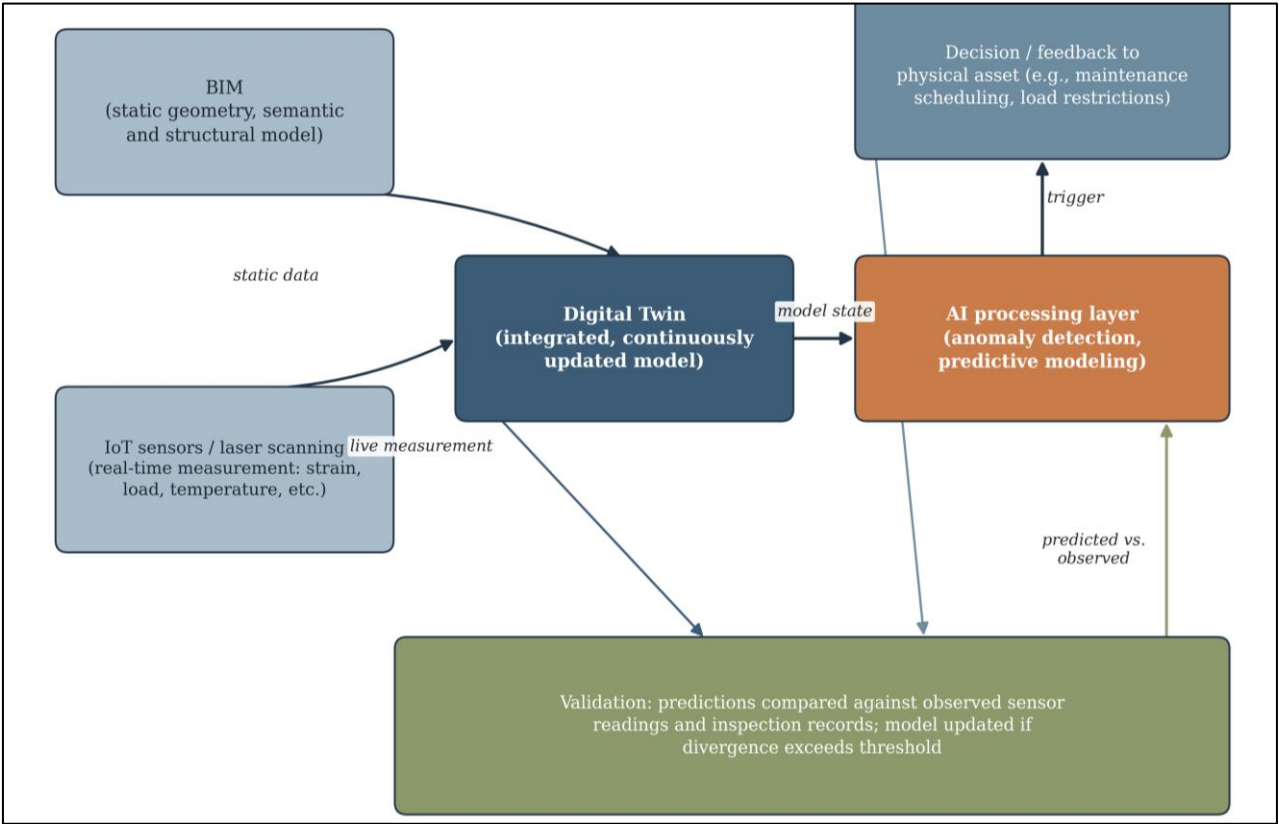


Figure 10. Full digital twin (DT) architecture with closed-loop, artificial intelligence (AI)-driven feedback: predictive maintenance of a highy bridge

5. CONCLUSIONS

This hybrid systematic, bibliometric, and thematic review demonstrates that the convergence of AI, BIM, and DT technologies is rapidly redefining the landscape of smart city development. The PRISMA-based selection process identified a growing and increasingly interdisciplinary research domain, with publication trends rising sharply after 2020 and clustering around key themes such as real-time decision-making, sustainability, interoperability, infrastructure management, and advanced visualization. Bibliometric findings highlight the central influence of open-access platforms, leading authors, and strong keyword linkages that collectively reveal an evolving intellectual structure focused on integrated urban digitalization. The thematic synthesis also demonstrates that AI can improve predictive abilities, BIM models can represent multifaceted spatial information, and DTs offer dynamic feedback mechanisms to simulate and optimize each other in a unified technological ecosystem, which allows smarter and more resilient cities to emerge. In spite of this, there is still a problem of data standardization, privacy, interoperability, and scalability. The resolution of these problems will play a key role in the translation of research innovations into urban applications on a large scale. In general, the presented review offers a clear background and conceptual framework that can guide future studies to make AI, BIM, and DT integration more robust such that it could be used to support sustainable, efficient, and smart city ecosystems.

DECLARATION ON THE USE OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES

The authors used generative AI and AI-assisted technologies solely for language editing and polishing during the preparation of this manuscript. These tools were used to improve grammar, clarity, and readability without generating or altering the scientific content, data, results, or conclusions. The authors reviewed and verified the final manuscript and take full responsibility for its content.

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