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REVIEW

Digital Twin and AI-Driven Carbon Management in Sustainable Construction and Urban Design

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ABSTRACT

The built environment and construction industry are another significant source of carbon emissions to the environment in the world, through the production of materials, construction activities, and the energy consumed during the lifecycle of an asset. These emissions are difficult to manage effectively because the data are not consolidated, the operating conditions are dynamic, and the traditional assessment tools are not able to support continuous and data-driven decisions. The new technologies, especially Digital Twins (DT) and artificial intelligence (AI), have some potential solutions, which will combine the lifecycle data and provide a predictive, adaptive carbon management in the building and urban systems. The given paper is a systematic review of the integration of DT and AI (DT–AI) into carbon management in operational construction and urban planning. Structured database searches and filters on the basis of DT-facilitated carbon monitoring, prediction, optimization, and operational control were used to identify peer-reviewed studies that were published within the last few years and filtered through to gather them. Three main functions of DT–AI systems are outlined in the review: predicting carbon emissions on the basis of data-driven models, optimizing low-carbon design and planning with multi-objective approaches, and providing intelligent control of the energy systems. Some of the major issues are data interoperability, model validation, and a lack of evidence of large-scale deployment. This study combines integrated DT–AI models and their contribution to lifecycle carbon management, unlike the previous reviews of either DT or AI alone. The paper ends with a conclusion and recommendations to create scalable, validated DT–AI solutions to

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accomplish carbon-neutral built environments.
Keywords: Digital Twin; Artificial Intelligence; Carbon Management; Sustainable Construction; Urban Design

1. Introduction

The built environment and construction industry play a central role in mitigating climate change globally. A large proportion of the energy used and the greenhouse gases emitted worldwide is associated with buildings and infrastructure, both in the production of materials, construction, operations of the structures, and their dismantling. These emissions are active in various stages of the lifecycle, such as design, construction, use, renovation, and demolition. With increasing carbon neutrality goals and stricter environmental standards in different countries and governments, better carbon management across the lifecycle of built assets has become a primary concern among researchers, practitioners, and policymakers [1–3].

Nevertheless, proper management of carbon in the built environment is not easy. Lifecycle emissions are caused by a wide range of sources, including the manufacturing of materials, construction logistics, energy consumption, maintenance, and other aspects, and include numerous stakeholders working at time-dispersed project phases. The conventional methods of carbon accounting tend to be based on fixed lifecycle and simplistic forms of energy modeling that are incapable of reflecting the dynamic conditions of operations or changing design choices. It is therefore observed that most carbon reduction strategies are reactive as opposed to proactive and consequently are limited in their effectiveness. To overcome these challenges, digital systems that will continuously combine lifecycle data, simulate future scenarios, and help in making real-time decisions are needed [4–6].

Digital Twin (DT) is a new technology that has come in as a potential solution to such needs. A Digital Twin can be described as a digital manifestation of a physical system or object, which is constantly updated with both real-time and historical data about it throughout its lifecycle. In the built environment, DT platforms combine information about building information modeling (BIM), sensors, Internet of Things (IoT) devices, and operational databases to form an ever-changing model of buildings, infrastructure, or urban systems. It is an integrated digital space that allows tracking and simulating asset behavior under various conditions, and analyzing it. Within the framework of sustainability, DTs have the potential to monitor energy consumption, screen design options, and test operational strategies that have effects on carbon emissions [7–9].

As much as DT platforms give us the digital infrastructure that allows integrating data and representing systems, analytical abilities that are offered by artificial intelligence (AI) offer the solution that converts data into actionable insights. The AI methods, such as machine learning, optimization algorithms, and reinforcement learning (RL), help the system to identify patterns in complicated data, predict energy demand and emissions, optimize design settings, and assist in adopting operational controls. Integrated with DT environments, AI models have the potential to keep learning on the operational data, update predictions, and assist in making decisions at different stages of the lifecycle. This DT AI combination is thus a potent solution towards developing carbon-conscious planning, construction management, and building operation [10].

Even though there has been an increasing interest in the integration of DT and AI, the current body of research is still disjointed. The current literature usually looks at each technology separately, i.e., DT platforms to monitor building construction or AI models to predict energy consumption, but does not systematically investigate the interactions of these elements to help with the overall carbon management. Additionally, most of the publications focus on technical advancement or application-specific cases without generalizing the methodology trends and implementation issues. Consequently, such critical questions have remained unanswered: what are the most suitable AI approaches to various carbon management tasks, how can DT infrastructures be used to incorporate life cycle carbon, and what impediments prevent the use of DT–AI systems in the real-life construction and urban environmental setting?

The literature also has one more weakness in that there is no critical synthesis of the outcomes of implementation and real-world constraints. Numerous researchers prove the theoretical advantages of DT–AI systems by simulation or pilot projects, and fewer of them report factual evidence of carbon reduction functionality under operational conditions. Problems connected to data interoperability, model validation, governance frameworks, and lifecycle data availability are often identified but seldom looked at at a systematic level throughout the literature. Therefore, it is unclear how DT–AI interplay would impact sustainable construction and city planning[11].

To fill these gaps, this paper will give an in-depth review of Digital Twin and AI integration to manage carbon in the built environment. With the review, the role of DT infrastructures in integrating lifecycle carbon data and the role of AI methods in predictive analytics, optimization, and intelligent control to minimize emissions are analyzed. However, instead of concentrating on individual technologies, the paper can generalize on the relationship between DT platforms and AI techniques in various application settings, such as building design, building management, and operational energy systems[12].

Certain attention of the review is also paid to defining methodological patterns and limitations of research in the new DT–AI literature. The research compares the various AI strategies, which include supervised learning, reinforcement learning, and hybrid physics-AI models, to determine their appropriateness in performing different carbon management tasks. Moreover, the review examines the challenges in implementation, such as quality of data limitation, interoperability and lack of long-term deployment studies. It is imperative to comprehend these factors to translate the DT–AI research into scalable solutions that can be used to facilitate carbon-neutral built environments[3,13].

This review has threefold objectives. First, it summarizes existing studies on Digital Twin technology as a lifecycle carbon monitoring and analysis of buildings and cities. Second, it analyzes how AI methodology can be used to provide carbon prediction, optimization, and adaptive control using DT environments. Third, it determines gaps in research, practical issues, and future deployment of integrated DT–AI systems to facilitate low-carbon construction and sustainable urban development. This review will assist researchers and practitioners in the development of the next generation of intelligent carbon management systems in the built environment by offering a systematic review of the technological techniques and implementation concerns. **Figure 1** illustrates that Digital Twin infrastructures offer the integrative base to the data and models that are carbon-related, whilst strategies to AI are applied to predict, optimize, and modify control in designs, construction, operational, and urban planning environments.

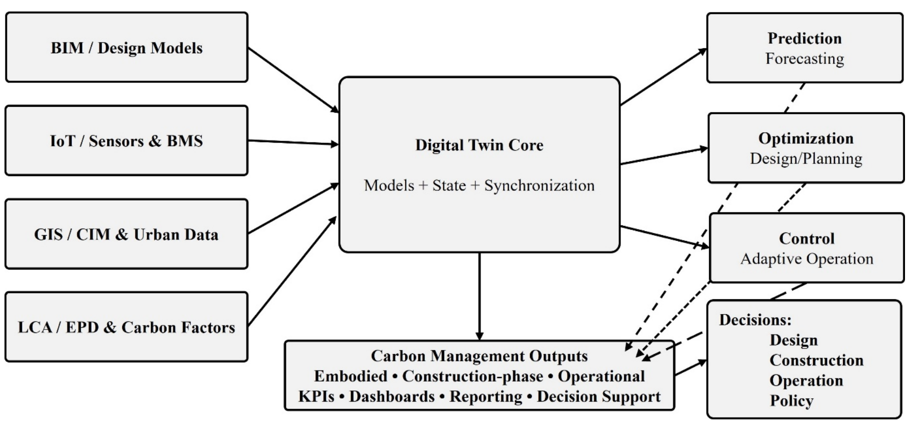

Figure 1. Conceptual Framework of Digital Twin and AI-Driven Carbon Management.

2. Conceptual Foundations and Review Methodology of Digital Twin and AI for Carbon Management

AI-inspired carbon management and digital Twin are located at the junction point between digital engineering, data science, and sustainability measurement. The conceptual definition is required since the literature tends to use somewhat interchangeable notions of BIM-enabled analytics, smart buildings, cyber-physical systems, and city digital twins to denote systems with highly differing degrees of data connectivity, model fidelity, and decision autonomy[14]. In this part, we define the key concepts on which this review is framed. We conceptualize the Digital Twin paradigm of the built environment and differentiate it from other related digital representations. Then we sum up AI method families that are most applicable in carbon intelligence, and the reason why they can do more than prediction, but also optimization and control. Last, we also challenge the definition of carbon management at lifecycle stages and scales and highlight the distinction between the embodied and operational emissions as well as the implications of these on data, modeling, and governance.

2.1. Digital Twin Paradigm in the Built Environment

A Digital Twin is usually seen as a digital model of a physical object, process, or system that is linked to the physical one by data flows and can behave in a way that it responds to the changes in state over time [15]. This definition, in the context of sustainable construction and urban design, has three implications. To begin with, the so-called twin is not a fixed model but a dynamic digital object that can be updated with the measurements of the actual world. Second, the digital object is not only geometry but a bundle of behavior and performance, including the use of energy, the functioning of equipment, environmental traits, and factors that are emissions-relevant at carbon-oriented uses. Third, a Digital Twin is most useful where it can be used to make actionable decisions, and this means it should not be used as a repository only.

The Digital Twins of the built environment are generally based on BIM, Geographic Information System (GIS), and building management systems; however, their defining principle is constant synchronization [16]. BIM offers the structured representation of both design intent and as-built information, whereas GIS and city information models expand the representation to the urban level and allow spatial analytics. When such representations are connected with sensor networks, operational logs, schedules, and maintenance records, the system will be able to transition to a twin that monitors operational reality in place of a descriptive digital model. This is not a binary transition but exists on a maturity spectrum. The initial applications can be periodic updates of data and reporting of performance, whereas the more advanced twins have near real-time streams, automated model software upgrading, and closed-loop feedback to the decision-making systems.

The theoretical development in the process of transforming the BIM-based representation of the state into the dynamic and carbon-aware Digital Twin can be summarized in **Figure 2**, with the growing connections to different types of data, the level of system intelligence, and the autonomy in the choice [17].

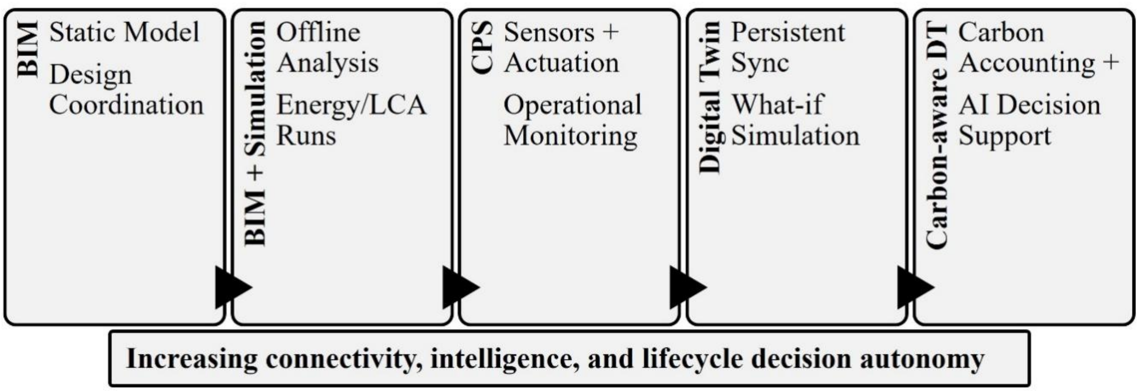

Figure 2. Evolution from BIM to Carbon-Aware Digital Twins.

One of the key conceptual differences between the literature and the other forms of digital representation, including BIM-based simulation systems or cyber-physical systems, is the difference between a Digital Twin and other representation types. Simulations in BIM are able to provide an estimate of the energy demand or embodied carbon during the design phase, though they are often based on assumptions that may not be realized after construction and are often not correlated with operational data. Cyber-physical systems focus on actuation and sensing but do not necessarily have a rich digital model that can simulate scenarios or do lifecycle reasoning. Digital Twins can be regarded as a conceptual framework that integrates formalized digital representations and sensing, analytics, and response, and has the objective of aiding the decision-making process across the lifecycle of an asset[18]. In the case of carbon management, this integrating feature is important since all the emissions are formed where there are interactions between design decisions, construction processes, operational control plans, and external factors like weather and grid carbon intensity.

Nowadays, carbon-oriented twins also introduce more conceptual requirements. In contrast to most performance measures, carbon is, in part, a derived figure that is reliant on the emission factors, definitions of the boundaries, and accounting conventions[19]. A carbon-conscious Digital Twin has to, therefore, not just incorporate operational measurements, but also incorporate accounting logic that connects activity data to emissions. This involves mapping of energy use to time-varying grid emission factors, materials, and quantities to the embodied carbon coefficient, and scopes and boundaries that are set the same way across lifecycle stages. The twin, therefore, has to symbolize the physical behavior as well as the carbon accounting model that explains the behavior. In order to make further terminological differences in the literature, **Table 1** compares BIM, cyber-physical systems, and Digital Twins based on lifecycle coverage, data integration, and their use in carbon management.

Table 1. Comparison of Digital Representations in the Built Environment.

Aspect	BIM	Cyber–Physical System (CPS)	Digital Twin
Primary Purpose	Design documentation and coordination	Monitoring and control of physical systems	Continuous lifecycle representation and decision support
Temporal Nature	Mostly static or periodically updated	Real-time sensing and actuation	Persistent synchronization over time
Data Connectivity	Limited or manual	Real-time data streams	Real-time and historical data integration
Lifecycle Coverage	Design and construction focused	Operation focused	Design, construction, operation, and renewal
Simulation Capability	Offline and scenario-based	Limited	Integrated “what-if” and predictive simulation
Carbon Management Role	Embodied carbon estimation	Operational emission monitoring	Integrated embodied, construction, and operational carbon intelligence

2.2. AI Techniques Supporting Carbon Intelligence

The use of AI has become part of carbon management since emissions in the built environment address non-linear dynamics, uncertain human actions, and high-dimensional decision space[20]. In this respect, AI can be viewed not as a one-and-only technology but as a collection of approaches allowing for offering various kinds of intelligence. Predictive learning will aid in forecasting the energy demand or emissions in different conditions. Prescriptive analytics and optimization prescribe measures that minimize carbon and hold other goals. Adaptive control strategies can make systems learn and enhance their carbon performance with time as the conditions vary.

Regression models, tree-based models, and deep neural networks are common supervised learning algorithms to predict operational energy consumption and related emissions based on inputs of weather, occupancy indicators, equipment condition, building features, and so forth[21]. They are attractive because they are able to capture complex relationships in cases where adequate historical information can be used. Nevertheless, prediction is in itself not enough to ensure decarbonization since it will need interventions, trade-offs assessment, and a change of operations. This encourages the application of optimization techniques, such as evolutionary algorithms and multi-objective optimization, with carbon being among the objectives, other objectives being cost, comfort, constructability, schedule, and resilience. Such methods can be used in design settings to search in large design spaces and to find Pareto-efficient solutions. In construction, they may be useful in supporting the low-carbon scheduling and logistics decisions by balancing the time and resources with fuel consumption and transport emissions of equipment.

Sequential decision-making methods like reinforcement learning are also becoming applicable to operational carbon control since they are able to study policies that reduce cumulative emissions without violating constraints[22]. This can include learning strategies of Heating, Ventilation, and Air Conditioning (HVAC), lighting, storage, or demand response in buildings that react to the time-varying carbon intensity of the grid. The use of multiple assets and energy can be orchestrated in districts. However, the implementation of such approaches in practice is restricted due to the issues of safety, reliability, and interpretability. It is difficult not only to identify an optimal policy in simulation but also to achieve consistent work in the uncertain environment, prevent unwanted behavior, and rely on compliance with the norms of comfort and indoor environment.

Explainability, robustness, and governance should also be taken into consideration in order to implement AI trustworthily in carbon-critical systems. Explainable AI methods are designed to be decipherable by the designers, operators, and policymakers of the system they are used in, which is essential when there are trade-offs in carbon decisions that impact safety, cost, or usability. The strength of the issue is relevant since the training data might not be a manifestation of future conditions, particularly in the climate change scenario, changing occupation trends, retrofits, or differing grid decarbonization efforts. Furthermore, the results of AI are based on assumptions in the nature of carbon accounting, including emission factors and boundary demarcation, which implies that transparency is required to prevent false assurance in the accurate appearance of figures [23].

In a Digital Twin environment, AI is connected to models and data in a more organized manner than in separate analytics. The twin will be able to offer context-related features, impose physical and operational constraints, and promote constant learning with new streams of data. On the other hand, the twin can be improved using AI so that the model parameters are updated, anomalies are identified, and real-time decision support is provided. The conceptual change is to focus on AI as a prediction tool, to AI as a part of a cyber-physical decision system, where the quality of carbon management is determined by integration, validation, and human-in-the-loop management [24,25].

2.3. Carbon Management across Lifecycle Stages and Scales

Sustainable construction and urban design dealing with carbon management is lifecycle in nature due to the interdependence of choices made at one stage of the process on the other stages of the process, and in some cases, counterintuitive [26]. Embodied carbon and operational carbon are usually differentiated in the literature. Embodied carbon is the type of emissions that are related to the production of materials, transportation, construction, maintenance, replacements, and end-of-life. Operational carbon is that collected through the use of energy, usually electricity, and the fuels used in heating, cooling, ventilation, lighting, plug loads, and associated services. Although this is a conceptually useful distinction, it can result in interactions being separated. Indicatively, choosing low-embodied-carbon materials can impact thermal or strength, overturning operational energy consumption and long-lasting emissions. Equally, electrification may decrease on-site combustion but offload emissions to the grid, leading to dependent results based on grid strength and temporal demand profile.

Carbon management should have regular boundaries and an accounting method according to lifecycle considerations [27]. Initial design processes are based on estimates, benchmarks, and representative emission factors. As projects advance, further quantity takeoffs, records of procurement, and construction logs become accessible. Measured energy data and performance information of the system can be used in operation to facilitate more accurate accounting. Digital Twins have the conceptual ability to form these phases, in essence, to offer these stages of design intent, as-built circumstances, and operational execution into a single content information platform. This continuity is, however, hard to achieve due to changes in the tools, stakeholders, and incentives across phases. Carbon management is then not only a technical process but also a coordination problem with information transfer, distribution of responsibility, and governance [28].

The scale also makes the management of carbon complex. Operational emissions may be controlled at the scale of the building level by optimizing the system and by involving users, whereas embodied emissions are heavily reliant on material selection and construction techniques. On the scale of the construction process, there are temporary energy consumption and equipment operation, as well as logistics, where schedule information, equipment telemetry, and supply chain data should be combined. Carbon results on the district and city levels are influenced by building interactions, transport, infrastructure network, and energy provision. The pattern and the structure of the demand are determined by the urban form, land use, as well as mobility behavior, adjusting the grid operation and investment possibilities on infrastructure. These cross-scale dependencies mean that optimizations in one building are not necessarily going to achieve optimal results at the district level because, e.g., load shifting can cause network limits or can tend towards peaks that add to marginal emissions [29].

The other conceptual layer deals with the temporality of carbon. Operating emissions are becoming more time-varying based on grid emission factors, in that an identical amount of electricity use can produce a varying amount of emissions based on the time of the day it is used. This brings the concept of carbon-conscious operation and planning, where control and scheduling techniques are adopted in order to match the demand with the low-carbon supply periods. In embodied carbon, the effects of time can be seen in decarbonizing supply chains, changing manufacturing processes and transforming material markets. A carbon-centric Digital Twin should hence be able to support spatial and temporal variability, and AI models should be trained and evaluated in a manner that takes into account the dynamics and not the static factors [30].

Lastly, the management of carbon cannot be separated as it relates to decision-making situations and stakeholder goals [31]. Designers need to have guidance that is practical in the event of uncertainty and can comply with codes, requirements of safety, and constructability. Contractors require the tools that are incorporated with the scheduling, procurement, and site operations. Owners and operators are concerned about reliability, satisfaction of occupants, and operating costs, and they might have regulatory or reporting requirements. Citizens and policymakers in urban areas are constrained by the need to strike a balance between carbon targets and equity, affordability, and the overall societal results. Ideally, the carbon management made possible by DT–AI-based carbon management, therefore, should be conceptualized as a socio-technical system: the technical models and algorithms should be aligned to organizational workflows, data governance policies, and responsibility systems. It is critical to conduct this framing to read the literature as it is and find research directions that will go beyond prototypes towards scalable, verifiable, and meaningful deployment.

Overall, the theory behind this review makes Digital Twins lifetime, data-linked models that can host carbon accounting logic and performance simulators, and AI can offer predictive, prescriptive, and adaptive intelligence to help make carbon reduction decisions. The very concept of carbon management should be perceived as a multi-scale, dynamic, and problem-specific governance issue, whereby embodied and operational emissions co-exist over time, and across project, district, and city boundaries [32]. These are the cornerstones of discussing the ways in which carbon-related data and models can be incorporated into Digital Twin settings and analyzed using AI-based approaches to predictive data and models, optimization, and control in the following chapters.

2.4. Review Methodology

The proposed research uses a systematic literature review to summarize existing literature on the adoption of Digital Twin and Artificial Intelligence to manage carbon in the built environment. The relevant literature was found with the help of searching the major academic databases such as Scopus, Web of Science, and Google Scholar. The search was restricted to publications published between 2018 and 2025 and included such combinations of keywords as Digital Twin, artificial intelligence, machine learning, carbon management, building energy, and sustainable construction [33]. Following the elimination of duplicates, title and abstract screening included the elimination of articles that did not deal with DT technologies, AI-based techniques of analysis, or a combination of both in carbon-related services in buildings, construction processes, or in the city. Peer-reviewed English publications that had definite methodological or application contributions were used, and studies that were not related to carbon management or gave no analytical information were excluded. The chosen papers were subsequently read in their full text and analyzed using the thematic synthesis approach in order to divide the research into major topics such as lifecycle carbon monitoring, AI-driven emission prediction, multi-objective optimization of the design of a low-carbon, and smart operational control. It was possible through this process to identify methodological trends, domains of application, and research gaps in DT carbon management with AI [34,35].

3. Digital Twin-Based Carbon Data Modeling and Integration

Carbon management based on Digital Twin relies heavily on the acquisition, structuring and integration of carbon-related information into a consistent representation that can be used over lifecycle phases and spatial scales [36]. Such carbon-oriented twins need data pipelines to enable continuous or periodic synchronization and enable carbon measures to be recalculated as conditions evolve, unlike the conventional digital models, which are only updated periodically or to serve one purpose, such as design documentation or energy simulation. The following section will overview the conceptual and practical basis of carbon data modeling in Digital twins, including the sources of data, the digital infrastructure, how carbon is represented in the twin, and interoperability and data quality issues defining the reliability and scalability.

3.1. Carbon Data Sources and Digital Infrastructure

The construction and urban systems comprising carbon-related data are always heterogeneous due to the presence of a variety of processes and sources of these emissions. In the case of operational carbon, the most immediate sources of data are measures of energy taken in the form of utility meters, submeters, and building management systems [36]. Such measurements can have various temporal scales, including monthly billing data down to sub-minute sensor streams, and can have various end-uses, including HVAC, lighting, plug loads, household hot water, and on-site generation. Contextual variables to estimate the operational carbon, such as weather, internal loads, occupancy proxies, equipment status, and maintenance events, are also required to forecast the demand. These contextual variables are more and more available on the IoT in modern smart buildings and standard building automation protocols, but system fragmentation is still typical. **Table 2** summarizes the types of data that are relevant to carbon, their origins, time aspects, and functions in carbon modeling in a Digital Twin.

The data on embodied carbon is more difficult because it is less directly quantified and rather relies on the data about procurement and supply chain. Early design stages provide embodied carbon estimates that may be based upon generic databases or benchmark factors relating to material types and quantities based on BIM models [37]. Further in project development, the specific product details are revealed, such as the environmental product declaration, the supplier data, and the transportation distances. Other embodied-related contributions to construction are those of temporary construction work, packaging, waste, and substitutions through damage or rework that are often not recorded systematically unless digital procurement and site tracking systems are in place. A Digital Twin designed to embody carbon management consequently requires systems to connect objects and quantities in BIM to carbon factor datasets, as well as adapt to changes when product choices and supply chain decisions change.

Table 2. Carbon-Relevant Data Sources and Digital Twin Integration.

Carbon Category	Data Type	Typical Data Source	Temporal Resolution	Role in Carbon Modeling
Embodied Carbon	Material quantities	BIM models, quantity take-offs	Static/revision-based	Baseline embodied emission estimation
Embodied Carbon	Emission factors	Life Cycle Assessment (LCA) databases, Environmental Product Declarations (EPDs)	Periodic updates	Carbon coefficient mapping
Construction-Phase Carbon	Equipment fuel use	Telematics, fuel logs	Daily to real-time	Construction emission tracking
Operational Carbon	Energy consumption	Smart meters, Building Management System (BMS)	Minute to hourly	Operational carbon accounting
Operational Carbon	Grid emission factors	Utility data, grid operators	Hourly to sub-hourly	Carbon-aware operation
Urban Carbon	Mobility and land-use data	GIS, traffic sensors	Aggregated/dynamic	City-scale carbon analysis

Another category of data, which is between operational and embodied views, lies with construction-phase emissions. These emissions are due to the consumption of equipment fuel, electricity on site, transport logistics and workforce movements [38]. The estimated values can be based on the data of activities, including equipment hours, fuel receipts, telematics streams, and delivery logs. In the case of telematics and fleet management systems, they will give detailed operational profiles of the machinery, but these systems are not necessarily easily integrated with project schedules and site workflows. Moreover, the construction logistics could entail the use of several subcontractors and transport services, which produce data access and ownership challenges and bear on completeness. Digital Twins may be used as a common integration interface by connecting schedule models, site layout representations, and equipment states to have standardized carbon accounting at process levels.

The carbon data sources are further extended at the urban level to incorporate the land-use data, grid-carbon intensity profiles, as well as mobility data and district energy systems [39]. GIS and city information models offer the spatial context and can depict stocks of buildings, networks of infrastructure, and environmental ones. Urban morphology can be analyzed with the help of remote sensing and aerial images, and, in certain situations, proxies associated with energy demand or material stock can be inferred. Data on mobility based upon traffic sensors, transit systems, and anonymized location data are used to estimate transportation-related emissions as well as assess the effects of land-use and network interventions. To include such datasets in a city digital twin, it is necessary to coordinate spatial resolution, temporal resolution, and semantic meaning, particularly to connect urban-scale models with building-level twins.

The information beneath these data sources is called digital infrastructure, which renders them actionable. Cloud storage and computing can be scaled to provide analytics and simulation storage and processing, whereas edge computing can be used to provide low-latency and privacy-preserving data processing and operations in buildings or construction sites [40]. Sensible streams are increasingly managed by message brokers, time-series databases, and data lakes. Nonetheless, carbon-oriented Digital Twins do not only require data storage capabilities, but also utilize data mapping to model entities, the possibility of version management to help track changes in the design and as-built condition, and provenance, through which carbon outputs can be audited. As a matter of fact, the usefulness of a twin in carbon management is tightly linked to its capability to allow reproducibility and transparency of its data pipeline, and not only to provide dashboards [41].

3.2. Carbon Representation within Digital Twins

The visualization of carbon in a Digital Twin entails the representation of raw activity data into metrics of emissions in a manner that is consistent, auditable, and adaptable to alternative premises. Carbon is not a directly measured state variable of an asset; it is a derived final value that is reliant on both the emission factors and system boundaries and accounting conventions. As a result, the carbon representation should be considered as a modeling layer integrated into the twin instead of an output field that is directly added to a digital model [42].

To work with operational carbon, the basis relationship is that of energy use versus emissions using emission factors, which are usually stated in kilograms of CO_2-equivalent per unit of energy. The factors of emission can be used in the form of annual averages, marginal factors, or time-varying factors, which are used in electricity systems to represent fluctuations in the generation mix [43]. The implication of the choice is that time-averaged factors are easier to compute and more compatible with a variety of reporting frameworks, whereas marginal or time-varying factors allow more opportunities to optimize operations but need more data and interpretation. The carbon-oriented Digital Twin should thus encode the chosen accounting method, which should also be sensitive to an analysis, since different stakeholders might have varying accounting or regulatory demands.

In the case of embodied carbon, representation is often in the form of a mapping of quantities of materials to embodied emission factors, often broken down into life cycle stages, like the manufacturing of a product, transportation, construction/installation, maintenance/replacement, or end-of-life. Digital Twins can use BIM object properties and quantity takeoffs to auto-map this, and the quality of this mapping is as good as the semantic consistency of the model and the specificity of carbon factor data. Some of the challenges that the twin has to deal with when using EPD-based factors are functional unit alignment, proclaimed units' differences, boundary mismatches, and comparability of EPDs across product categories. In most real-world examples, hybrids will be formed: the initial design screening is carried out using generic factors, which will be progressively replaced by supplier-specific ones as the procurement decisions are made. An effective twin model, therefore, requires a progressive carbon model that is layered or staged to accommodate further refinement and trace back the previous assumptions [44].

The emissions during the construction phase should be represented through the process approach, where activities and resources are associated with fuel and electricity consumption. A twin can be taken to denote construction operations as task sequences, and resource assignment and emissions can be determined as a product of equipment operating hours and fuel consumption rates or fuel burn calculated using telematics. The emissions of logistics may be obtained using the records of deliveries and the distance of transport routes, yet, to be able to accurately quantify these flows, one has to define them regularly, considering the specifics of the boundaries of trips, load factors, and allocation rules of multiple-project deliveries [45]. In this case, the Digital Twin is expected to connect different datasets to a single process model to enable the assignment of emissions to tasks, trades, or work packages and have specific mitigation actions instead of generalized reporting.

One modeling inquiry is whether the carbon model in the twin must be physics, data, or hybrid-based. Scenario exploration and generalization can be achieved with the help of physics-based models, including energy simulation engines or thermodynamic models of HVAC systems, in particular, when the data about the past is minimal. More predictive accuracy can be achieved with data-driven models in well-instrumented settings, and a range of complex behavioral patterns like occupancy or equipment degradation can be accommodated. Hybrid models seek to merge such strengths in a constrained way through physics or a data-driven way through calibration of uncertain components. Hybrid methods are especially appealing as a tool in carbon management since they can achieve a trade-off between predictive performance and interpretability, and can lower the risk of AI models using spurious relationships that are no longer valid in changing conditions [46].

Making the carbon representation dynamic determines the carbon representation based on synchronization mechanisms. The operational twins need regular updates whenever measurements are received, but operational carbon models also need to change as design changes are made, value engineering choices are made, and procurements are changed. This suggests that versioned representations are required to be able to follow geometry and specifications and quantities changes, and update carbon metrics without losing comparability with history. The problem of conflicting versions arising in the twin renders it hard to respond to questions like whether the changes to the design increased the carbon performance, or whether it was just the modifications in the accounting. The idea of a carbon ledger in the twin is becoming more and more topical, whereby carbon contributions are recorded at a particular point in time, allocated to particular model states and data sources, and auditable by stakeholders [47].

3.3. Interoperability and Data Quality Issues

The ability to scale carbon-oriented Digital Twins rarely goes beyond prototypes and into actual projects and city programs due to interoperability. Built Environment (BE) data ecosystems are disjointed, and the design models, construction management software, operational systems, and urban data platforms have been built separately [48]. All systems have their data structures, identifiers, and semantics. Although data exchange formats could be present, the meaning of fields in one organization with another and one geography with another may not be the same, and there may be too much or too little detail than is required in carbon accounting. One example is that BIM models can depict material assemblies at a coordination level that is adequate but not at an embodied carbon mapping level, whereas operational systems may be providing energy information without explicit connection to particular zones or equipment in the digital model.

Carbon management is one area where semantic interoperability is paramount since calculations are done on carbon based on proper classification. Examples of items misclassified, inaccurate unit transformations, and omission of information concerning the type of products can lead to huge errors in the estimation of embodied carbon. The same problem can happen with operational carbon, where submeters are mislabeled, sensor drift is present or time stamps are misaligned. In an urban context, the effect of spatial misalignment and aggregation may cause some errors in the process of linking building stock data to district energy or mobility data. To overcome such problems, Digital Twins may enforce ontologies and standard identifiers, although it is difficult to implement such semantics across all stakeholders [49,50].

Uncertainty and incompleteness are also causes of data quality problems. Carbon factors are not inherently stipulated since they vary in manufacturing technology, supply chains and distribution of allocation in environmental declarations. Electrical operational emission factors are grid-dependent, and can change significantly with time and place. Measurement data could be contaminated or have no measurement, like the failure of the sensor, communication loss, or irregular commissioning. Subcontractors may withhold data on construction data (e.g., fuel receipts, equipment telemetry, etc.) or report on deliveries in a disorganized fashion. The Digital Twins that are carbon conscious should therefore be constructed to operate within the uncertainty domain as opposed to making carbon approximations to be deterministic outputs [51].

Uncertainty handling may be of various kinds. At least, the twin must give provenance and confidence indicators that report what portions of the carbon estimate are founded on measured data, based on generic assumptions, and based on inferred or imputed values. Other, more sophisticated methods use probabilistic models of the emission factors and propagate the uncertainty by calculating them in such a way that the decision-makers can compare the alternatives based on ranges rather than based on point estimates. This is particularly relevant in cases where there are small differences between the design alternatives when compared to uncertainty (whereby premature optimization may be drawn). When dealing with carbon optimization problems, the uncertainty-aware strategies can rank the interventions, which are robust over a range of possible emission factors and future operational conditions [52,53].

Scalability increases other interoperability and quality issues. The larger the system grows, beyond a single building to portfolios, districts, and cities, the more complex information governance becomes and the more heterogeneous the types of assets are. The balance between model granularity and the cost of computations: more detailed representations can provide better results in both the attribution and the targeting of interventions, but it might be too expensive to sustain too large a selection of potential inventories. Aggregated representations will make it cheaper, but they might blur emission sources and decrease the interpretability of AI suggestions. Within the framework of this trade-off, the digital twin design options are closely linked to the planned carbon management functions. A twin intended to serve regulatory reporting purposes can be interested in standardized and auditable metrics at coarse resolution, whereas a twin intended to serve operational control purposes can be interested in high-frequency data and actionable attribution at the equipment level [54].

Lastly, the problem of interoperability and quality is not necessarily a technical issue, but it is an institutional matter. Information security is subject to contracts, privacy regulations, and organizational incentives. Without a well-defined governance, the stakeholders might be reluctant to provide operational information, procurement information, or construction telemetry, which will limit the completeness of the twin. Likewise, the integration of standard practices would need coordination among the companies, states, and software platforms. In the case of SCI-standard research, this means that the contributions must not only be assessed in terms of the novelty of the model but also on the reproducibility of the data, both the ability of the data to be integrated, and the clarity of the assumptions. The carbon-oriented Digital Twins should be able to offer credible decision support only when they can be maintained reliably with transitioning through the lifecycle, and their carbon calculations can be explained and auditable as the data sources change [55].

To recap it all, a carbon data modeling based on Digital Twins needs an integrated infrastructure that is able to accept heterogeneous data at lifecycle stages and scale, model carbon using explicit accounting logic using model entities and emission factors, and interoperability and uncertainty as first-class issues. These factors determine the accuracy of AI-based prediction and optimization capabilities, which are based on the quality and semantic stability of inputs [56]. Based on this background, the following section discusses the application of AI methods in DT environments to predict carbon, use multi-objective optimization, and adaptive control in construction and urban systems. Following these data integration issues, **Figure 3** depicts a layered Digital Twin scheme, in which there are links between heterogeneous data sources and carbon accounting logic, uncertainty management, and lifecycle model synchronization.

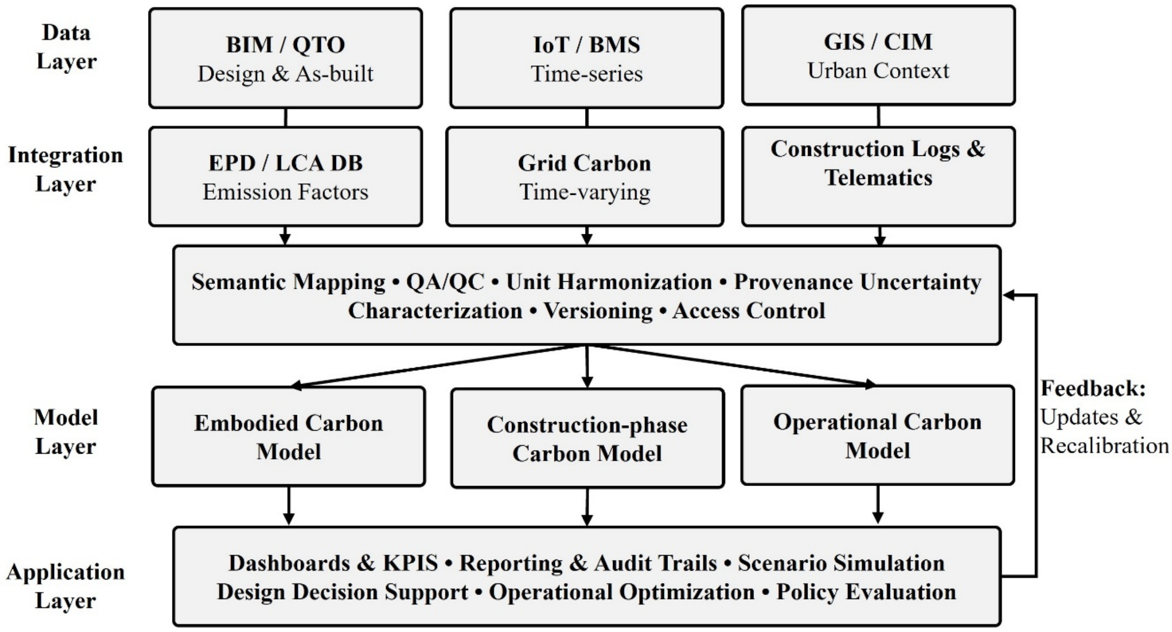

Figure 3. Carbon Data Integration Architecture within a Digital Twin.

4. AI-Driven Carbon Prediction, Optimization, and Control

Digital Twin infrastructures provide a dynamic digital representation of built assets and processes; however, their value for carbon management emerges when analytical intelligence is integrated to interpret data and guide decisions. Artificial intelligence enables this transformation by identifying relationships between operational variables and emissions, forecasting future carbon trajectories, and recommending interventions that balance carbon reduction with cost, performance, and operational constraints. Within DT environments, AI functions typically operate in three complementary domains: carbon prediction, multi-objective optimization, and adaptive operational control [57].

Different families of AI techniques support these functions with varying strengths. Supervised learning methods are widely used for carbon and energy prediction due to their ability to learn complex nonlinear relationships from historical data. Optimization algorithms are often employed in design and planning stages to evaluate alternative low-carbon configurations under multiple constraints. Reinforcement learning and adaptive control approaches are increasingly explored for operational decision-making where systems must respond dynamically to changing conditions. Hybrid approaches that integrate physics-based models with machine learning are gaining attention because they improve interpretability and robustness in environments characterized by uncertainty and limited data [58]. **Table 3** summarizes the main AI method categories and their typical roles in DT-based carbon management.

4.1. Carbon Emission Prediction and Forecasting

Prediction of carbon emission is an accurate predictive requirement of proactive carbon management. Within most systems that are DT-enabled, the derivation of emissions is done by taking a combination of the forecasts of the energy consumption, the material flows or operational activities, and the emission factors. Since operational emissions exist in most building systems, much research has been conducted to predict building energy demand by machine learning trained on historical operational data and environmental factors, including weather, occupancy, and system conditions [59].

Such extensive time-series data, especially regression models, random forests, and deep neural networks, are effectively used in supervised learning methods to forecast short-term. These models are effective at forecasting short-term operational carbon paths as well as justifying demand response policies. Nevertheless, as they are used to predict the future on longer time scales or adapt to new operating conditions, their predictive reliability can be poor, which underscores the need to keep retraining their models in DT scenarios.

Table 3. AI Methods and Their Roles in DT-Based Carbon Management.

AI Method Category	Typical Algorithms	Carbon Management Function	Application Context
Supervised Learning	Regression, Random Forest, Deep Neural Networks	Carbon and energy prediction	Building and district operation
Unsupervised Learning	Clustering, anomaly detection	Fault detection and inefficiency diagnosis	Building operation and construction
Optimization Algorithms	Genetic algorithms, Non-dominated Sorting Genetic Algorithm II (NSGA-II)	Low-carbon design and planning	Design and urban planning
Reinforcement Learning	Q-learning, deep reinforcement learning (RL)	Adaptive carbon-aware control	HVAC, storage, demand response
Hybrid Physics–AI Models	Machine learning (ML)-calibrated simulations	Robust carbon modeling	Lifecycle and cross-scale analysis

Another option that can be applied to the scenario where purely data-driven models might not be interpretable or extrapolative is hybrid physics-AI. Hybrid methods combine machine learning calibration with simulation-based building models to utilize knowledge about physical systems and adjust to observed data about the operation of that system. These methods are especially handy in lifecycle analysis or when making cross-scale projections in which incomplete datasets are being worked with, or when physical consistency of predictions is required [60–63].

4.2. Low-Carbon Design and Planning Optimization

In addition to prediction, AI techniques can also assist the decision-making process by finding design or planning options that reduce carbon emissions but meet other project goals. Decision-making in construction and urban design is multi-objective in nature by involving the trade-off between emissions, cost, performance, safety, and constructability. Genetic algorithms or multi-objective evolutionary algorithms are thus popular optimization algorithms that can be used to search a large space of designs and find Pareto-optimal solutions [64].

In the design of a building, optimization models can be used to test other combinations of building envelope properties, building materials, HVAC systems, or renewable energy systems. Such optimization can be used at district and urban levels when analyzing a scenario to electrify a strategy, create an energy sharing network, or invest in infrastructure. In such settings, AI can be seen as a decision-aiding instrument, but not as an independent controller, where planners can compare carbon results under different conditions.

The optimization method used is dependent on the degree of system complexity and accessible information. Data-driven surrogate models can be applied when there is a need to evaluate a large design space quickly, but physics-based or hybrid models are more applicable when the decision should be consistent with physical constraints or regulations. Notably, the results of the optimization process should be viewed with care due to the possibility of the surrogate models extrapolating outside of the training sample. By incorporating optimization software into DT settings, this risk can be addressed by ensuring that model assumptions can be traced, emission factors are updated, and that findings are related to real-world scenarios of operation [44,51,65].

4.3. Intelligent Operational Carbon Control

Adaptive operational control is the most vibrant AI implementation in DT settings. Systems based on building and district energy are designed to work in constantly changing conditions, including weather variations, occupancy levels, and changing carbon intensity in the grid over time. The point of AI-based controllers is to minimize emissions by modifying the work of systems without impairing the comfort, safety, and reliability of the work [66,67].

The rule-based control systems have continued to be popular in the management of buildings because they are easy and reliable. Model predictive control (MPC) is an improvement of these methods by optimizing the actions in the control of the system across a forecast horizon, taking into account the constraints of the system. Nonetheless, MPC is also computationally intensive and requires sound system models. The growing interest in reinforcement learning has consequently arisen since it can learn control policies as the system interacts with the environment, and thus can adapt to dynamic conditions [68].

In carbon-conscious control processes, reinforcement learning agents can opt to vary energy use at times with reduced grid carbon intensity or manage storage and renewable generation. Digital Twins offer a secure simulated environment to train and test such controllers and reduce the risks associated with the violation of comfort or operation instability in the real building [69].

Although these advances have been made, they are still not practical. There can be incompleteness of operational data or noisiness of data, considerable uncertainty exists with occupant behavior, and control policies should be able to adhere to safety and regulatory limits. Moreover, most studies show that performance improvement is only observed in simulated conditions with minimal evidence of long-term field deployment. To get to the maturity stage of DT–AI carbon management, the validation measures should not be limited to model accuracy criteria, but should provide evidence of reduction in emissions under actual operating systems, along with the tests of comfort, reliability, and system sturdiness [70].

All in all, AI will turn Digital Twins into active carbon management systems, capable of forecasting emission trends, assisting in low-carbon design decisions, and adaptive operational strategies. Data-based intelligence and domain knowledge that are most likely to help are combined, explicit carbon accounting is included in DT infrastructures, and uncertainty and validation are taken throughout the life cycle. Further studies must thus be devoted not only to the creation of more advanced algorithms but also to the ability to show quantitative carbon savings by deploying constructions of DT and AI to real-world settings [71].

5. Applications across Building, Infrastructure, and Urban Scales

The use of Digital Twin and AI-based carbon management varies significantly depending on the scale since the leading sources of emissions, existing data streams, decision variables, and stakeholder duties vary between buildings and construction processes, infrastructure networks, and cities [72]. At smaller scales, e.g., individual buildings, operational optimization can be optimized down to high resolution through detailed sensing and control, whereas embodied carbon interventions are dependent on design and procurement choices. At the bigger scales, say on the districts and cities, data is more aggregated and heterogeneous, and carbon consequences are more and more determined by interactions between systems between buildings, mobility, and energy supply. The following section summarizes the key application areas, highlights how the field of DT–AI integration is implemented in practice, the priorities of carbon management functions, and the types of evaluations.

5.1. Building-Level Applications

At the building level, DT–AI carbon management is highly focused on operational emission reduction and comfort, indoor air quality, and reliability. Construction of digital twins can combine metadata of assets derived by BIM, system schematics, and spatial zoning with smart meter, submeter, and building automation system time-series data [73]. The granularity of carbon accounting in this integration is possible, such that we can now report on emissions that are allocated to end uses, zones, or large groups of equipment compared to the traditional utility-based reporting. Combined with AI-based prediction, the twin can simulate the immediate energy and emissions paths based on the expectations of the weather and occupancy, which can be used to help in the proactive planning of operations.

Among them, carbon-conscious building operation is one of the major applications, where AI-driven policies cut emissions not just by means of energy efficiency but also by adjusting the building to cleaner electricity supply cycles. This necessitates the connection of building demand predictions and time dependent grid-carbon intensity that allows the regulation and arrangement of effort, like a pre-cool or pre-heat, altering domestic hot water heating, maximizing storage dispatch, and organizing on-site photovoltaic use. Under these conditions, a digital twin would be used, and it would act as an intermediary between material requirements and carbon targets and making proposed measures possible given equipment limits, thermal dynamics, and comfort settings. Contributions made by AI models include learning building response characteristics, and control action suggestions that minimize emissions during uncertainty [74].

The other significant building-level implementation is verifying performance and retrofit planning. Decarbonization of existing buildings is impossible without retrofitting, but the results of the retrofit process are questionable due to the heterogeneity of previous systems and their insufficient documentation. Digital twins have the capacity to meaningfully amalgamate-as-is documentation and sensor records as well as logs of operations, in order to develop a baseline carbon performance profile. Then, AI can be used to efficiently diagnose inefficiencies with the help of anomaly detection, equipment faults, and to estimate the potential savings of certain interventions. With retrofit in place, the twin would be able to support measurement and verification through prediction and observed performance comparison, and also through consideration of the external drivers, like changes in the weather and occupancy. This is of the essence to the management of carbon since the reduction of emissions should be of credible quality to facilitate financing schemes, performance contracts, and reporting [75].

Building-level embodied carbon applications are aimed at design-level decision support. In this case, the twin is normally pegged in BIM and connected to LCA databases and EPD repositories. AI may help by suggesting changes in material that would reduce carbon emissions, locating highly influential elements (structure and facade) in designs, and allowing exploration of embodied and operational carbon compromise design solutions. Although most studies are still at a prototype phase, the theoretical implications of such proposals are to incorporate embodied carbon accounting into the evolving design model in such a way that carbon implications become apparent as a normal design process. Building-level applications are giving more focus to lifecycle views, linking embodied decisions to operational performance models to prevent the reduction of embodied emissions by the narrow focus of operational carbon reduction or vice versa [76].

Measures which are commonly used at the building level include percent reduction in operational emissions, energy savings, violations of comfort constraints, and payback periods [55,77]. To be carbon conscious in operation, further stress is laid on the congruence of demand with the periods of low carbon and the sensitivity of outcomes to the selection of emission factors. In the case of retrofit, the plausibility of the baseline estimation and the strength of savings attribution in the presence of confounding factors take center stage. In all these applications, the common difficulty is to keep digital twin models compatible with actual building modifications like equipment replacements, changes in control logic, and shifts in occupancy regime, since these modifications may invalidate AI models when undetected and uncontrolled.

5.2. Construction and Infrastructure Systems

In construction and infrastructure works, the primary area of application changes to embodied emissions, emissions during construction, and the carbon considerations of the project delivery process [78]. Construction digital twins tend to be process-focused, as opposed to asset-focused. They combine schedule models, resource allocation, site logistics plans, and (where applicable) telematics data of equipment fleets. The twin can then be used to denote construction as a developing system of work, resources, and constraints in such a way that emissions can be attributed to work packages and trades as well as to time. The attribute is helpful since construction emissions are traditionally viewed as a secondary source to embodied and operational carbon, but they can become significant in large projects and are now more frequently exploited via the electrification of equipment and low-carbon construction.

One of them is carbon tracking and reporting of construction activities. The twin will utilize equipment usage data and fuel consumption estimates combined with schedule information to determine the profile of the emissions through the project timeline and pinpoint areas or activities with high intensity. Organizing AI can refine this process because it can predict probable emissions with different schedules, can spot abnormalities, like atypical high fuel usage that should signify gear difficulties, and propose methods to mitigate these, like resequencing work to create less waiting and overcrowding. In logistic-intensive projects, it is possible to combine the data on delivery and the site layout representation to estimate the transport emissions and optimize the time of delivery, as well as the delivery route to minimize the emissions and the schedule risk [79].

The system of infrastructures will pose more complexities due to the long lifespan of the assets, the presence of important embodied emissions, including concrete, steel, and asphalt, amongst others. Carbon management has expanded the traditional areas of interest of digital twins in infrastructure management, where structural health monitoring and maintenance planning were applied, to condition-based maintenance decisions based on emissions outcomes [80]. To give an example, maintenance plans that lengthen service life need not lead to carbon-intensive replacements; however, more interventions may also be required at their own cost. These trade-offs can be facilitated by AI as it proposes to predict degradation, schedule maintenance, and assess carbon implications in the lifecycle under uncertainty.

Another area of application where DT–AI integration has the potential to cut carbon emissions is prefabrication and modular construction, which should enhance the efficiency of materials, minimize waste, and enhance manufacturing and logistics. Digital twins may bridge the gap between design models and fabrication processes and supply chain scheduling, and allow for closer control of quantities and minimization of rework. AI can help to streamline cutting patterns, sequence production, inventory, and delivery arrangements [81]. Carbon advantages in this area tend to be of system-level increases in efficiency and the allowance of alternative materials and assemblies that are low-carbon to be implemented with increased confidence.

Assessment, when used across construction and infrastructure projects, historically focuses on the intensity of emissions required in each unit of output, e.g., per cubic meter of concrete placed, ton of material installed, or kilometer of infrastructure implemented. Nevertheless, SCI-standard research is becoming aware of the fact that these systems are of value because of their decision impact: the capability to alter procurement, scheduling, equipment selection, and maintenance approaches in a manner that results in confirmed emissions reductions without unacceptable cost and schedule repercussions. The challenge is that access to the data is usually discontinuous among subcontractors and suppliers, and most of the emissions estimates are based on assumptions and not measured directly. As a result, functionality applications are likely to focus on integration functionality, doubt and uncertainty management, and auditability over algorithmic complexity.

5.3. Urban and District-Level Carbon Management

Urban and district-level DT–AI carbon management is a problem of system integration where buildings, energy systems, mobility, and land use interact to influence the results of emissions. City digital twins are generally a combination of GIS layers, building stock models, infrastructure networks, and environmental data, with operational data of energy utilities, transportation networks, and municipal services. This is aimed not at measuring emissions alone but also at planning, scenario assessment, and governance. AI technologies are applied to predict the demand trends, predict the emissions under different futures, and optimize intervention portfolios of the assets of a spatial distribution [82].

Applications at the district scale tend to concentrate on concerted energy management since a district energy system, microgrids, and shared thermal networks present the possibilities of carbon mitigation due to aggregation, and flexibility. An example of building loads, renewable generation, storage assets, and network constraints as a district digital twin can be coordinated through AI to reduce emissions through load shifting, peak management, as well as effective dispatch of shared resources. In these applications, carbon goals can be defined in a more subtle way since the emissions are based on marginal electricity generation and the impacts that the activities by the districts have on the overall grid. Thus, carbon accounting, along with clear assumptions, becomes critical in order not to overestimate benefits.

Scenario-based evaluation of carbon is usually seen in urban planning applications, but not in real-time control. The carbon effects of building land use, changing the density, investing in transit, electrification, and building retrofits can be verified through city digital twins [83]. These analyses can be assisted by AI, which understands how cities are structured by learning to predict the association of urban form and energy needs, coming to predict the adoption of heat pumps and electric vehicles, and determining how incentives or retrofit resources should be allocated by optimizing the carbon reduction, given the budget limits. Reluctance to uniformly allocate costs and benefits within communities as a community is also being reflected in such uses, where the risk of inequity and vulnerability is becoming prevalent in how it is executed.

Urban carbon management is another dominant factor that constitutes mobility-related emissions. Combining traffic models, transit data, and land-use patterns via digital twins can be used to estimate vehicle flow emissions and analysis of interception, like transit priority, active mobility infrastructure, congestion management, and fleet electrification. The applications of AI to forecast travel demand, to detect bottlenecks, and to assess the effect of land use or transit service changes on the mode choice can be utilized [84]. When combined with building and energy modeling, these applications would help to conduct more all-encompassing evaluations of the effect of urban design choices on building-associated and transportation-associated emissions, which is needed to prevent a siloed approach.

Urban evaluation is usually more concerned with scenario comparability, transparency, and usability by the stakeholders. The usual reporting of carbon is as absolute reductions, per-capita emissions, or sector-based contributions, and uncertainty is one of the primary issues since the long-term projections are based on an estimate of socio-economic trends, the cost of technology, adoption of the policy, and climate conditions [85]. Digital twins can offer a systematic setting to deal with this uncertainty through keeping explicit assumptions of scenarios and performing sensitivity analysis. In the case of SCI-standard contributions, credibility depends on the quality of model validation with respect to observed data, documented assumptions, and the assumption that decision recommendations are consistent with the governance processes in the form of building performance standards, zoning, and infrastructure investment cycles.

To conclude, building-scale applications also use detailed sensing and control to minimize operational emissions, as well as support retrofit verification, process emissions, and lifecycle interventions are used in construction and infrastructure applications, and integrated scenario planning and coordinated energy and mobility strategies in urban-scale applications. In smaller and smaller scales, the most successful DT–AI solutions are those that tie carbon accounting with tangible decision levers, integrate data in tracks, and show carbon impact within attainable real-world conditions. These application insights provide preconditions to analyze the challenges, limitations, and perspectives of future research in the following section on DT–AI-enabled carbon management [50]. To emphasize the insights of applications at spatial scales, **Table 4** undertakes a comparison of the prevailing carbon focuses, DT–AI functions, and implementation issues of the building, construction, infrastructure, district, and city levels.

Table 4. DT–AI Carbon Management Applications across Scales.

Scale	Primary Carbon Focus	Typical DT–AI Functions	Key Challenges
Building	Operational and embodied carbon	Carbon-aware operation, retrofit evaluation	Data drift, occupant behavior uncertainty
Construction	Construction-phase emissions	Equipment tracking, low-carbon scheduling	Fragmented data ownership
Infrastructure	Embodied and maintenance carbon	Lifecycle optimization, condition-based planning	Long lifetimes, uncertain degradation
District	Coordinated operational carbon	Energy sharing, demand shifting	System-level coordination
City	Integrated sectoral emissions	Scenario planning, policy evaluation	Governance, uncertainty, data heterogeneity

6. Challenges, Limitations, and Future Research Directions

Although it is likely to expand faster in the academic literature and more pilot projects are introduced, the concept of Digital Twin and AI-based carbon management in sustainable construction and urban design is limited by background issues that cut across technology, data, organizations, and governance [86]. Most of the systems that have been reported to perform well in controlled case studies have been found to exhibit challenges when scaled to asset portfolios, or over a lifetime cycle of operation, or operating within real operational constraints. Such constraints do not mean that there is no potential; however, they display that DT–AI carbon management should be considered a socio-technical change where digital infrastructures, analytical modeling, and decision-making processes are co-evolved. This part is a summary of the most enduring impediments and develops research principles that can transfer the research field out of fragmented prototypes to dependable, scalable, and verifiable carbon effect.

Consistent with these challenges and opportunities, **Figure 4** conceptualizes a Digital Twin architecture on a multi-scale, in which building-, district-, and city-level twins engage with one another to help coordinate carbon management within governance and data-sharing limitations.

6.1. Technical and Computational Challenges

One important technical issue is to have a good model fidelity with scalability and traceability. The Digital Twins of buildings, construction sites, and cities should be models of complicated physical systems at different levels of detail and with uncertain boundaries [49]. Physics-based simulations are sometimes computationally expensive and hard to calibrate, and purely data-driven models may have generalization failures in the case of a change in conditions. Practically, built assets change continuously with retrofits, equipment replacement, alteration of operations policy, and occupant behavior changes. These dynamics bring in non-stationarity, which can worsen both the predictive models and control policies. Consequently, the management of the carbon system will need to accommodate constant calibration and updating, but the current literature applies rather limited research to model training and validation as a one-time process instead of a process that persists throughout the lifecycle.

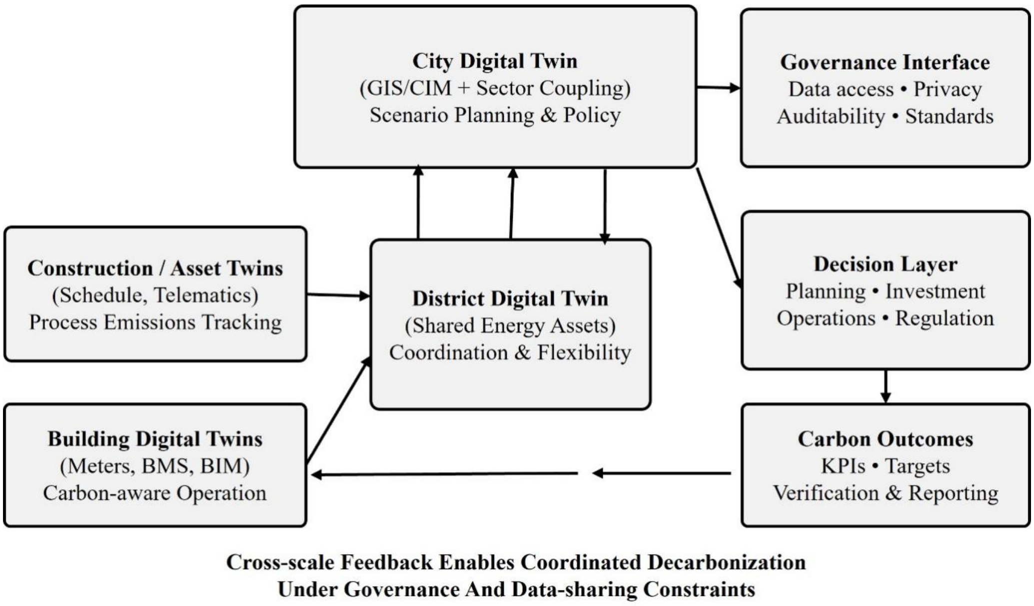

Figure 4. Multi-Scale Digital Twin Architecture for Carbon Management.

Latency of data and data reliability also make it difficult to manage carbon in near-real time. Urban data pipelines and building tend to have gaps as a result of sensor failures, network failures, or uneven commissioning. The data on construction can be incomplete due to the possibility of equipment telemetry not being available between subcontractors and logistics records not tracking entire journeys and load factors. Carbon quantification (in situations where operational data at high frequencies is known) needs time-varying and context-specific emission factors, and their association with measurements can usually add extra latency and uncertainty[87]. All of these problems are barriers to the effectiveness of closed-loop carbon control measures and reduce the credibility of reported carbon performance.

Interoperability is also a technical choke point, not due to file format differences only, but due to semantic misalignment as well. Carbon calculations are based on proper mapping of digital entities and accounting policies such as units, material classifications, system boundaries, and allocation procedures[23]. The object libraries are not always consistent, the metadata is incomplete, and the classification systems across organizations are not the same, which complicates automating the estimation of embodied carbon and propagating changes as the designs are changed. At the city scale, interoperability issues become more about spatial harmonization over datasets and reconciliation of aggregated and disaggregated representations. In the absence of sound semantic integration, DT–AI systems will be prone to generating results that look accurate but cannot be reproduced and audited.

The cross-scale applications are especially sensitive to the issue of computational burden. Twin-scale urban models that combine building stock models, energy network models, mobility models, and policy scenarios may be computationally costly, particularly when the optimization loops are applied in order to evaluate intervention portfolios. Real-time operational twins should also have latency constraints of control and monitoring that can require edge computing and strong failover. The dichotomy between computational efficiency and representational fidelity thus lies at the heart of DT–AI carbon management, and is made worse by the fact that, to quantify uncertainty and to do sensitivity analysis, both of which involve repeated model analysis, makes the computation necessary [88].

Other technical restrictions are cybersecurity and resilience. Digital twins combine operation technology and information technology, and usually provide additional access to building automation and control of infrastructure [49]. When a carbon-conscious twin is introduced to suggest or implement control action, it is a possible attack point that may compromise comfort, safety, or other important services. A great deal of the existing studies refer to cybersecurity issues, yet do not offer much technical detail regarding threat models, authentication, access control, secure data pipelines, or safe operational modes. To achieve research that can be scaled, cyber-resilient designs and validation are an essential requirement, and it should be on the front burner instead of an afterthought.

6.2. Organizational, Economic, and Governance Barriers

A characteristic of construction and urban development is organizational fragmentation, which severely constrains the continuity needed in lifecycle Digital Twins [89]. The operation, construction, and design are usually handled by various entities using various tools and incentives that cause information discontinuities during handover. This is to the detriment of carbon management: the embodied carbon data might not be carried forward to operation; the operational data might not be fed back to make better design decisions, and the construction emissions may not be well-documented since this is not a typical reporting practice. These discontinuities further diminish the practicality of constant updating of AI models, which requires a consistent availability of data and a clear responsibility of stewardship over the models.

Economic obstacles consist of initial implementation expenses, integration burdens, and indefinite returns. The creation of a carbon-oriented Digital Twin involves spending on sensing, data infrastructure, model building, and training of the organization. Not only is it a technological cost, but also a procedural cost because the workflows have to be restructured to enable them to take into consideration carbon intelligence in decision-making. In most undertakings, the party making payment on digital infrastructure is not the party enjoying the long-term operational carbon savings, resulting in imbalanced incentives. This is particularly accentuated in speculative development, whereby assets can be sold soon after completion, making it difficult to invest in operational optimization abilities.

Adoption is also limited by skills and capacity constraints. DT–AI carbon management requires disciplinary skills that cut across the fields of construction engineering, building physics, data engineering, AI, and sustainability assessment [90]. Most organizations do not have teams that can sustain these systems past pilot stages, and outsourcing may create the aspect of dependency and loss of internal learning. Moreover, practitioners might also be wary of following AI-based recommendations that cannot be easily interpreted or are incongruent with existing operational heuristics. This is not a simple opposition towards change, but it is a valid concern of reliability, liability, and accountability.

The governance issues define the type of data that can be gathered, distributed, and used. Operation data can include sensitive data with references to occupancy trends, business operations, or even individual conduct, which makes it an issue of privacy. The information in procurement and supply chains may be commercially confidential, which does not allow access to specific embodied carbon factors of the products. The complexity of governance in city-scale twins has been attributed to the presence of multiple agencies and other players who manage the data of interest to emissions, and policy results made on the basis of model outcomes should be transparent and challengeable [89]. In the absence of transparent data ownership governance structures, data access control, data consent, and accountability, DT–AI carbon governance systems will likely be restricted in scope to organizational segments and fail to enhance integrated decarbonization initiatives.

Regulatory preparedness is also a limiting factor to deployment. Although the requirement to report on carbon is growing in most jurisdictions, there are no standardized rules of digital carbon accounting, model validation, or audit [91]. The lack of clarity on the issue of how AI-generated carbon estimates are to be checked, the way to report uncertainty, and how the digital evidence is to be accepted in enforcement situations generates uncertainty that turns away investors. On the other hand, too stringent rules may limit creativity in case they fail to be flexible to changing digital twins and updating the datasets on the emission factors. It then follows that a standardization versus flexibility in the field is necessary to maintain a balance between credibility and innovativeness.

6.3. Future Research Opportunities

The first initiative to undertake in future research is the creation of hybrid carbon modeling methods that integrate physics-based representation with data-driven learning in a manner that is interpretable and resilient to changing conditions. Hybrid models have the ability to make use of physical constraints to achieve better generalization and may result in data-driven components to tune uncertain parameters, and are able to identify performance drift as well as adapt to changes in operation [46]. In the case of carbon management, these models must explicitly include both embodied and operational aspects and must be in a position to deal with time-dependent emission factors and changing supply chain attributes. This requires studies of model architectures, calibration techniques, and validation procedures that attempt to treat the twin as an ever-changing system and no longer a fixed simulation object.

The second key opportunity is explainable and reliable AI applied to carbon-related critical decisions. Most of the available research is on improvements in accuracy; however, the adoption level will require the ability of the decision-makers to comprehend why a model suggests a specific intervention and the ability to evaluate the risk of acting on a specific intervention. Further work in this area should thus focus on explainability approaches that are significant to the stakeholders of the built environment, including assigning the drivers of emissions to individual building areas, equipment, materials or construction activities and providing uncertainty in a way that can be used in a decision-making process. Robustness is also the need for trustworthiness that undergoes distribution shift and adversarial or worst-case testing and incomplete data that simulates actual deployments [92].

The high-impact research areas include interoperability and semantic integration. The further development will not be feasible without enhanced data exchange formats but shared ontologies and semantic mappings that will link BIM objects, GIS features, IoT signals, and carbon datasets on a consistent basis. Future studies ought to look at the way in which semantic layers can be placed to allow automated mapping of embodied carbon, lifecycle information transfer, as well as cross-scale aggregation without losing traceability. These encompass planning to maintain identifiers across a lifecycle, standardized metadata of carbon-related attributes, and versioning and provenance management to ensure that carbon computing can be audited in the long term [36].

Another characteristic frontier is cross-scale integration. Most carbon management opportunities can be found in the interactions between buildings, districts, and cities, but most DT–AI efforts are implemented at one scale because of data and computing limitations [93]. Further development of hierarchical and federated twin architecture should proceed, whereby building twins offer extensive local control and district and city twins set high-level planning and network limits. These architectures need to trade off privacy and data ownership with system optimization, and studies on federated learning, privacy-conserving analytics, and decentralized coordination approaches are needed to provide carbon benefits without necessarily having access to all raw data at a centralized location.

Self-adaptive and autonomous carbon-aware systems are a more distant trend, but their implementation requires stringent safety and governance systems [52]. This may be adaptive controllers in buildings that are constantly optimizing carbon performance to ensure comfort and indoor air quality constraints. In construction, it may include dynamic scheduling and systems of logistics reacting to disruptions and reducing emissions, and preventing safety risks. On a city-level, it may entail the implementation of policy experimentation, where models are simulated to test interventions first, and then a real-world implementation is done. To achieve these dreams, it will be necessary to develop safe reinforcement learning, constraint satisfaction, and formal verification techniques that will suit the intricacies of the built environment.

Lastly, future studies should focus on the methods of evaluation that reveal the actual carbon impact. Most of the studies advertise the precision of the model or simulated savings; fewer show data of protracted reductions of emissions in operational settings. Standardized standards would be a good idea in SCI-standard contributions, open datasets where feasible, and in reporting structures that provide uncertainty, constraints, and contain information about implementation. Field experiments, seasonal assessment, Field experiments Field experiments and longitudinal validation. It is imperative to understand the role of models in season-to-season, systems-to-systems, and human action with algorithm recommendations. Through evaluation that is consistent with policy and financial mechanisms is equally crucial, including the way the use of DT–AI evidence can facilitate reporting on compliance, performance-based rewards, and plausible assertions in Environmental, Social, and Governance (ESG) settings [94].

To conclude, the potential challenges to the implementation of DT-driven carbon management are difficult to keep in a reliable, interoperable, and secure digital representation of the lifecycle levels and scales, and organizational and governance factors that predetermine access to and accountability of data. Further studies must shift towards hybrid modeling, reliable AI, semantic interoperability, cross-scale architecture, and rigorous real-world testing, the general purpose of which is to transform the potential of digital into practical and verifiable decarbonization levels of buildings, infrastructure, and cities.

7. Conclusions

This review has explored the new field of Digital Twin technologies and Artificial Intelligence to manage carbon in sustainable construction and city planning. The synthesis emphasizes the benefits of DT infrastructures through facilitating the ongoing incorporation of lifecycle information, and the benefits of AI techniques by offering predictive, optimization, and control services that can be used to support more proactive strategies regarding carbon management throughout the design, construction, and operation phases.

According to the literature, DT–AI systems are capable of improving the transparency of carbon and decision-making in the built environment significantly. Machine learning is commonly used to predict energy and carbon; optimization algorithms can be used in multi-objective decisions in design and planning, and reinforcement learning is becoming a common methodology in adaptive operational control. Integrated into DT systems, these techniques allow ongoing monitoring of performance, analysis of scenarios, and responsiveness to changes in the environmental and operating conditions.

In spite of this possibility, there are a number of obstacles to large-scale implementation that still exist. One of the main obstacles is the failure in the availability of lifecycle data, interoperability between digital platforms, and the necessity of stronger validation of AI models in practice. There is a lot of evidence of promising findings in simulation or pilot-scale experiments, but longitudinal empirical data on carbon reduction in running systems are limited.

Instead, in practical terms, the implementation of DT–AI systems will not take place successfully without the implementation of integrated data infrastructures, standard carbon accounting frameworks, and open model validation practice. Future studies should then be directed at hybrid models that integrate both physical and data-driven learning, better data management policies, and large-scale demonstration projects that assess the quantifiable effects of carbon reduction metrics over time.

Altogether, the adoption of Digital Twins and AI is a promising direction for intelligent and lifecycle-based carbon management in the built environment. Connecting digital infrastructure with advanced analytics, DT–AI systems will allow tailoring more informed planning, streamlined building operations, and a long-term process of moving towards carbon-neutral construction and urban development.

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The author declares no conflict of interest.

References

[1] Soares, F., Silva, M., Azevedo, I., 2025. Urban decarbonization policies and strategies: A sectoral review. Renewable and Sustainable Energy Reviews. 215, 115617.

[2] Schiller, G., 2007. Urban infrastructure: Challenges for resource efficiency in the building stock. Building Research and Information. 35(4), 399–411.

[3] Držečnik, M., Klanšek, U., 2025. Advances and Challenges of Enhancing Operational Efficiency and Maintenance Protocols in the Construction Industry by Combining DT, AI, and Optimization. In: Carvalho, L., Reis, L., Figueiredo, A., et al. (Eds.). Leveraging Technology for Organizational Adaptability. IGI Global Scientific Publishing: Hershey, PA, USA. pp. 225–284.

[4] Iliuţă, M.-E., Moisescu, M.-A., Pop, E., et al., 2024. Digital twin—A review of the evolution from concept to technology and its analytical perspectives on applications in various fields. Applied Sciences. 14(13), 5454.

[5] Fu, X., 2017. Developing an Integrated Scenario-based Urban Resilience Planning Support System [PhD Thesis]. University of Cincinnati: Cincinnati, OH, USA.

[6] Peer, S., Streicher, W., Wagner, G., 2025. Built environments and mobility. In: Huppmann, P., Keiler, M., Riahi, K., et al. (Eds.). Second Austrian Assessment Report on Climate Change (AAR2) of the Austrian Panel on Climate Change (APCC). Austrian Academy of Sciences Press: Vienna, Austria.

[7] Adewale, B.A., Ene, V.O., Ogunbayo, B.F., et al., 2024. Application of artificial intelligence (AI) in sustainable building lifecycle: A systematic literature review. Buildings. 14, 2137.

[8] Tang, Q., Luo, L., 2014. Carbon management systems and carbon mitigation. Australian Accounting Review. 24(1), 84–98.

[9] Wu, W., Yang, H., Chew, D., et al., 2014. A real-time recording model of key indicators for energy consumption and carbon emissions of sustainable buildings. Sensors. 14(5), 8465–8484.

[10] Iyiola, O.O., 2025. Autonomous Building Envelope Systems: AI-Driven Optimization for Climate-Adaptive Facades and Energy Efficiency. International Journal of Research Publication and Reviews. 6(3), 8549–8565.

[11] Drici, H., Carpio-Pinedo, J., 2025. Urban land use mix and AI: A systematic review. Cities. 165, 106102.

[12] Digkoglou, P., Papathanasiou, J., 2025. Application of multiple criteria decision aiding in environmental policy-making processes. International Journal of Environmental Science and Technology. 22(8), 6967–6982.

[13] Chen, S.-Y., 2026. BIM-based Climate Action for Mitigation and Adaptation: Carbon-Neutral Buildings and Regional Carbon Footprint Management. Computer-Aided Design & Applications. 23(1), 68–84.

[14] Sepasgozar, S.M., Khan, A.A., Smith, K., et al., 2023. BIM and digital twin for developing convergence technologies as future of digital construction. Buildings. 13(2), 441.

[15] Rasheed, A., San, O., Kvamsdal, T., 2020. Digital twin: Values, challenges and enablers from a modeling perspective. IEEE Access. 8, 21980–22012.

[16] Piras, G., Agostinelli, S., Muzi, F., 2024. Digital twin framework for built environment: A review of key enablers. Energies. 17(2), 436.

[17] Mehmood, A., Arif, M., Mehmood, F., 2025. Towards a Unified Digital Ecosystem: The Role of Platform Technology Convergence. Electronics. 14(24), 4787.

[18] Hakimi, O., Liu, H., Abudayyeh, O., et al., 2023. Data fusion for smart civil infrastructure management: A conceptual digital twin framework. Buildings. 13(11), 2725.

[19] Hartmann, F., Perego, P., Young, A., 2013. Carbon accounting: Challenges for research in management control and performance measurement. Abacus. 49(4), 539–563.

[20] Chen, T., Debnath, R., 2025. The need of explainability in low-carbon urban system design using AI: A systematic review. Machine Learning: Earth. 1(1), 011001.

[21] Hosamo, H., Mazzetto, S., 2024. Performance Evaluation of Machine Learning Models for Predicting Energy Consumption and Occupant Dissatisfaction in Buildings. Buildings. 15(1), 39.

[22] Li, S.E., 2023. Reinforcement Learning for Sequential Decision and Optimal Control. Springer: Singapore.

[23] Tang, Q., 2025. Emerging Technologies, Sustainability and Carbon Accounting. In Carbon Accounting and Sustainability, Volume II: Corporate Sustainability Development. Palgrave Macmillan: Cham, Switzerland. pp. 177–223.

[24] Emmanouilidis, C., Pistofidis, P., Bertoncelj, L., et al., 2019. Enabling the human in the loop: Linked data and knowledge in industrial cyber-physical systems. Annual Reviews in Control. 47, 249–265.

[25] Abadi, A., Abadi, C., Abadi, M., 2025. Artificial Intelligence and Digital Twins for Sustainable Production Systems. Sensors and Transducers. 270(3), 1–10.

[26] Pan, W., Li, K., Teng, Y., 2018. Rethinking system boundaries of the life cycle carbon emissions of buildings. Renewable and Sustainable Energy Reviews. 90, 379–390.

[27] Gibassier, D., Schaltegger, S., 2015. Carbon management accounting and reporting in practice: A case study on converging emergent approaches. Sustainability Accounting, Management and Policy Journal. 6(3), 340–365.

[28] Tang, Q., Tang, L.M., 2019. Toward a distributed carbon ledger for carbon emissions trading and accounting for corporate carbon management. Journal of Emerging Technologies in Accounting. 16(1), 37–46.

[29] Park, B., Dong, J., Liu, B., et al., 2023. Decarbonizing the grid: Utilizing demand-side flexibility for carbon emission reduction through locational marginal emissions in distribution networks. Applied Energy. 330(Part A), 120303.

[30] Sharma, N., De, P.K., 2022. Towards Net-Zero Targets: Usage of Data Science for Long-Term Sustainability Pathways. Springer Nature: Berlin, Germany.

[31] Thabrew, L., Wiek, A., Ries, R., 2009. Environmental decision making in multi-stakeholder contexts: Applicability of life cycle thinking in development planning and implementation. Journal of Cleaner Production. 17(1), 67–76.

[32] Neo, H., Pow, C.P., 2015. Eco-cities and the promise of socio-environmental justice. In: Bryant, R.L. (Ed.). The International Handbook of Political Ecology. Edward Elgar Publishing: Cheltenham, UK. pp. 401–416.

[33] Wang, Y., Schnabel, M.A., Zhang, Y., et al., 2026. AI-Enabled Digital Twins in the Built Environment: A Bibliometric Review of Applications, Trends, and Future Directions. Buildings. 16(4), 809.

[34] Eze, E.N., Sanusi, A.N., Iheoma, I.J., 2025. Artificial intelligence in climate change mitigation and adaptation: A review of emerging technologies and real-world applications. Global Journal of Engineering and Technology Advances. 24(2), 235–250.

[35] Cong, C., Page, J., Kwak, Y., et al., 2024. AI analytics for carbon-neutral city planning: A systematic review of applications. Urban Science. 8(3), 104.

[36] Xu, J., MacAskill, K., 2024. Carbon data and its requirements in infrastructure-related GHG standards. Environmental Science and Policy. 162, 103935.

[37] Hunt, J., Osorio-Sandoval, C.A., 2023. Assessing embodied carbon in structural models: A building information modelling-based approach. Buildings. 13(7), 1679.

[38] Kennedy, C., Pincetl, S., Bunje, P., 2011. The study of urban metabolism and its applications to urban planning and design. Environmental Pollution. 159(8–9), 1965–1973.

[39] O'Shaughnessy, E., Heeter, J., Keyser, D., et al., 2016. Estimating the National Carbon Abatement Potential of City Policies: A Data-Driven Approach. National Renewable Energy Laboratory (NREL): Golden, CO, USA.

[40] Trigka, M., Dritsas, E., 2025. Edge and cloud computing in smart cities. Future Internet. 17(3), 118.

[41] Singhal, S., Sharma, A.J., Sharma, K.A., et al., 2025. Integrating AI, IoT, and Data Science for a Comprehensive Carbon Management System. In: Pandey, H.M., Goel, P.K., Balyan, V., et al. (Eds.). Advanced Systems for Monitoring Carbon Sequestration. IGI Global Scientific Publishing: Hershey, PA, USA. pp. 219–246.

[42] Thelen, A., Zhang, X., Fink, O., et al., 2022. A comprehensive review of digital twin—Part 1: modeling and twinning enabling technologies. Structural and Multidisciplinary Optimization. 65(12), 354.

[43] Goldsworthy, M., Aryai, V., 2023. On the use of time varying marginal and time varying average emissions factors in building energy analysis. Sustainable Energy, Grids and Networks. 35, 101103.

[44] Wang, Q., Yin, Y., Chen, Y., et al., 2024. Carbon peak management strategies for achieving net-zero emissions in smart buildings: Advances and modeling in digital twin. Sustainable Energy Technologies and Assessments. 64, 103661.

[45] Janné, M., 2020. Construction Logistics in a City Development Setting [PhD Thesis]. Linköping Universitet: Linköping, Sweden.

[46] Gambhir, A., Schulz, N., Napp, T., et al., 2013. A hybrid modelling approach to develop scenarios for China's carbon dioxide emissions to 2050. Energy Policy. 59, 614–632.

[47] Alotaibi, E.M., Khallaf, A., Abdallah, A.A.N., et al., 2024. Blockchain-driven carbon accountability in supply chains. Sustainability. 16(24), 10872.

[48] Sawhney, A., Odeh, I.S., 2020. Digital ecosystems in the construction industry—Current state and future trends. In: Sawhney, A., Riley, M., Irizarry, J. (Eds.). Construction 4.0: An Innovation Platform for the Built Environment. Routledge: London, UK. pp. 42–61.

[49] Omrany, H., Al-Obaidi, K.M., Husain, A., et al., 2023. Digital twins in the construction industry: A comprehensive review of current implementations, enabling technologies, and future directions. Sustainability. 15(14), 10908.

[50] Tzachor, A., Sabri, S., Richards, C.E., et al., 2022. Potential and limitations of digital twins to achieve the sustainable development goals. Nature Sustainability. 5(10), 822–829.

[51] Zhao, X., Zhang, Y., 2024. Integrated management of urban resources toward Net-Zero smart cities considering renewable energies uncertainty and modeling in Digital Twin. Sustainable Energy Technologies and Assessments. 64, 103656.

[52] Alevizos, V., Gerolimos, N., Leligkou, E.A., et al., 2025. Sustainable Swarm Intelligence: Assessing Carbon-Aware Optimization in High-Performance AI Systems. Technologies. 13(10), 477.

[53] Zhang, Y., Tian, J., Guo, Z., et al., 2025. Uncertainty-Aware Economic Dispatch of Integrated Energy Systems with Demand-Response and Carbon-Emission Costs. Processes. 13(6), 1906.

[54] Agbossou, I., 2023. Multi-Scalar urban digital twin design: Architecture and OpenUSD standards based methodology. PriMera Scientific Engineering. 4(1), 33–48.

[55] Mesa, J.A., Kwak, M., Shevchenko, T., et al., 2025. Proposing a carbon reduction engineering framework for product design: A multi-scenario perspective. Re-

search in Engineering Design. 36(4), 17.
[56] Yitmen, I., Almusaed, A., Hussein, M., et al., 2025. AI-Driven Digital Twins for Enhancing Indoor Environmental Quality and Energy Efficiency in Smart Building Systems. Buildings. 15(7), 1030.
[57] Awuzie, B., Ngowi, A., Aghimien, D., 2024. Towards built environment Decarbonisation: A review of the role of Artificial intelligence in improving energy and Materials' circularity performance. Energy and Buildings. 319, 114491.
[58] Fang, Y., Zhang, X., Cao, Y., 2025. Digital technologies framework and future trends of carbon sequestration research in urban green spaces: A review. International Journal of Environmental Science and Technology. 22(13), 13277–13296.
[59] Gao, H., Wang, X., Wu, K., et al., 2023. A review of building carbon emission accounting and prediction models. Buildings. 13(7), 1617.
[60] Ivanov, D., 2023. Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. International Journal of Production Economics. 263, 108938.
[61] Gaur, L., Afaq, A., Arora, G.K., et al., 2023. Artificial intelligence for carbon emissions using system of systems theory. Ecological Informatics. 76, 102165.
[62] Sadefo Kamdem, J., Miano Mukami, P., Njong, J.B., 2025. Time-frequency analysis and machine learning models for carbon market forecasting. Annals of Operations Research. 352(3), 543–562.
[63] Huang, B., Xing, K., Ness, D., et al., 2022. Rethinking carbon–neutral built environment: Urban dynamics and scenario analysis. Energy and Buildings. 255, 111672.
[64] Makhloufi, A.W., Louafi, S., 2024. Optimising building performance for a resilient Future: A Multi-Objective approach to Net Zero energy strategies. Energy and Buildings. 324, 114869.
[65] Anyanya, D., Paulillo, A., Fiorini, S., et al., 2025. Evaluating sustainable building assessment systems: A comparative analysis of GBRS and WBLCA. Frontiers in Built Environment. 11, 1550733.
[66] Mozo, A., Karamchandani, A., Gómez-Canaval, S., et al., 2022. B5GEMINI: AI-driven network digital twin. Sensors. 22(11), 4106.
[67] Ghazaly, N.M., Chaudhari, P.B., 2024. AI-Based Adaptive Control Systems for Power Electronics. Research Journal of Computer Systems and Engineering. 5(1), 34–44.
[68] Saif, M., Kiran, R., Dansena, P., et al., 2025. Anomaly Detection in Carbon Sequestration: Advancements, Challenges, and Future Directions. In: Wahid, A., Kumar Donta, P. (Eds.). Advanced Techniques for Anomaly Detection. CRC Press: Boca Raton, FL, USA. pp. 1–33.
[69] O'Dwyer, E., Pan, I., Charlesworth, R., et al., 2020. Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. Sustainable Cities and Society. 62, 102412.
[70] Kanthila, C., Boodi, A., Beddiar, K., et al., 2021. Building occupancy behavior and prediction methods: A critical review and challenging locks. IEEE Access. 9, 79353–79372.
[71] Kapinski, J., Deshmukh, J., Jin, X., et al., 2016. Simulation-based approaches for verification of embedded control systems: An overview of traditional and advanced modeling, testing, and verification techniques. IEEE Control Systems Magazine. 36(6), 45–64.
[72] Elghaish, F., Matarneh, S., Hosseini, M.R., et al., 2024. Predictive digital twin technologies for achieving net zero carbon emissions: A critical review and future research agenda. Smart and Sustainable Built Environment. 15(2), 680–709.
[73] Babu Saheer, L., Garbagna, L., Sasidharan, M., 2025. Systematic review of air quality modeling in digital twins for sustainable green cities. Discover Environment. 3(1), 199.
[74] Hanafi, A.M., Moawed, M.A., Abdellatif, O.E., 2024. Advancing sustainable energy management: A comprehensive review of artificial intelligence techniques in building. Engineering Research Journal (Shoubra). 53(2), 26–46.
[75] Nutkiewicz, A., Choi, B., Jain, R.K., 2021. Exploring the influence of urban context on building energy retrofit performance: A hybrid simulation and data-driven approach. Advances in Applied Energy. 3, 100038.
[76] Liang, Y., Li, C., Liu, Z., et al., 2023. Decarbonization potentials of the embodied energy use and operational process in buildings: A review from the life-cycle perspective. Heliyon. 9(10), e20190.
[77] Harvey, L.D., 2009. Reducing energy use in the buildings sector: measures, costs, and examples. Energy Efficiency. 2(2), 139–163.
[78] Amarasinghe, I., Liu, T., Stewart, R.A., et al., 2025. Paving the way for lowering embodied carbon emissions in the building and construction sector. Clean Technologies and Environmental Policy. 27(4), 1825–1843.
[79] Karri, J., 2014. Evaluating the Effects of Logistic Costs in Accounting to Improve Reliability and Efficiency-Case Stora Enso Logistics [Master's Thesis]. Aalto University: Espoo, Finland.
[80] Zou, G., Banisoleiman, K., González, A., et al., 2019. Probabilistic investigations into the value of information: a comparison of condition-based and time-based maintenance strategies. Ocean Engineering. 188, 106181.
[81] Nweje, U., Taiwo, M., 2025. Leveraging Artificial Intelligence for predictive supply chain management,

focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization. International Journal of Science and Research Archive. 14(1), 230–250.
[82] Uddin, M.S., Mohamed, O.E.B., Ebert, J., 2024. Artificial intelligence-powered carbon emissions forecasting: implications for sustainable supply chains and green finance. Energy, Environment, and Economy. 2, 1–13.
[83] Ramnarine, I.D., Sherif, T.A., Alorabi, A.H., et al., 2025. Urban revitalization pathways toward zero carbon emissions through systems architecting of urban digital twins. Environment and Planning B: Urban Analytics and City Science. 52(8), 1920–1948.
[84] Abduljabbar, R., Dia, H., Liyanage, S., et al., 2019. Applications of artificial intelligence in transport: An overview. Sustainability. 11(1), 189.
[85] Tong, D., Cheng, J., Liu, Y., et al., 2020. Dynamic projection of anthropogenic emissions in China: methodology and 2015–2050 emission pathways under a range of socio-economic, climate policy, and pollution control scenarios. Atmospheric Chemistry and Physics. 20(9), 5729–5757.
[86] Ghafari, R., Samaei, S.R., 2025. An AI-driven and digital twin-based framework for holistic risk and green project management in sustainable urban megaprojects: The case of Tehran under climate and population pressures. In Proceedings of the 18th International Conference on Mechanical, Construction, Industrial, and Civil Engineering, Saint Petersburg, Russia, 21 May 2025.
[87] Saglam, M.S., Yilanci, V., Kongkuah, M., 2025. Decoupling economic growth and carbon emissions: A time-varying analysis of the environmental kuznets curve hypothesis in France (1890–2019). Environment, Development and Sustainability. DOI: https://doi.org/10.1007/s10668-025-06310-4
[88] Bickford, J.F., Bozada, T.A., Chen, W.W., et al., 2025. The Future of Digital Twin Research and Development. Journal of Computing and Information Science in Engineering. 25, 080801.
[89] Mazzetto, S., 2024. A review of urban digital twins integration, challenges, and future directions in smart city development. Sustainability. 16(19), 8337.
[90] Ehtsham, M., Parisi, G., Pedone, F., et al., 2025. AI-Powered Advanced Technologies for a Sustainable Built Environment: A Systematic Review on Emerging Challenges. Sustainability. 17(17), 8005.
[91] Ogunyemi, F.M., 2025. Harmonizing global carbon accounting standards: Comparative analysis of GHG protocol, ISO 14064, and emerging regulatory frameworks for multinational corporations. International Journal Research in Marketing Manage Sales. 7(2), 425–434.
[92] Roy, P., 2024. Enhancing Real-World Robustness in AI: Challenges and Solutions. Journal of Recent Trends in Computer Science and Engineering (JRTCSE). 12(1), 34–49.
[93] Li, J., Shirowzhan, S., Pignatta, G., et al., 2024. Data-driven net-zero carbon monitoring: Applications of geographic information systems, building information modelling, remote sensing, and artificial intelligence for sustainable and resilient cities. Sustainability. 16(15), 6285.
[94] Yan, F., Chen, L., Jia, F., 2025. Environmental, social, and governance disclosure in supply chains: A systematic literature review. Production Planning and Control. 36(14), 1951–1972.