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Review

Applications of Information Technology in Building Carbon Flow

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Abstract: The construction industry, as one of the three major carbon emission (CE) industries, accounts for about 39% of the global CE. Thus, approaches for energy saving and emission reduction (ES/ER) cannot be delayed. With the advent of the Industry 4.0 era, information technology (IT) is used to investigate CE in the construction industry, which provides great convenience for measuring and calculating building carbon emissions (BCE) and proposing effective ES/ER measures. However, limited studies have provided a holistic overview of the application of IT in BCE. To fill this gap, this study searched related articles and screened 170 relevant papers. Based on the characteristics of the literature, building carbon flow (BCF) was defined. Based on scientometric analysis and network mapping analysis, combined with quantitative and qualitative analysis methods, the functions, advantages, and limitations of IT in each stage of BCF research were reviewed. Finally, the research trends and future research directions of IT in the BCF were discussed. Specifically, the building information model technology penetrates the whole process of BCF research, deep learning and artificial intelligence have great potential in BCF research, and multi-information technology integration will become the focus of subsequent research in the construction industry.

Keywords: building carbon emissions; building carbon flow; information technology; literature review

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1. Introduction

According to the latest data, the average temperature of the Earth has increased by about 1.7 °C compared with the pre-industrial revolution [1]. The main contributor to global warming is greenhouse gas emissions; CO_2, as the main component of greenhouse gases, is of great concern [2], and reducing carbon emission (CE) has become one of the effective ways to curb global warming. According to research, CE mainly comes from transportation, industry, and construction [3]; CE from the construction industry accounts for nearly 40% of the world's energy and process-related CE [4] and the construction industry, as a major contributor to CE, should not delay energy saving and emission reduction (ES/ER).

With the advent of Industry 4.0, digital technologies, smart machines, sensor systems, and smart materials are entering the construction industry with their undeniable advantages [5]. Additional information technology (IT) is used to study building carbon flow (BCF), which provides great convenience for measuring and calculating building carbon emission (BCE) and proposing effective ES/ER measures. For example, the building information modeling (BIM) is an intelligent parametric digital representation of facilities that contains a large amount of project information and is object-oriented [6], through which users can obtain a large amount of building-related data to quantify embodied carbon emissions (ECE) from building materials [7,8]. Combined with building analysis software

(BAS), it can also quantify operational carbon emissions (OCE) [9,10]. Radiofrequency identification (RFID) technology is being used in the construction sector because of its high efficiency and low-cost advantages in identifying and tracking assets. In previous studies, RFID has been used to track assets in building construction [11,12] and has long been used to study CE [13], which provides a technical basis for quantifying CE in buildings. Existing research has already tracked the CE of building construction based on RFID [14]. Digital twin (DT) provides an integrated, effective way to manage, plan, forecast [15], and present a building or asset that can simultaneously analyze various data provided by the Internet of Things (IoT) world and the real world, and existing research has combined it with building energy consumption to test and compare multiple scenarios for building energy and carbon efficiency to achieve building ES/ER [16]. In addition, IoT provides data on building energy consumption and indoor conditions [17]. The global positioning system (GPS) is used for outdoor asset location tracking [18] and provides transportation carbon data, and additional IT serves to quantify BCE and ES/ER.

An effective way to understand current CE trends and predict future CE is to analyze and study past trends in CE [19]. Therefore, a review is particularly important to understand the application of IT in BCF. In the existing reviews, most scholars only focus on the impact of a single IT on BCE. Eleftheriadis et al. (2017) provide an overview of how BIM can improve energy efficiency throughout the building lifecycle [20], and Sepasgozar (2021) outlined the current development of DT, which enables digital transformation to improve productivity and reduce energy consumption through DT technology [21]. Few, if any, scholars have conducted a comprehensive overview of IT applications in BCF. To fill this gap, this study retrieved relevant articles from mainstream journals based on scientometrics and network mapping analysis, combined with quantitative and qualitative analysis methods, comprehensively summarized and analyzed the application of IT in BCF, discussed the functions, advantages, and limitations of IT in BCF, and identified the future research directions to facilitate the further research of related scholars.

This study summarizes and analyzes the management and application of IT in BCF. BCF is a new concept proposed in this paper in conjunction with steps to study BCE. The full definition of BCF refers to the study of the whole process of BCE, starting from the identification of carbon sources, to the quantification of BCE, and, finally, to the proposal of building ES/ER measures. This study is divided into four main parts. First, the literature collection and screening methods are briefly introduced. Second, scientometrics and network mapping analysis of the selected literature are presented to capture the current research trends and identify the IT applied to BCF research in existing studies. Third, the functions, advantages, and limitations of these ITs in BCF are discussed. Finally, based on the above analysis, potential future research directions are identified.

2. Methodologies

This study achieves its objectives based on scientometric analysis and network mapping analysis, combining quantitative and qualitative analysis methods; that is, to understand the current research trends, to comb through and analyze the functions, advantages, and limitations of IT in BCF, and to propose future research directions. Scientology analysis is an "intellectual structure that attempts to quantify and resolve the field of research, beginning with a mathematical and statistical analysis of patterns emerging from the use of publications and literature" [22]. This study analyzes a large body of literature on the use of IT in BCF based on scientometrics, as shown in Figure 1.

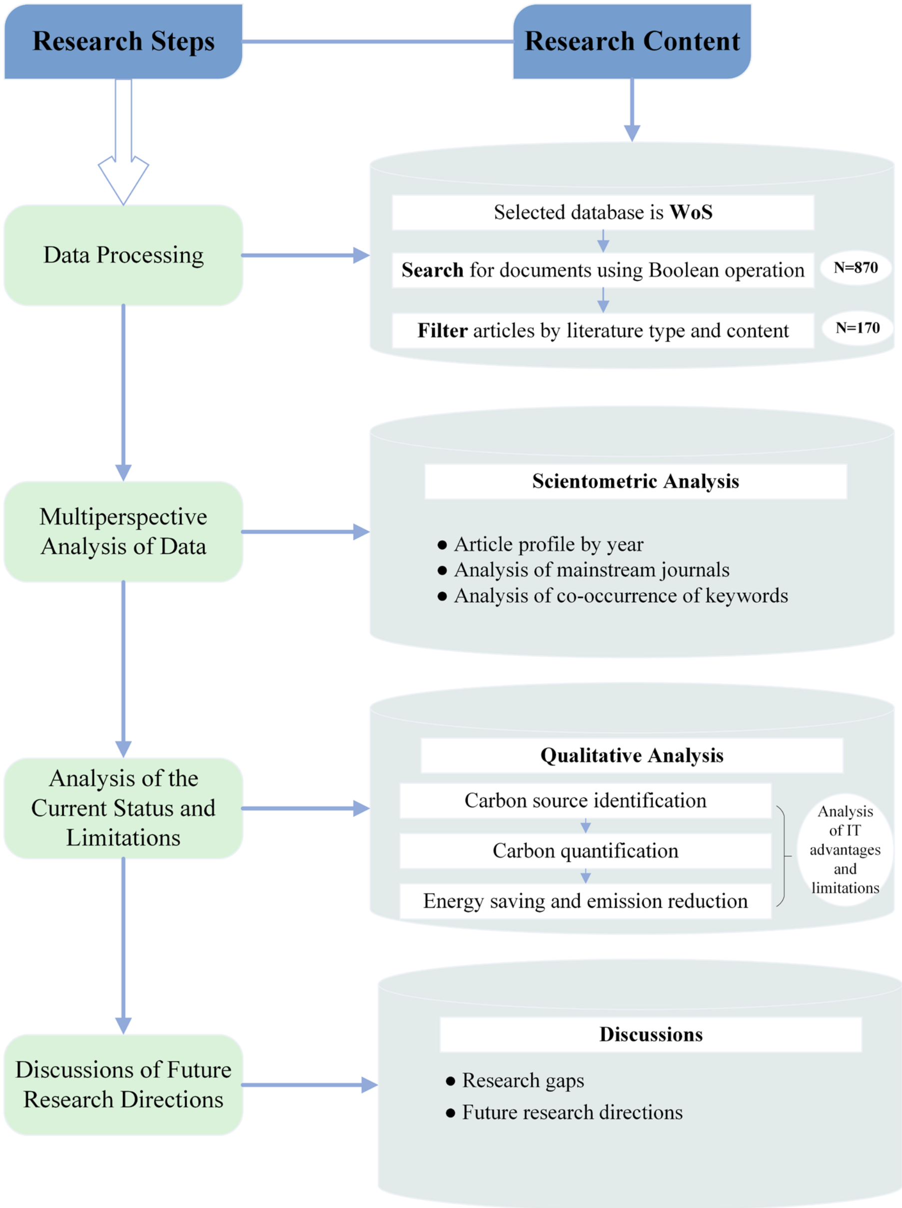

Figure 1. Research design summary.

2.1. Data Processing

2.1.1. Data Collection

(1) Science Database Selection

Selecting a suitable scientific database is a prerequisite for performing scientometric analysis. Three commonly used databases are available, ISI Web of Science (WoS), Google Scholar, and Scopus. Most of the publications in WoS and Scopus overlap, and Google Scholar has a broader scope. However, Google Scholar has problems in terms of accuracy compared with the first two. In this study, based on previous studies [22,23], searches were conducted with the three databases, and WoS covered mainstream journals; therefore, this study decides to use WoS as a database.

(2) Literature Search

Reviews related to BCE were investigated, and the keywords related to BCE in the current research field including "building carbon emissions", "building carbon footprint", "building implied carbon", "building operational carbon", and "building energy efficiency" were selected and searched in the WoS core collection database. The 4362 retrieved documents were analyzed by keywords, and the IT serving the BCF in the existing studies were mainly BIM, DT, IoT, and RFID. In the advanced search query builder, the Boolean operation "TS = ((building*) AND (energy* OR carbon emissions*) AND (BIM OR digital twin OR radio frequency identification OR IoT))" was used to search for article titles, keywords plus, and author keywords, and 870 papers were obtained.

2.1.2. Data Filtering

Among the 870 documents, conference papers and books with low recognition as well as journal documents and relevant industry standards that did not match the research topic were included, and further filtering of the documents was required. First, conference papers and books were quickly filtered out using the toolbar search tool, leaving 769 journal articles. "*" indicates a fuzzy search, so the obtained journal articles contained articles and standards that did not match the topic, and the 769 remaining articles needed to be refined according to the general topic of the article. By artificially screening the abstracts and keywords of 769 papers, the remaining 170 journal articles were finally used as the sample for this study.

After keyword checking, this sample of 170 papers contains most of the keywords identified at the beginning, and only the size of the keyword nodes in focus changed, which resulted from the removal of some articles of low relevance, and thus this study considers these 170 papers to be representative of the entire literature on the use of IT in BCF studies in existing research.

2.2. Result Analysis

2.2.1. Scientific Mapping Tool Selection

Choosing the right scientific mapping tool is essential to analyze research trends and patterns in the scientific field [24]. Among the available tools, CiteSpace and VOSviewer are the two most used software, and can analyze and visualize bibliometric data, but some differences are observed in the analysis results [25]. Studies have shown the analysis results of VOSviewer are closer to those of WoS data. Therefore, VOSviewer was selected as the scientific mapping tool for processing and visualizing bibliometric data in this article.

2.2.2. Multi-Perspective Analysis

The articles retrieved and extracted from the WoS database were analyzed from multiple perspectives. First, the year of publication of the articles was examined, and the main reasons for the change in the rising trend of publications were explained. Then, the bibliometric data were visualized using VOSviewer, mainly including mainstream journal analysis and keyword co-occurrence analysis. Based on the analysis results, the significance and the problems reflected were discussed.

2.3. Qualitative Analysis

Based on the scientometrics, this study provides a more in-depth and comprehensive qualitative analysis of the application of IT in BCF. The functions, advantages, and limitations of IT in each stage of BCF in the existing studies are mainly explored. Among the three stages of BCF, only the carbon quantification and ES/ER stages involve the use of IT, and the carbon source identification stage does not. This section digs deeply into the relevant information and makes a summary, filling the gaps in the current research field.

2.4. Discussions

Finally, this study discusses the problems that emerged from the scientometric and qualitative analyses. On the one hand, it identifies the existing research gaps in the whole research area. On the other hand, based on the limitations of current research, potential future research directions are proposed, which will provide a reference for scholars' subsequent research.

3. Multi-Perspective Analysis of Data

3.1. Related Research Trends

By comparing the number of publications in the literature in recent years, trends in IT in BCF research can be visualized. Figure 2 presents a chronological analysis of the 170 selected sample literatures, counts the number of publications of the literature in each year, and visualizes them. The earliest publication in the sample literature was in 2010, and the number of publications in the literature showed a rapid growth trend between 2010 and 2022. Of these, two time periods saw significant growth, one from 2015 to 2016 and the other from 2018 to 2019. A review of the information shows that such changes in these two time periods relied on policy drivers. In 2015, the Paris Climate Change Conference adopted the Paris Agreement, where the parties pledged to limit global temperature rise to 2 °C, and people gradually realized the importance of controlling CE. Research output powerhouse China also issued the "Made in China 2025" in 2015, the deployment of comprehensive promotion of the implementation of the manufacturing power strategy. Germany's "Industry 4.0" cooperation docking clearly stated the goal of "Industry 4.0" is to achieve industrial production, and this has laid a solid platform for IT growth in the construction industry. The two-party policy drive led to the highly efficient use of IT in BCF research, resulting in twice as many literature publications in 2016 compared with 2015. The number of articles published from 2016 to 2018 was relatively flat, and checking the articles published during that period reveals that research on IT in BCF entered a plateau. Since the concept of Industry 4.0 was introduced in 2013, it has been growing rapidly in various industries, and the most important opportunity is the application of Industry 4.0 to a smart, environmentally friendly world that can adapt to climate change, making Industry 4.0 a key theme throughout Sustainability Week 2018. Additional researchers are joining the field of this research, resulting in 1.64 times the number of literatures published in 2019 compared with 2018.

Figure 2. Yearly publications from 2010 to 2022.

3.2. Related Research Fields

3.2.1. Analysis of Mainstream Journals

Journals facilitate the sharing and transferring of knowledge, criticism, and innovation among scholars [26], and scientometrics helps researchers assess the value and effect of academic journals, provides readers with quick access to valuable information, and is a common method for research reviews [27]. In VOSviewer, set the minimum number of files to threer and the minimum number of references to 33. Out of 53 journals, 12 journals reached the set threshold, as shown in Figure 3.

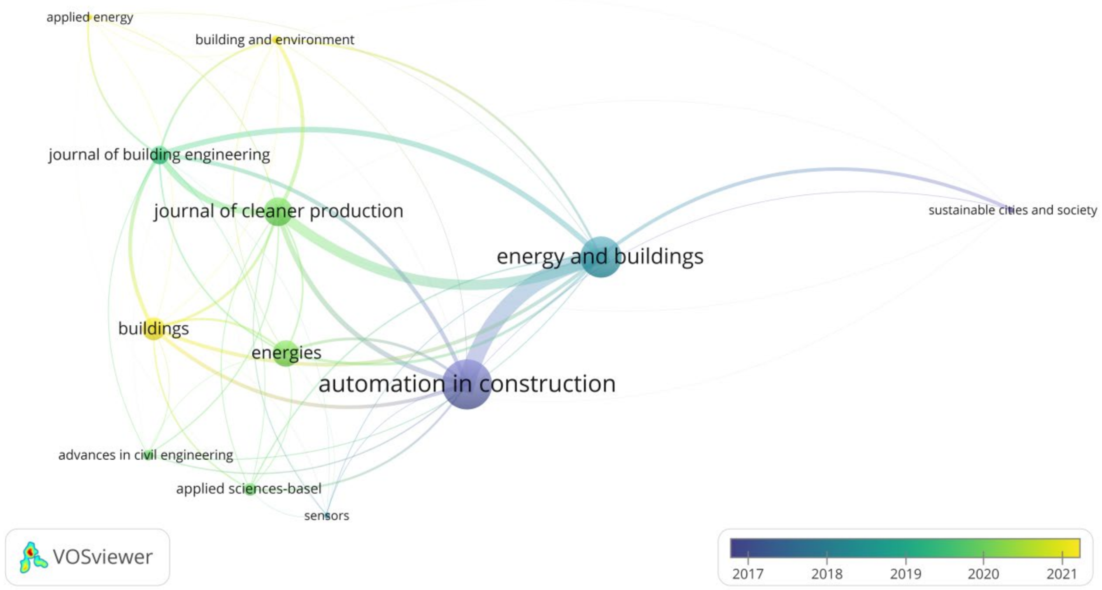

Figure 3. Visualization of mainstream journals.

Figure 3 illustrates the relationship between the mainstream journals. Nodes become larger with more relevant articles. *Automation in Construction* published the most articles, the application of IT in BCF research is an emerging field, and early related articles are published in journals with high impact factors, which can guide more research scholars to new directions. The next most published journals are *Energy and Buildings* and *Journal of Building Engineering*. The lines between the nodes represent the citation frequency of these journals. The increasing number of citations among *Automation in Construction, Energy and Buildings, Journals of Building Engineering,* and *Energies* may be due to their high impact factor and the preference of research scholars to submit to these journals. Consequently, the number of relevant publications in these journals is increasing, entering a virtuous circle. Among them, *Automation in Construction* is most closely connected with *Energy and Buildings*.

In addition, Documents, Citations, Avg.pub.year, and Avg.norm.citations can be used to characterize the impact of journals. The 12 most influential journals are listed in Table 1. *Automation in Construction* is the most influential from all perspectives, followed by *Energy and Buildings*. However, *Applied Energy* has the highest number of Avg.norm.citations among journals with the same number of publications and, together with *Building and Environment* and *Buildings*, has been more active in the last two years.

3.2.2. Analysis of Co-Occurrence of Keywords

Keywords respond to appropriate research priorities and help scholars understand relevant related research fields and the correlation of each subject [27]. VOSviewer can perform keyword co-occurrence analysis, as shown in Figure 4. Since this research area is an emerging field with a small literature sample, the minimum number of keyword occurrences was set to two in this study, and 181 keywords were selected from 817 author keywords and keywords plus. Among these 181 keywords, a variety of IT and its related meaningful keywords, “design”, “system”, “performance”, and “construction”, were selected, and other normal but meaningless keywords were removed; keywords with the same meaning such as “BIM” and “Building Information Model”, “RFID” and “Radio-Frequency Identification”, and “Digital Twin” and “Digital Twins” were integrated. Finally, 32 keywords were obtained.

Table 1. Quantitative analysis of mainstream journals.

Journals	Documents	Citations	Avg.pub.year	Avg.norm.citations
Advances in Civil Engineering	5	61	2020	0.49
Applied Energy	3	74	2021	1.17
Applied Sciences-Basel	6	97	2020	0.55
Automation in Construction	24	2068	2017	1.76
Building and Environment	4	34	2022	1.24
Buildings	11	128	2021	0.81
Energies	13	146	2020	0.54
Energy and Buildings	20	847	2018	1.18
Journal of Building Engineering	9	347	2019	1.29
Journal of Cleaner Production	14	535	2020	1.25
Sensors	3	44	2018	0.62
Sustainable Cities and Society	3	86	2017	0.88

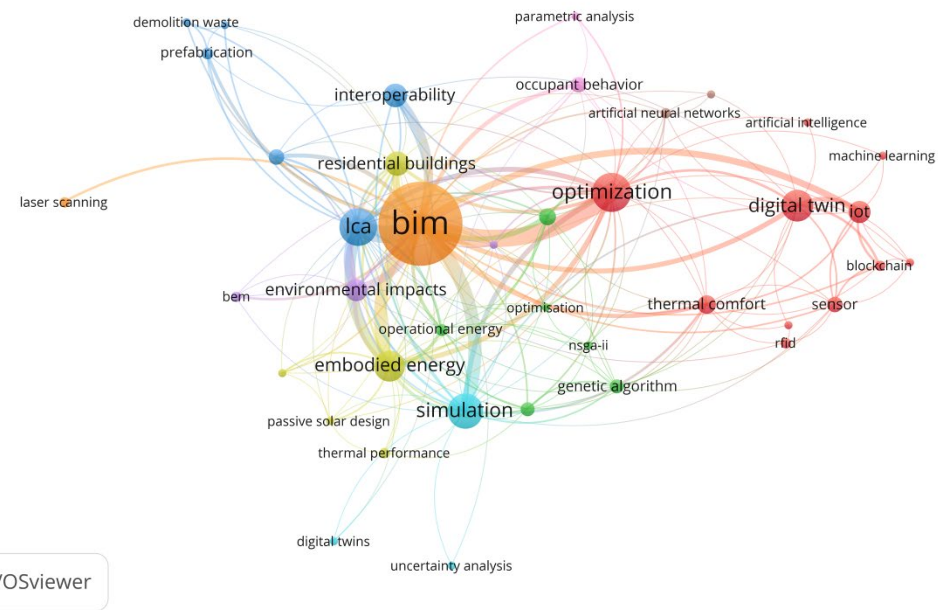

Figure 4. Analysis of co-occurrence of keywords.

The size of the node is related to the number of keyword occurrences, and the larger the node, the more keyword occurrences there will be. Figure 4 shows "BIM" (104 times) appears most frequently, and "Optimization" (29 times), "LCA" (27 times), and "Simulation" (24 times) follow closely behind. The IT used in the study of BCF are BIM (104 times), DT (20 times), IoT (11 times), deep learning (DL, 2 times), sensor (6 times), RFID (3 times), BEM (3 times), laser scanning (3 times), artificial intelligence (AI, 2 times), and genetic algorithm (5 times). The current research area mainly uses them to solve the problems of building simulation [28,29] (24 times), optimization [30,31] (29 times), and interoperability [32,33] (12 times) among building-related software, thus reducing the use of embodied energy [34,35] (19 times) and operational energy [31] (4 times). In this process, many scholars discussed the impact of occupant behavior [36] (6 times) on ES/ER as well as on environmental effects [37] (11 times). ES/ER and thermal comfort [38] (8 times) have also become a key concern for scholars.

Table 2 lists the keywords involving IT among the 32 keywords. Based on the number of occurrences, BIM (104 times) has been widely cited in the study of BCF, and IT such as AI (2 times), artificial neural networks (2 times), DL (2 times), DT (20 times), and genetic algorithms (5 times) have only started to be used in the study of BCF in the last two years. Although the Avg.pub.year of DL (2 times) and AI (2 times) are very close to the present, their Avg.norm.citations are ranked first or second, indicating the existence of good prospects for DL (2 times) and AI (2 times) in the research of BCF.

Table 2. Quantitative analysis of keywords related to IT.

Keywords	Occurrences	Avg.Pub.Year	Avg.Citations	Avg.Norm.Citations
Artificial Intelligence	2	2022	22.50	2.44
Artificial Neural Networks	3	2021	6.00	0.22
BEM	3	2020	20.33	0.77
BIM	104	2019	41.94	1.07
Deep Learning	2	2022	33.00	2.69
Digital Twin	20	2021	27.50	1.63
Genetic Algorithm	5	2021	28.00	1.45
IoT	11	2020	54.00	2.12
Laser Scanning	3	2015	64.67	1.10
RFID	3	2012	73.33	0.64
Sensor	6	2019	58.50	2.42
Simulation	24	2019	37.92	0.75

4. Analysis of the Current Status and Limitations

This section focuses on the functions, advantages, and limitations of IT in BCF in existing studies. The main IT applied to BCF research were identified based on scientometric analysis: BIM, DT, RFID, and IoT. Based on this, a more in-depth qualitative analysis of the sample literature was conducted, as shown in Figure 5.

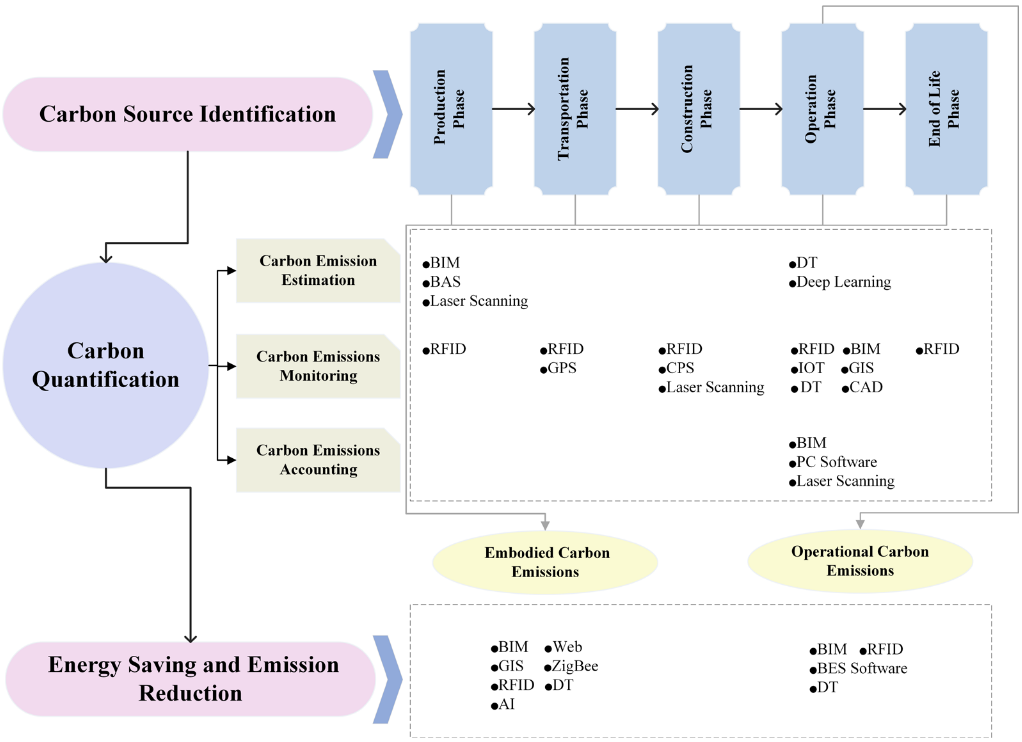

Figure 5. Application of IT in the whole process of BCF.

4.1. Carbon Source Identification

Carbon source identification refers to the documentation of all possible sources of CE throughout the lifecycle of a building, and the delineation of carbon sources helps provide a source basis for building carbon quantification. Different scholars divide the carbon source into several phases [39], and most of them classify the phases into materialization, operation, and demolition [40]. On this basis, some scholars refine the classification, dividing it into design, production, transportation, construction, operation, maintenance, and demolition phases according to the formation of the product [41]. Compared with the two divisions, the materialization phase refers to the whole process of building implementation on the ground, including design, production, transportation, and construction phases [42], and the latter division breaks down each step of the building after completion. This paper aims to comb through the use of IT in each phase of BCF. The materialization phase is too broad in scope, while the design phase involves too minute CE, and the operation and maintenance phases involve mostly the same use of IT. Thus, this study integrates the two divisions and divides the carbon source phases into production, transportation, construction, operation, and end-of-life phases.

According to the EN15978 standard, BCF contains two parts: ECE and OCE. ECE refers to the CE related to the materials and construction during the whole lifecycle of the building, not the direct CE [43,44]. OCE refers to the emissions from the use of energy in the operation of the building [45], mainly the CE directly generated by the consumption of energy such as HVAC, lighting, elevators, and gas. According to the definition of ECE and OCE, the CE generated in the whole cycle of the building from design and planning to abandonment and demolition is a quantifiable value, which can provide a reference for the measurement and evaluation of green buildings.

Carbon source identification does not involve the use of IT. Analyzing the whole construction industry chain and inclusively identifying the basic carbon sources at each stage ensures the comprehensiveness of IT in the subsequent combing of carbon quantification and ES/ER sections.

4.2. Carbon Quantification

The first step in achieving ES/ER in buildings requires the accurate quantification of BCE [46]. However, no clear method of CE has been given yet. Three methods can be used in carbon quantification in the construction industry:

(1) Emission factor method.
(2) Mass balance method.
(3) Actual measurement method.

The emission factor method has been widely used in existing studies.

The quantification of CE by different scholars starts from dissimilar periods. The literature review revealed the quantification of CE in existing studies is divided into three main periods:

(1) CE estimation when building CE does not occur.
(2) CE tracking when the building is under construction or operation stage.
(3) CE accounting after the building is completed.

This section discusses the application of IT when quantifying CE in each of these three periods.

4.2.1. Carbon Emission Estimation

CE estimation is the approximation of CE that will occur in the future based on existing data. Most of the CE estimation is carried out at the time of building design planning, that is, before the construction of the building starts. Table 3 provides a summary of the functions, benefits, and limitations of IT in carbon quantification during this period, and is analyzed in the following subsections.

Table 3. Summary of IT used in CE estimation.

Application Time	IT		Functions	Benefits	Limitations
Design Phase	BIM		• Automatically obtaining the usage of building materials [47] • Automation compilation bill of quantities [48]	• Efficient, accurate dynamic statistics of various data [17] • Self-renewing design [49]	• Information is still limited [34] • Particularly high demand for model accuracy [10]
	Scanning Laser		• Capturing building information [50]	• Improve BIM model accuracy [50,51]	• Needs improvement in accuracy, applicability, and automation [52]
	BAS	Energy Plus	• Building energy analysis	• Simulate building operations	• Third-party modeling program required
		DOE-2		• Simulate building operations	• Third-party modeling program required
		DesignBuilder		• No third-party software required	• Single-use model
		eQuest		• No third-party software required	• Single-use model
		GreenBuildingStudio		• Model universal	• Time consuming and error prone [53]
Operation Phase	Digital Twin		• Estimating the CE of each energy-consuming machine tomorrow [53]	• Reduce unnecessary CE [52]	• Dependence on the prediction method and the choice of variables [54]
	Deep Learning		• Energy consumption forecasting for individual households [55]	• High accuracy [56]	• High cost [56]

(1) Building Information Modeling

- Provide Embodied Carbon Data

BIM technology creates comprehensive, reliable, easily accessible, and changeable building information for stakeholders [47], and the automated compilation of a bill of quantities (BoQ) is one of the most critical capabilities of BIM [48]. Studies integrated BIM with life cycle assessment (LCA) to automatically capture the amount of building materials used, and the acquired BoQ can be used to calculate the ECE of a building using the emission factor method.

- Dynamically Replace and Count Data

The advantage of BIM technology in measuring the ECE of buildings is that it can dynamically, efficiently, and accurately count various data in the design stage, and it has the function of updating the design independently, which saves the time and cost of manual counting.

- Limited Information Availability and High Model Accuracy Requirements

However, the application of BIM to the calculation of ECE has limitations: the BIM model does not contain the full set of information of the construction project, BIM model still carries a limited amount of information, and the calculation of ECE based on the BIM model requires particularly high accuracy of the model. To solve these problems, scholars have proposed an application-oriented scan-to-BIM framework [51], in which laser scanning is used to capture building information and build BIM models as a way to improve the accuracy of BIM models.

(2) Building Analysis Software

- Quantifying Operational Carbon Emissions

For OCE, BAS has been shown in earlier studies to simulate building operations and quantify building OCE using the CE factor method [57,58]. Three approaches to quantifying building operational carbon using BAS have emerged from existing research.

3D modeling software (e.g., Auto CAD 2014) is used to construct a 3D geometric model, which then consists of simple lines only, lacking information for building performance analysis. Importing the 3D geometry into a BAS, such as Energy Plus or DOE-2, which requires user input of information on the envelope, as well as the HVAC system and occupant behavior, ultimately generates simulation results.

On this basis, integrated simulation software such as DesignBuilder and eQuest emerged, which can be used to directly construct building geometry, set space and element information, and directly perform simulation.

With the development of BIM technology, BIM tools, such as Revit, can be used to create building geometries containing information related to maintenance structures, HVAC systems, and other building loads, export them as gbXML files, recognize them directly with BAS such as GreenBuildingStudio, make simple modifications, and then perform efficient simulations.

- Forming Efficient Workflows

BAS provides technical support for estimating the OCE, and the estimated OCE obtained becomes a criterion for determining whether the OCE is out of the normal value when tracking CE. The addition of BIM technology establishes a platform for multiparty collaboration, allowing the BIM model to integrate the building design and simulation and carry a large amount of building data, creating an efficient workflow and improving the efficiency of the BAS.

- High Time Costs and Poor Interoperability

In the first method, the model and building information are not combined, and the input information is only for building simulation services. In the second method, the model needs to be rebuilt in the simulation software, as the model built in the early stage for other needs cannot be used directly; the model costs time to build, and the rebuilt model can only be used for simulation of specific software. The third approach is more efficient than the first two.

However, using the third method for building simulation and obtaining calculated operational carbon data has limitations. BIM is error-prone, non-intuitive, and very time consuming when generating energy simulation models. Not all information in BIM needs to be converted into building energy models (BEM); inconsistent information in BIM and BEM needs to be converted manually, and manual checking is time consuming when examining models of complex building structures [59].

(3) Other Information Technology

In addition to the use of IT such as BIM and BAS, DT and DL are used in CE estimation. Unlike the first two, which are used in the building design phase, DT and DL estimate CE in the operation phase.

- Digital Twin

Using the concrete data of the building DT model, the energy consumption and CE of the next day are predicted according to the CE factor method [55]. The advantage of this method is that it can estimate the CE of each energy-consuming machine for the next day and remind users to control the energy of the next day in time to reduce unnecessary CE behaviors. However, the accuracy of such a method depends on the prediction method and the choice of variables, in addition to the need to use an accurate data set.

- Deep Learning

DL is a neural network that solves complex problems by learning from raw data [60]. It has had great success in areas as diverse as computer vision [56] and self-driving cars [61]. DL neural networks, which allow energy consumption prediction for individual households [62], enable CE estimation. One of the DL models, convolutional neural networks, was developed to predict building energy consumption using dilated convolutions, enabling capture of the time of dependence of the sequence. DL has a high accuracy in predicting building energy, but it has a high cost.

4.2.2. Carbon Emission Monitoring

CE monitoring refers to the real-time tracking and measurement of BCE, and then analyzing and controlling BCE. CE estimation is a simulation to predict the possible values of BCE from different stages, while CE monitoring is onsite real-time monitoring to visualize the real-time CE at a specific life cycle stage. Efficiency and visualization of CE monitoring have been improving due to IT RFID, IoT, and DT, which have become the mainstream IT for BCE monitoring in existing studies. The specific applications are summarized in Table 4.

Table 4. Summary of IT used in CE monitoring.

Categories	IT	Function	Advantages	Limitations
Mainstream	RFID	• Construction asset tracking [13,14]	• No line of sight, close proximity, personal reading, and direct contact [63]	• Performance degrades when close to metals and liquids [63]
	GPS	• Road tracking [64]	• Automatic collection of BCE data [64]	• Cannot be used indoors properly [14]
	IoT	• Successful application in carbon monitoring [65]	• Provide real-time status data on buildings [66]	• Theoretical not practical [67]
	BIM	• Provide construction information [68]	• Integration with other IT [33]	• Information conversion problems [69]
	DT	• Bridging the virtual and real [70]	• Real-time tracking [71] • Assessment of BCE [71]	• Long creation time [72]
Others	CPS	• Real-time monitoring and visualization [65]		• Few related studies
	Scanning laser	• Collect geometric and spatial data for BIM [51]		
	GIS	• Monitor and analyze BCE [73]		
	Sensors	• Collecting real-time carbon information [74]		

(1) Information Technology for Collecting Real-time Carbon Data

- Radiofrequency Identification

In the early days of BCE monitoring, monitoring data needed to be collected manually for CE calculation, which is not only time consuming and labor intensive, but the quality of the data collected and extracted manually may also be low [64]. RFID has been applied to the tracking of construction assets to achieve automatic collection of building construction data [13], which solves this problem well.

RFID tags do not require line-of-sight, close distance, direct contact, and personal reading; active RFID can read a wider range and also has the capacity to store carbon data directly [63].

When RFID is in close proximity to metals and liquids, its performance degrades, especially when in high-frequency environments [63]. Although RFID enables accurate, efficient data collection, it requires frequent inspection and maintenance [8].

- Global Positioning System

In addition to RFID, GPS can collect building carbon data automatically [64]. It serves as a location tracking tool to collect transportation carbon data corresponding to the transportation phase, but it cannot be used properly indoors, limiting the scope of BCE monitoring.

- 3D Laser Scanning

Laser scanning technology enables the original geometry of existing installations to be restored. This function is achieved by transmitting a laser and detecting the laser signal to measure the distance to the target. Compared to conventional measurement tools, 3D laser scanning offers millimeter-level accuracy and a measurement speed of 100,000 points per second, which can be used to solve the problems of inaccurate, outdated, and missing information in the construction industry, and to collect geometric and spatial data for BIM for better construction [74].

- Sensors

Smart sensors are used to capture, analyze, and store data, and are the bases for IoT technology to enable real-time carbon data tracking. Temperature, force, and positioning sensors also contribute significantly in collecting real-time carbon information [74].

(2) Information Technology for Analysis and Control of Carbon Emission

- Internet of Things

IoT technology can collect energy consumption data in real time through sensors and devices such as smart meters, enabling real-time carbon tracking. It has long been successfully applied to carbon monitoring in transportation, industry, manufacturing, and many other systems. Currently, IoT technology has also been explored to achieve building carbon monitoring. Compared with BIM models that can carry physical and functional characteristics of a building such as material features and geometry, IoT technology can provide real-time status data about the building [66], thus tracking CE in real time. In the existing research, some scholars have integrated BIM and IOT technology for CE tracking in the operation phase of buildings, but the related research is still in its infancy, and all the possibilities are proposed from the theoretical point of view [67].

- Digital Twin

DT uses digital virtual models to simulate physical entities in the real environment through interactive feedback between the virtual world and the real world, data integration and analysis, and iterative optimization for decision making [65] and serves as a bridge to connect physical and information models for real-time tracking and evaluation of building carbon data. Some studies have shown that the carbon tracking framework built based on the IoT-supported sensor network to build DT supports the monitoring of CE throughout the building life cycle and facilitates sustainability decisions [71]. However, the construction of DT requires the installation of many sensors on the building to collect real-time data, which is not possible in existing buildings, and creating DT takes a long time [72]. The possibility of building DT to achieve carbon tracking has been demonstrated in existing studies, but few cases use this concept.

- Cyber–Physical Systems

The physical information system is an effective bidirectional integration of the computing resources supported [75] by the network implementation of the CPS with the physical processes. It can provide real services in the face of real-time limitations [76], and based on continuous tracking, can automatically control a physical system that integrates several different communication systems and devices [77]. Some studies have shown the feasibility of CPS for real-time monitoring and visualization of CE data at construction sites [70,78].

- Geographic Information Systems

Geographic information systems (GIS) can collect, compute, manage, analyze, and describe geospatial data information to support decision making; they can also digitize and visualize abstract information [79]. Integrating data from other heterogeneous data sources such as GIS, BIM, or IoT enables real-time monitoring and simulation to predict a building's energy consumption [73,80]. Some scholars have proposed visualization methods based on

GIS and computer-aided design to visualize GIS-based design and construction data, and to enhance spatial reality simulation for advanced analytical capabilities that can be used to monitor and analyze BCE [81].

(3) Data Transmission Method

The development of IT has not only extended the way of CE monitoring but also changed the way of transmission of data obtained from BCE monitoring. Traditional building energy consumption monitoring systems generally use wired data transmission methods, but with the development of IoT technology, wireless communication methods have been widely used, effectively solving the problem of complicated wiring for monitoring systems. At present, the commonly used wireless communication technologies for IoT mainly include ZigBee, long-range radio (LoRa), Wi-Fi, infrared communication, Bluetooth low energy (BLE), and ultra-wideband (UWB). The specific advantages and disadvantages are summarized in Table 5. Among them, ZigBee provides a low-cost, reliable, and easy-to-deploy wireless sensor network solution [82], but it has the disadvantages of slow transmission rate and poor penetration. The Wi-Fi communication method can extend the communication distance, but its power consumption is large. Compared with other communication methods, BLE has the advantages of low cost, low power consumption, and high reliability, but it has a shortage of communication distance.

Table 5. Summary of wireless communication technologies.

Types	Advantages	Limitations
ZigBee	• Low cost • Reliable • Easy to deploy	• Slow transmission rate • Poor penetration
LoRa	• Extended communication distance	• Insufficient precision
Wi-Fi	• Extended communication distance	• High power consumption
Infrared Communication	• Short distance • Poor penetration	• Improve efficiency
BLE	• Low cost • Low power consumption • High reliability	• Short communication distance
UWB	• High accuracy • Good energy efficiency	• High price • High power consumption

4.2.3. Carbon Emission Accounting

CE accounting refers to the verification of the actual CE generated by a building after its completion. The significance of CE accounting for buildings in existing studies is to identify a more energy-efficient building design by comparing the actual values of CE of different types of buildings. The use of IT enables comparing the CE of traditional cast-in-place buildings with those of assembled buildings at all stages of their full lifecycle.

- Building Information Modeling

Similar to CE estimation, BIM technology plays a significant role in CE accounting. CE accounting can use site construction records and settlement documents to obtain data to build BIM models, export the BoQ from various related software, such as Chenxi software V18.5.1.7 to obtain mechanical engineering quantities [83], analyze real building information through digital information simulation, and, finally, obtain accounting CE according to the CE factor method. The data used for building a BIM model for CE estimation are theoretical data, and the resulting CE is an estimated value, while the data used for building a BIM model for CE accounting are real data, and the resulting CE is the actual value. However, due to the complexity of construction projects, the real data used for CE accounting are limited, so this actual value is only close to the real value, but not the real value.

- 3D Laser Scanning

Laser scanning can also be used to build a BIM model using real building data to calculate the actual BCE value after the building is completed. It can compare the CE values of the completed buildings with different design solutions to determine the reasons for the variances and optimize the building design, thus achieving sustainable building development.

The purpose of CE accounting in existing studies is only to select better architectural design solutions; the types of advanced IT used are not many, the integration between IT is not enough, and more IT use needs to be explored at this stage.

4.3. Energy Saving and Emission Reduction

The accurate quantification of CE lays a solid foundation for building energy efficiency and emission reduction, which is the key to mitigate global warming. According to the carbon source identification section, BCE is divided into ECE and OCE. This section focuses on combing the use of IT in ES/ER from these two types.

4.3.1. Embodied Carbon Emissions

Numerous studies have shown that among ECE in buildings, building materials produce a high proportion of CE, followed by CE related to the building process, so an obvious way to achieve ES/ER objectives is to select green building materials with low CE.

(1) Mainstream Information Technology

- Building Information Modeling

Numerous studies have shown that building materials produce a high proportion of CE. Therefore, to achieve the purpose of ES/ER, green building materials with low CE should be selected. BIM technology is extensively used in the early design stage due to its advantages of improving the reliability of design decisions and optimizing design [84], and BIM plays a vital role in material selection. The BIM model constructed by the Revit platform based on BIM technology contains various information such as composition of components and material types, so that building materials can be selected according to the needs. Through the secondary development of BIM, relevant standard values can be embedded in the system to automatically count and evaluate the input building material information to achieve the effect of ES/ER. BIM can also be used to reduce construction waste [53,85] and optimize the built environment [86]. BIM has an important role in all phases of the building lifecycle, but its use in waste management has yet to be developed.

- Artificial Intelligence

AI, also known as machine intelligence, is defined as the ability of a computer to perform tasks related to humans [87]. It can use algorithms to tune models and propose multi-objective optimal designs that address "net zero carbon." Based on AI, building materials with low CEs can be designed directly, and scholars have already obtained the optimal concrete mix ratio based on AI [88], which greatly reduces the ECE of buildings. The application of AI in building ES/ER is still in its infancy, but it has great potential. Existing studies to achieve ES/ER based on AI have limitations, and few have considered the design output index of CE when conducting multi-objective optimization design.

- Geographic Information System

Many studies have demonstrated the great potential of GIS-based visualization for spatial and nonspatial data management, data modeling, terrain visualization, site layout, and construction planning [81]. Information from GIS can facilitate the use of BIM for site selection and layout of material sites. Combined with BIM technology, GIS can be applied to reduce emissions in building construction operations. Early scholars used BIM and GIS technology integration to optimize concrete truck mixing routes to reduce CE during construction [85]. In contrast to BIM, which focuses on the building itself, GIS provides geospatial information that focuses on the exterior of the building. They focus on their respective fields according to their characteristics. The integration of these two technologies means they can provide comprehensive data on the building itself and its surrounding environment [89], which is beneficial to scholars' research on ES/ER in the building industry, but they have the problem of insufficient integration.

(2) Other Information Technology

In addition to the above mainstream IT, many ITs are significant in reducing ECE. An example is creating a real-time CE recording system based on RFID and ZigBee, which can be used to track building assets throughout their life cycle, facilitate the management of building materials and their replacement at a later stage, and reduce CE in the process [82]. Web-based DT can build a framework for evaluating ECE [14], enabling monitoring of the entire building process, reacting to future scenarios, and reducing unnecessary CE. The use of IT above all suffers from the same problem—how to handle the explosive growth of data—because the project progress is yet to be studied.

4.3.2. Operational Carbon Emissions

Studies have shown that artificial lighting in buildings consumes 18% of the world's total energy [90], and HVAC systems consume 48% of a building's energy. Reducing OEC is a major way to achieve ES/ER in the building industry.

(1) Mainstream Information Technology

- Building Information Modeling

BIM tools allow users to see the path of the sun and the shadows on the building, select the optimal orientation of the building, and use daylight efficiently to reduce the need for electricity. BIM software such as GBS V5.1.0 can calculate the yield of renewable energy sources such as solar and wind power and assess their feasibility [30,91]. Through the multi-objective optimization model, BIM technology can help users choose an optimal solution that balances CE, energy, and cost. BIM also has ES/ER purposes such as rainwater collection and water recycling [86].

- Digital Twin

As mentioned in the previous article on CE estimation, the use of BIM and BAS can simulate the operation of the building at the design stage, and make it a benchmark to build a DT framework to compare the actual carbon data of building operation with the simulated carbon data [16], analyze the reasons for the gap in CE, and make timely adjustments, which can reduce the consumption of energy.

- Radiofrequency Identification

Achieving ES/ER in HVAC systems is a priority to reduce the carbon footprint of building operations. RFID-based occupancy monitoring systems can be built to support demand-driven HVAC operations by simultaneously detecting and tracking multiple fixed and mobile occupants in multiple spaces, thereby reducing HVAC system energy consumption [91].

(2) Other Information Technology

In addition to the use of the above advanced IT, systems built on IT such as IoT and CPS have proven to be of great advantage in CE monitoring and carbon data management, but gaps still exist in research on systems based on this technology to collect and analyze CE data in real time, reducing energy consumption.

5. Future Research Directions

The analysis of the functions, advantages, and limitations of the application of IT in BCF identifies research gaps throughout the research area and points to future research directions, as shown in Figure 6.

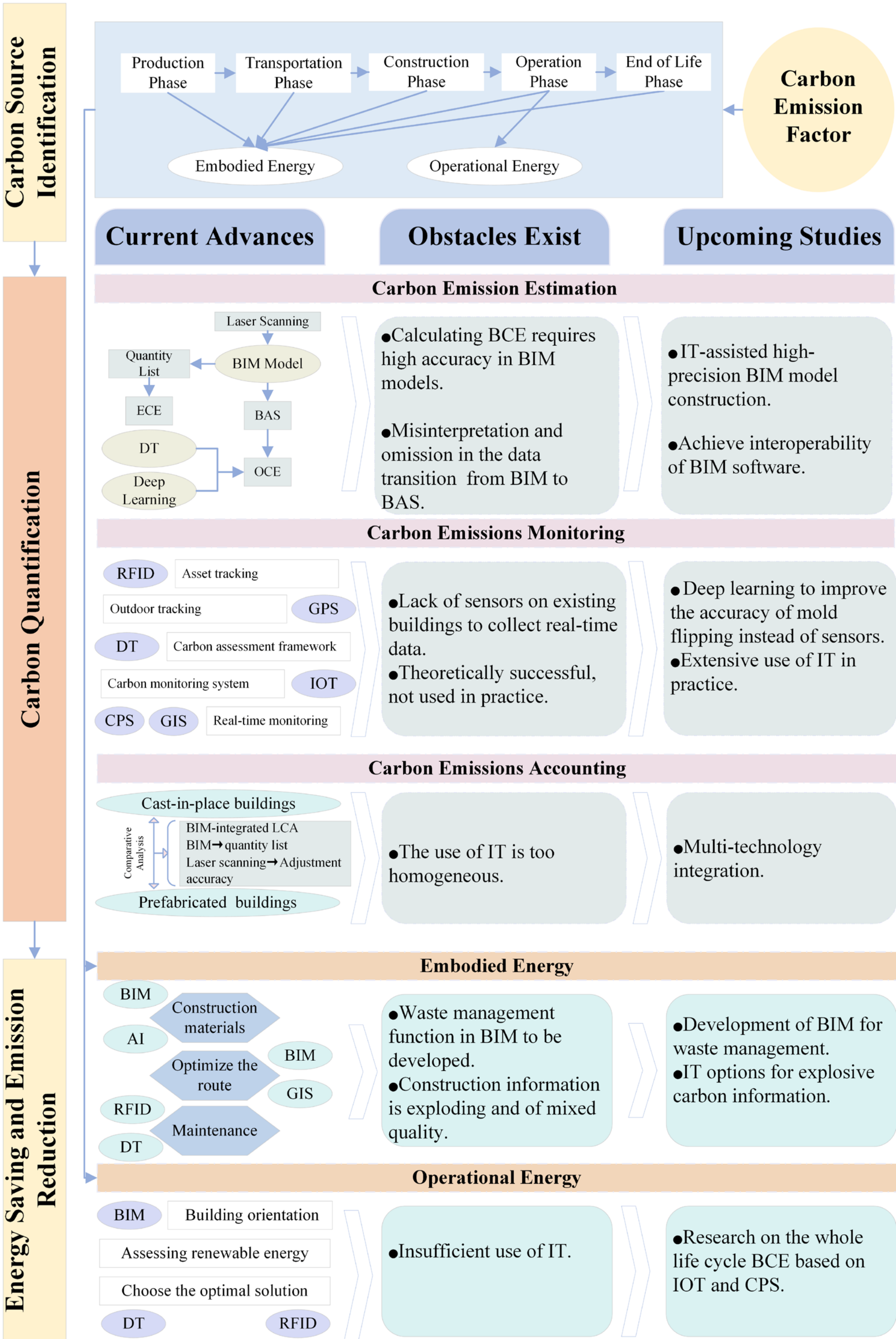

Figure 6. Framework that combines the current state of research with future research directions.

5.1. Future Research Directions Based on Building Information Modeling

5.1.1. Achieve Interoperability among Building Information Modeling Software

Components and information are lost in the process of interoperability between BIM and BIM-based software, such as the conversion between BIM and BEM, which requires a large amount of manual time and experience to check and correct. By achieving interoperability between BIM software, the effectiveness of activities such as the calculation of quantity tables and energy simulation can be guaranteed, and research on building ES/ER can be carried out efficiently.

5.1.2. Information Technology Assists in Improving the Accuracy of Building Information Modeling

The accuracy of BIM models is particularly important as the information base for researchers to analyze BCE, and the rapid development of IT has brought new opportunities to improve the accuracy of BIM models. In existing research, laser scanning technology has been used to capture building information with improved accuracy, but improvement is still needed in terms of accuracy, applicability, and automation. How to use IT to help improve the accuracy of BIM models will become a mainstream direction in future research.

5.1.3. Development of Building Information Modeling for Waste Management

BIM has been implemented in all phases of the building life cycle. In addition to providing basic project-related information, the use of BIM can reduce energy consumption and construction waste to a greater extent, and improve the quality of the project [92]. Additional construction activities are noticing the impact of construction waste, which, in addition to causing damage to the built environment, has its own value for recycling, and the use of BIM in waste management is yet to be developed. Efforts by researchers have been devoted to this end, proposing to create BIM-based tools to estimate the waste caused by building demolition [24].

5.2. Deep Learning Improves the Accuracy of Existing Building Models

Based on scientometric analysis, DL has good advantages for future research. Accounting for CE from existing buildings requires sensors to collect carbon data, and supplementing the installation of sensors is time consuming and uneconomical. Using DL to train models and improve the accuracy of models, replacing sensors, can be a good solution to the CE accounting problem.

5.3. Multitechnology Integration

Each IT has its own advantages. While continuously improving and optimizing each IT, multiple ITs can be integrated to complement one another's strengths and improve the efficiency of comprehensive energy saving in buildings. For example, DT enables monitoring, understanding, and optimizing physical entities by seamlessly bridging data from the real physical world and the virtual world. This process relies on IoT technology to realize the extraction of data from the real physical world and BIM technology to link the virtual world before it can transition from the physical room to the conceptual framework of the DT. The combination of various network technologies such as Wi-Fi and ZigBee can reduce costs and extend the communication distance, enabling remote data collection and information exchange, and providing data support for building energy optimization.

5.4. Information Technology Options for Explosive Carbon Information

The information about BCE has exploded from the design phase to the demolition phase of a project, and the quality of it varies. How to select high-quality carbon information to optimize the operation of buildings has become the key for IT to promote ES/ER. The development of advanced statistical methods such as AI and DL optimizes the selection of carbon data by IT, and the combination of statistical methods and IT will become an emerging field of BCE research.

5.5. Research on the Whole Life Cycle Building Carbon Emission Based on Internet of Things and Cyber–Physical System

In current research, IoT technology has been successfully used in carbon research in manufacturing, industry, transportation, medical, and many other systems. In the construction sector, it has been used for safety management, facilities management, supply chain management, and activity monitoring. CPS technology is well suited for the process of real-time data collection, computing, storage, and visual display, and its concept is similar to IoT, which also emphasizes control [93]. CPS has been used for monitoring and control in the smart grid, in transport and healthcare industries, and in manufacturing. In the construction industry, CPS has been used in temporary structure monitoring and project delivery, and the application involves the acquisition, transmission, storage, and processing of large amounts of data and information [94]. Existing research shows IoT technology and CPS technology have great advantages in real-time monitoring, and their application in other fields can be borrowed from BCE monitoring because the real-time monitoring of BCE is also realized through the collection and processing of onsite data information. Therefore, in future research, IoT and CPS will be the key technology to realize the whole life cycle carbon research of buildings.

6. Conclusions

This study combined the use of IT in BCF based on scientometric analysis, combined with network mapping analysis and quantitative qualitative analysis methods. This study first retrieved and screened 170 articles, and based on these 170 articles, quantitatively analyzed the current status of the application of IT in BCF by combining scientometric analysis and network mapping analysis methods. The following conclusions were drawn:

- Between 2010 and 2022, the number of publications on the use of IT in BCF research rapidly grew, with an increasing number of scholars taking the plunge. The two time periods with a fast growth in the number of publications due to policy drivers are 2015 to 2016 and 2018 to 2019.
- The most influential journals are *Automation in Construction* and *Energy and Buildings*, and in recent years, additional high impact factor journals are more active in this research direction.
- Keyword co-occurrence analysis showed the most widely used IT in this research direction is BIM, and DL and AI have good prospects in the study of BCF.

Based on the qualitative analysis, this study composed the functions, advantages, and limitations of IT in BCF. Based on deep excavation and analysis, the research gaps in this field were summarized, and future research directions were indicated.

- BIM is the most popular IT in this research field, but some functions still need to be improved and optimized. For example, the interoperability between BIM software still has problems, the accuracy of the BIM model still needs to be improved, and the functions of BIM in construction waste management still need to be developed.
- DL can be used to train existing building models instead of sensors to improve model accuracy and solve CE accounting problems.
- Various ITs have been introduced into the study of BCF, and further attention may be paid to the integration of multiple technologies in the future to complement one another's strengths and improve the overall energy efficiency of buildings.
- DL and AI have good prospects in BCF research, and they will be used in future research to select the exploding carbon information.
- IoT and CPS technologies have been used for whole life cycle carbon research in buildings, but gaps exist in the related research. In future research, IoT and CPS will be key technologies to achieve whole life cycle carbon research in buildings.

This study is only a review of the application of IT in BCF research based on a sample of 170 English literatures. Different categorization of the 170 literatures may have richer research results and solutions, which is also a follow-up upcoming work, but it is certain that IT has great potential in BCF research and will become a research hotspot for scholars in the future.

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References

1. Hansen, J.; Sato, M.; Kharecha, P.; Beerling, D.; Berner, R.; Masson-Delmotte, V.; Pagani, M.; Raymo, M.; Royer, D.L.; Zachos, J.C. Target Atmospheric CO: Where Should Humanity Aim? *Open Atmos. Sci. J.* **2008**, *2*, 217–231. [CrossRef]
2. Hu, W.; Tian, J.; Chen, L. Greenhouse gas emission by centralized wastewater treatment plants in Chinese industrial parks: Inventory and mitigation measures. *J. Clean. Prod.* **2019**, *225*, 883–897. [CrossRef]
3. Zou, C.; Xiong, B.; Xue, H.; Zheng, D.; Ge, Z.; Wang, Y.; Jiang, L.; Pan, S.; Wu, S. The role of new energy in carbon neutral. *Pet. Explor. Dev.* **2021**, *48*, 480–491. [CrossRef]
4. Wright, A.J.; Oates, M.R.; Greenough, R. Concepts for dynamic modelling of energy-related flows in manufacturing. *Appl. Energy* **2013**, *112*, 1342–1348. [CrossRef]
5. Craveiro, F.; Duarte, J.P.; Bartolo, H.; Bartolo, P.J. Additive manufacturing as an enabling technology for digital construction: A perspective on Construction 4.0. *Autom. Constr.* **2019**, *103*, 251–267. [CrossRef]
6. Gao, H.; Koch, C.; Wu, Y. Building information modelling based building energy modelling: A review. *Appl. Energy* **2019**, *238*, 320–343. [CrossRef]
7. Capper, G.; Matthews, J.; Lockley, S. *Incorporating Embodied Energy in the BIM Process*; CIBSE ASHRAE Technical Symposium: London, UK, 2012.
8. Memarzadeh, M.; Golparvar-Fard, M. Monitoring and Visualization of Building Construction Embodied Carbon Footprint Using DnAR-N-Dimensional Augmented Reality Models. In Proceedings of the Construction Research Congress 2012: Construction Challenges in a Flat World, West Lafayette, IN, USA, 21–23 May 2012; pp. 1330–1339.
9. Gan, V.J.L.; Deng, M.; Tse, K.T.; Chan, C.M.; Lo, I.M.C.; Cheng, J.C.P. Holistic BIM framework for sustainable low carbon design of high-rise buildings. *J. Clean. Prod.* **2018**, *195*, 1091–1104. [CrossRef]
10. Yang, X.; Hu, M.; Wu, J.; Zhao, B. Building-information-modeling enabled life cycle assessment, a case study on carbon footprint accounting for a residential building in China. *J. Clean. Prod.* **2018**, *183*, 729–743. [CrossRef]
11. Goodrum, P.M.; McLaren, M.A.; Durfee, A. The application of active radio frequency identification technology for tool tracking on construction job sites. *Autom. Constr.* **2006**, *15*, 292–302. [CrossRef]
12. Chae, S.; Yoshida, T. Application of RFID technology to prevention of collision accident with heavy equipment. *Autom. Constr.* **2010**, *19*, 368–374. [CrossRef]
13. Satoh, I. RFID-enabled carbon offsetting and trading. *Pervasive Mob. Comput.* **2013**, *9*, 149–160. [CrossRef]
14. Chen, C.; Zhao, Z.; Xiao, J.; Tiong, R. A Conceptual Framework for Estimating Building Embodied Carbon Based on Digital Twin Technology and Life Cycle Assessment. *Sustainability* **2021**, *13*, 3875. [CrossRef]
15. Lu, Q.; Parlikad, A.K.; Woodall, P.; Don Ranasinghe, G.; Xie, X.; Liang, Z.; Konstantinou, E.; Heaton, J.; Schooling, J. Developing a Digital Twin at Building and City Levels: Case Study of West Cambridge Campus. *J. Manag. Eng.* **2020**, *36*, 6796271. [CrossRef]
16. Zhu, M.; James, P. Daily Carbon Assessment Framework: Towards Near Real-Time Building Carbon Emission Benchmarking for Operative and Design Insights. *Buildings* **2022**, *12*, 1129. [CrossRef]
17. Desogus, G.; Quaquero, E.; Rubiu, G.; Gatto, G.; Perra, C. BIM and IoT Sensors Integration: A Framework for Consumption and Indoor Conditions Data Monitoring of Existing Buildings. *Sustainability* **2021**, *13*, 4496. [CrossRef]
18. Quinn, C.; Shabestari, A.Z.; Misic, T.; Gilani, S.; Litoiu, M.; McArthur, J.J. Building automation system—BIM integration using a linked data structure. *Autom. Constr.* **2020**, *118*, 103257. [CrossRef]
19. Hammond, G.P.; Norman, J.B. Decomposition analysis of energy-related carbon emissions from UK manufacturing. *Energy* **2012**, *41*, 220–227. [CrossRef]
20. Eleftheriadis, S.; Mumovic, D.; Greening, P. Life cycle energy efficiency in building structures: A review of current developments and future outlooks based on BIM capabilities. *Renew. Sustain. Energy Rev.* **2017**, *67*, 811–825. [CrossRef]

21. Sepasgozar, S.M.E. Differentiating Digital Twin from Digital Shadow: Elucidating a Paradigm Shift to Expedite a Smart, Sustainable Built Environment. *Buildings* **2021**, *11*, 151. [CrossRef]
22. Olawumi, T.O.; Chan, D.W.; Wong, J.K.W. Evolution in the intellectual structure of BIM research: A bibliometric analysis. *J. Civ. Eng. Manag.* **2017**, *23*, 1060–1081. [CrossRef]
23. Su, Y.; Yu, Y.; Zhang, N. Carbon emissions and environmental management based on Big Data and Streaming Data: A bibliometric analysis. *Sci. Total Environ.* **2020**, *733*, 138984. [CrossRef]
24. Tang, M.; Liao, H.; Wan, Z.; Herrera-Viedma, E.; Rosen, M. Ten Years of Sustainability (2009 to 2018): A Bibliometric Overview. *Sustainability* **2018**, *10*, 1655. [CrossRef]
25. Guo, Y.-M.; Huang, Z.-L.; Guo, J.; Li, H.; Guo, X.-R.; Nkeli, M.J. Bibliometric Analysis on Smart Cities Research. *Sustainability* **2019**, *11*, 3606. [CrossRef]
26. Serenko, A. The development of an AI journal ranking based on the revealed preference approach. *J. Informetr.* **2010**, *4*, 447–459. [CrossRef]
27. Darko, A.; Chan, A.P.C.; Huo, X.; Owusu-Manu, D.-G. A scientometric analysis and visualization of global green building research. *Build. Environ.* **2019**, *149*, 501–511. [CrossRef]
28. Yoon, S.; Seo, J.; Cho, W.; Song, D. A calibration method for whole-building airflow simulation in high-rise residential buildings. *Build. Environ.* **2015**, *85*, 253–262. [CrossRef]
29. Mahdavi, A.; Tahmasebi, F. The deployment-dependence of occupancy-related models in building performance simulation. *Energy Build.* **2016**, *117*, 313–320. [CrossRef]
30. Barnes, S.; Castro-Lacouture, D. BIM-Enabled Integrated Optimization Tool for LEED Decisions. In Proceedings of the Computing in Civil Engineering (2009), Austin, TX, USA, 24–27 June 2009; pp. 258–268.
31. Yang, C.; Li, H.; Rezgui, Y.; Petri, I.; Yuce, B.; Chen, B.; Jayan, B. High throughput computing based distributed genetic algorithm for building energy consumption optimization. *Energy Build.* **2014**, *76*, 92–101. [CrossRef]
32. Lai, H.; Deng, X. Interoperability Analysis of Ifc-Based Data Exchange between Heterogeneous Bim Software. *J. Civ. Eng. Manag.* **2018**, *24*, 537–555. [CrossRef]
33. Bracht, M.K.; Melo, A.P.; Lamberts, R. A metamodel for building information modeling-building energy modeling integration in early design stage. *Autom. Constr.* **2021**, *121*, 103422. [CrossRef]
34. Xu, J.; Teng, Y.; Pan, W.; Zhang, Y. BIM-integrated LCA to automate embodied carbon assessment of prefabricated buildings. *J. Clean. Prod.* **2022**, *374*, 133894. [CrossRef]
35. Nizam, R.S.; Zhang, C.; Tian, L. A BIM based tool for assessing embodied energy for buildings. *Energy Build.* **2018**, *170*, 1–14. [CrossRef]
36. Belazi, W.; Ouldboukhitine, S.-E.; Chateauneuf, A.; Bouchair, A. Uncertainty analysis of occupant behavior and building envelope materials in office building performance simulation. *J. Build. Eng.* **2018**, *19*, 434–448. [CrossRef]
37. Lee, S.; Tae, S.; Roh, S.; Kim, T. Green Template for Life Cycle Assessment of Buildings Based on Building Information Modeling: Focus on Embodied Environmental Impact. *Sustainability* **2015**, *7*, 16498–16512. [CrossRef]
38. Zahid, H.; Elmansoury, O.; Yaagoubi, R. Dynamic Predicted Mean Vote: An IoT-BIM integrated approach for indoor thermal comfort optimization. *Autom. Constr.* **2021**, *129*, 103805. [CrossRef]
39. Guangnian, X.; Qiongwen, L.; Anning, N.; Zhang, C. Research on carbon emissions of public bikes based on the life cycle theory. *Transp. Lett.* **2023**, *15*, 278–295. [CrossRef]
40. Hao, J.L.; Cheng, B.; Lu, W.; Xu, J.; Wang, J.; Bu, W.; Guo, Z. Carbon emission reduction in prefabrication construction during materialization stage: A BIM-based life-cycle assessment approach. *Sci. Total Environ.* **2020**, *723*, 137870. [CrossRef]
41. Dixit, M.K.; Culp, C.H.; Fernández-Solís, J.L. System boundary for embodied energy in buildings: A conceptual model for definition. *Renew. Sustain. Energy Rev.* **2013**, *21*, 153–164. [CrossRef]
42. Luo, Z.; Yang, L.; Liu, J. Embodied carbon emissions of office building: A case study of China's 78 office buildings. *Build. Environ.* **2016**, *95*, 365–371. [CrossRef]
43. Crowther, P. Design for Disassembly to Recover Embodied Energy. In Proceedings of the 16th International Conference on Passive and Low Energy Architecture, Melbourne, Australia, 22–24 September 1999.
44. Liu, K.; Leng, J.J.J.o.A.A.; Engineering, B. Quantitative research on embodied carbon emissions in the design stage: A case study from an educational building in China. *Archit. Hist. Theory* **2022**, *21*, 1182–1192. [CrossRef]
45. Fenner, A.E.; Kibert, C.J.; Li, J.; Razkenari, M.A.; Hakim, H.; Lu, X.; Kouhirostami, M.; Sam, M. Embodied, operation, and commuting emissions: A case study comparing the carbon hotspots of an educational building. *J. Clean. Prod.* **2020**, *268*, 122081. [CrossRef]
46. Qiao, C.; Hu, P.; Pan, Q.; Geng, J. Research on CO_2 Emission Reduction of a Steel Structure Prefabricated Building Considering Resource Recovery. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *237*, 022036. [CrossRef]
47. Grilo, A.; Jardim-Goncalves, R. Value proposition on interoperability of BIM and collaborative working environments. *Autom. Constr.* **2010**, *19*, 522–530. [CrossRef]
48. Plebankiewicz, E.; Zima, K.; Skibniewski, M. Analysis of the First Polish BIM-Based Cost Estimation Application. *Procedia Eng.* **2015**, *123*, 405–414. [CrossRef]
49. Haruna, A.; Shafiq, N.; Montasir, O.A. Building information modelling application for developing sustainable building (Multi criteria decision making approach). *Ain Shams Eng. J.* **2021**, *12*, 293–302. [CrossRef]

50. Li, Z.; Chen, Z.; Yang, N.; Wei, K.; Ling, Z.; Liu, Q.; Chen, G.; Ye, B.H. Trends in research on the carbon footprint of higher education: A bibliometric analysis (2010–2019). *J. Clean. Prod.* **2021**, *289*, 125642. [CrossRef]
51. Wang, Q.; Guo, J.; Kim, M.-K. An Application Oriented Scan-to-BIM Framework. *Remote Sens.* **2019**, *11*, 365. [CrossRef]
52. Bosché, F.; Guillemet, A.; Turkan, Y.; Haas, C.T.; Haas, R. Tracking the Built Status of MEP Works: Assessing the Value of a Scan-vs-BIM System. *J. Comput. Civ. Eng.* **2014**, *28*, 05014004. [CrossRef]
53. Ilhan, B.; Yaman, H. Green building assessment tool (GBAT) for integrated BIM-based design decisions. *Autom. Constr.* **2016**, *70*, 26–37. [CrossRef]
54. Khajavi, S.H.; Motlagh, N.H.; Jaribion, A.; Werner, L.C.; Holmstrom, J. Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings. *IEEE Access* **2019**, *7*, 147406–147419. [CrossRef]
55. Henzel, J.; Wróbel, Ł.; Fice, M.; Sikora, M. Energy Consumption Forecasting for the Digital-Twin Model of the Building. *Energies* **2022**, *15*, 4318. [CrossRef]
56. Chai, J.; Zeng, H.; Li, A.; Ngai, E.W.T. Deep learning in computer vision: A critical review of emerging techniques and application scenarios. *Mach. Learn. Appl.* **2021**, *6*, 100134. [CrossRef]
57. Mata, É.; Kalagasidis, A.S.; Johnsson, F. A modelling strategy for energy, carbon, and cost assessments of building stocks. *Energy Build.* **2013**, *56*, 100–108. [CrossRef]
58. Tettey, U.Y.A.; Dodoo, A.; Gustavsson, L. Effects of different insulation materials on primary energy and CO_2 emission of a multi-storey residential building. *Energy Build.* **2014**, *82*, 369–377. [CrossRef]
59. Kim, J.B.; Jeong, W.; Clayton, M.J.; Haberl, J.S.; Yan, W. Developing a physical BIM library for building thermal energy simulation. *Autom. Constr.* **2015**, *50*, 16–28. [CrossRef]
60. Dara, S.; Tumma, P. Feature Extraction by Using Deep Learning: A Survey. In Proceedings of the 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 29–31 March 2018; pp. 1795–1801.
61. Grigorescu, S.; Trasnea, B.; Cocias, T.; Macesanu, G. A survey of deep learning techniques for autonomous driving. *J. Field Robot.* **2020**, *37*, 362–386. [CrossRef]
62. Yan, K.; Li, W.; Ji, Z.; Qi, M.; Du, Y. A Hybrid LSTM Neural Network for Energy Consumption Forecasting of Individual Households. *IEEE Access* **2019**, *7*, 157633–157642. [CrossRef]
63. Kiziltas, S.; Akinci, B.; Ergen, E.; Tang, P.; Gordon, C. Technological assessment and process implications of field data capture technologies for construction and facility/infrastructure management. *J. Inf. Technol. Constr.* **2008**, *13*, 134–154.
64. Golparvar-Fard, M.; Peña-Mora, F.; Savarese, S. D4AR–a 4-dimensional augmented reality model for automating construction progress monitoring data collection, processing and communication. *J. Inf. Technol. Constr.* **2009**, *14*, 129–153.
65. Kaewunruen, S.; Rungskunroch, P.; Welsh, J. A Digital-Twin Evaluation of Net Zero Energy Building for Existing Buildings. *Sustainability* **2018**, *11*, 159. [CrossRef]
66. Tang, S.; Shelden, D.R.; Eastman, C.M.; Pishdad-Bozorgi, P.; Gao, X. A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends. *Autom. Constr.* **2019**, *101*, 127–139. [CrossRef]
67. Dave, B.; Buda, A.; Nurminen, A.; Främling, K. A framework for integrating BIM and IoT through open standards. *Autom. Constr.* **2018**, *95*, 35–45. [CrossRef]
68. Tushar, Q.; Bhuiyan, M.A.; Zhang, G.; Maqsood, T. An integrated approach of BIM-enabled LCA and energy simulation: The optimized solution towards sustainable development. *J. Clean. Prod.* **2021**, *289*, 125622. [CrossRef]
69. Wang, H.; Zhao, L.; Zhang, H.; Liu, P.; Sun, B.; Hou, K.; Sun, C. Building Information Modeling Assisted Carbon Emission Impact Assessment of Prefabricated Residential Buildings in the Design Phase: Case Study of a Chinese Building. *Int. J. Photoenergy* **2022**, *2022*, 2275642. [CrossRef]
70. Yuan, X.; Anumba, C.J.; Parfitt, M.K. Cyber-physical systems for temporary structure monitoring. *Autom. Constr.* **2016**, *66*, 1–14. [CrossRef]
71. Tagliabue, L.C.; Cecconi, F.R.; Maltese, S.; Rinaldi, S.; Ciribini, A.L.C.; Flammini, A. Leveraging Digital Twin for Sustainability Assessment of an Educational Building. *Sustainability* **2021**, *13*, 480. [CrossRef]
72. He, B.; Bai, K.-J. Digital twin-based sustainable intelligent manufacturing: A review. *Adv. Manuf.* **2020**, *9*, 1–21. [CrossRef]
73. Ronzino, A.; Osello, A.; Patti, E.; Bottaccioli, L.; Danna, C.; Lingua, A.; Acquaviva, A.; Macii, E.; Grosso, M.; Messina, G. The energy efficiency management at urban scale by means of integrated modelling. *Energy Procedia* **2015**, *83*, 258–268. [CrossRef]
74. Randall, T. Construction Engineering Requirements for Integrating Laser Scanning Technology and Building Information Modeling. *J. Constr. Eng. Manag.* **2011**, *137*, 797–805. [CrossRef]
75. Anumba, C.J.; Akanmu, A.; Messner, J. Towards a Cyber-Physical Systems Approach to Construction. In Proceedings of the Construction Research Congress 2010: Innovation for Reshaping Construction Practice, Banff, AB, Canada, 8–10 May 2010; pp. 528–537.
76. Wan, K.; Alagar, V. Resource Modeling for Cyber Physical Systems. In Proceedings of the 2012 International Conference on Systems and Informatics (ICSAI2012), Yantai, China, 19–20 May 2012; pp. 2541–2546.
77. Wan, J.; Suo, H.; Yan, H.; Liu, J. A General Test Platform for Cyber-Physical Systems: Unmanned Vehicle with Wireless Sensor Network Navigation. *Procedia Eng.* **2011**, *24*, 123–127. [CrossRef]
78. Hackmann, G.; Guo, W.; Yan, G.; Lu, C.; Dyke, S. Cyber-Physical Codesign of Distributed Structural Health Monitoring with Wireless Sensor Networks. In Proceedings of the 1st ACM/IEEE International Conference on Cyber-Physical Systems, New York, NY, USA, 13–15 April 2010; pp. 119–128.

79. Jones, D. Integrating Building Information Modelling and Geographic Information Systems for Characterising Urban Risk and Resilience—A Proposed Geospatial Workflow. Master's Thesis, University of Canterbury, Christchurch, New Zealand, 2019.
80. Bottaccioli, L.; Aliberti, A.; Ugliotti, F.; Patti, E.; Osello, A.; Macii, E.; Acquaviva, A. Building Energy Modelling and Monitoring by Integration of IoT Devices and Building Information Models. In Proceedings of the 2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC), Torino, Italy, 4–8 July 2017; pp. 914–922.
81. Hajibabai, L.; Aziz, Z.; Peña-Mora, F. Visualizing greenhouse gas emissions from construction activities. *Constr. Innov.* **2011**, *11*, 356–370. [CrossRef]
82. Wu, W.; Yang, H.; Chew, D.; Hou, Y.; Li, Q. A real-time recording model of key indicators for energy consumption and carbon emissions of sustainable buildings. *Sensors* **2014**, *14*, 8465–8484. [CrossRef] [PubMed]
83. Li, X.-J.; Xie, W.-J.; Jim, C.Y.; Feng, F. Holistic LCA evaluation of the carbon footprint of prefabricated concrete stairs. *J. Clean. Prod.* **2021**, *329*, 129621. [CrossRef]
84. Cang, Y.; Luo, Z.; Yang, L.; Han, B. A new method for calculating the embodied carbon emissions from buildings in schematic design: Taking "building element" as basic unit. *Build. Environ.* **2020**, *185*, 107306. [CrossRef]
85. Wong, J.K.W.; Zhou, J. Enhancing environmental sustainability over building life cycles through green BIM: A review. *Autom. Constr.* **2015**, *57*, 156–165. [CrossRef]
86. Maunula, A.; Smeds, R.; Hirvensalo, A. *The Implementation of Building Information Modeling (BIM): A Process Perspective*; Teknillinen korkeakoulu: Espoo, Finland, 2008.
87. Jaderi, F.; Ibrahim, Z.Z.; Nikoo, M.; Nikoo, M. Utilizing self-organization systems for modeling and managing risk based on maintenance and repair in petrochemical industries. *Soft Comput.* **2018**, *23*, 6379–6390. [CrossRef]
88. Zhu, F.; Wu, X.; Zhou, M.; Sabri, M.M.S.; Huang, J. Intelligent Design of Building Materials: Development of an AI-Based Method for Cement-Slag Concrete Design. *Materials* **2022**, *15*, 3833. [CrossRef]
89. Wang, H.; Pan, Y.; Luo, X. Integration of BIM and GIS in sustainable built environment: A review and bibliometric analysis. *Autom. Constr.* **2019**, *103*, 41–52. [CrossRef]
90. Hua, Y.; Oswald, A.; Yang, X. Effectiveness of daylighting design and occupant visual satisfaction in a LEED Gold laboratory building. *Build. Environ.* **2011**, *46*, 54–64. [CrossRef]
91. Liao, C.Y.; Tan, D.L.; Li, Y.X. Research on the Application of BIM in the Operation Stage of Green Building. *Appl. Mech. Mater.* **2012**, *174–177*, 2111–2114. [CrossRef]
92. Bonenberg, W.; Wei, X. Green BIM in Sustainable Infrastructure. *Procedia Manuf.* **2015**, *3*, 1654–1659. [CrossRef]
93. Bellagarda, A.; Cesari, S.; Aliberti, A.; Ugliotti, F.; Bottaccioli, L.; Macii, E.; Patti, E. Effectiveness of neural networks and transfer learning for indoor air-temperature forecasting. *Autom. Constr.* **2022**, *140*, 104314. [CrossRef]
94. Liu, G.; Yang, H.; Fu, Y.; Mao, C.; Xu, P.; Hong, J.; Li, R. Cyber-physical system-based real-time monitoring and visualization of greenhouse gas emissions of prefabricated construction. *J. Clean. Prod.* **2020**, *246*, 119059. [CrossRef]