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Review

The Application and Evaluation of the LMDI Method in Building Carbon Emissions Analysis: A Comprehensive Review

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Abstract: The Logarithmic Mean Divisia Index (LMDI) method is widely applied in research on carbon emissions, urban energy consumption, and the building sector, and is useful for theoretical research and evaluation. The approach is especially beneficial for combating climate change and encouraging energy transitions. During the method's development, there are opportunities to develop advanced formulas to improve the accuracy of studies, as indicated by past research, that have yet to be fully explored through experimentation. This study reviews previous research on the LMDI method in the context of building carbon emissions, offering a comprehensive overview of its application. It summarizes the technical foundations, applications, and evaluations of the LMDI method and analyzes the major research trends and common calculation methods used in the past 25 years in the LMDI-related field. Moreover, it reviews the use of the LMDI in the building sector, urban energy, and carbon emissions and discusses other methods, such as the Generalized Divisia Index Method (GDIM), Decision Making Trial and Evaluation Laboratory (DEMATEL), and Interpretive Structural Modeling (ISM) techniques. This study explores and compares the advantages and disadvantages of these methods and their use in the building sector to the LMDI. Finally, this paper concludes by highlighting future possibilities of the LMDI, suggesting how the LMDI can be integrated with other models for more comprehensive analysis. However, in current research, there is still a lack of an extensive study of the driving factors in low-carbon city development. The previous related studies often focused on single factors or specific domains without an interdisciplinary understanding of the interactions between factors. Moreover, traditional decomposition methods, such as the LMDI, face challenges in handling large-scale data and highly depend on data quality. Together with the estimation of kernel density and spatial correlation analysis, the enhanced LMDI method overcomes these drawbacks by offering a more comprehensive review of the drivers of energy usage and carbon emissions. Integrating machine learning and big data technologies can enhance data-processing capabilities and analytical accuracy, offering scientific policy recommendations and practical tools for low-carbon city development. Through particular case studies, this paper indicates the effectiveness of these approaches and proposes measures that include optimizing building design, enhancing energy efficiency, and refining energy-management procedures. These efforts aim to promote smart cities and achieve sustainable development goals.

Keywords: LMDI (Log Mean Divisia Index); carbon emissions; energy efficiency; sustainable development; urban energy consumption; environmental impact assessment

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1. Introduction

The elevation in energy usage and carbon emissions has a profound effect on global climate change and environmental sustainability. Therefore, scientifically analyzing their driving factors has become a key focus for researchers and policymakers [1,2]. They seek to uncover the deeper underlying factors that influence greenhouse gas emissions. The level of greenhouse gas emissions is determined by various factors, including a country's technological level, wealth, energy structure, economic structure, and demographic composition. The theory of the Divisia index was formerly proposed by François Divisia in 1926 to analyze the indexes for continuous-time data on prices and quantities of goods exchanged. With a high potential for its contribution to the digitalization of energy consumption data, the earliest research on the decomposition index in energy economics and environmental science aspects was based on the energy intensity of industrial sectors. This study aims to achieve a higher accuracy in energy-related field simulation by breaking down data with path independence.

Structural decomposition analysis (SDA) and index decomposition analysis (IDA) are the two main analysis methods that have been introduced that determine the factors related to energy consumption and carbon dioxide (CO_2) emissions. SDA is based on the input–output model for a long-term evaluation. Meanwhile, IDA, which is known for its short-term applications, with the need for periodic stimulation that adapts to changing times, receives significant attention and research in the relevant fields. The Laspeyres exponential decomposition method and the LMDI decomposition method are the two advancement methods of IDA that are most commonly used, and they have led to the development of various related theories and methods.

The LMDI method, as an important improvement of the IDA approach, features a user-friendly formula that can accurately handle zero and negative values, providing easy-to-use calculations. It not only overcomes many limitations of traditional decomposition methods but also offers more precise and flexible analysis tools. Due to its unique advantages, the LMDI has gradually become a mainstream tool for decomposition analysis. By applying identified factors influencing the target variable and the collected relevant data in the LMDI formula, the methods allow the decomposition of changes into contributions from each factor and interpretation of the results to understand which factors have the most impact. It provides precise insights into the factors driving changes in energy use and emissions, helping actors to develop targeted strategies for improving energy efficiency and reducing carbon emissions for a variety of aspects, including researchers, policymakers, businesses, and urban planners. It aids in smart city development by analyzing energy usage and carbon emissions in transportation, buildings, and power systems, providing a scientific foundation for optimizing energy efficiency and formulating low-carbon policies [3,4].

To address the lack of studies that support and demonstrate which methodology is more credible, researchers have dedicated the past 50 years to studying energy usage and carbon emissions. The continuous advancement of stimulation factors has gradually enhanced the credibility of these studies in related fields. This is particularly evident in academia, where critical attention to the lack of variance consideration in the Divisia index method has significantly improved the accuracy of related methodologies.

In the last 25 years, Ang conducted the first decomposition analysis in the energy sector, emphasizing two popular decomposition techniques: the Divisia index, which compares changes logarithmically, and the Laspeyres index, which is based on percentage change. He concluded that the Divisia index method is better and provided practical guidance on this method, giving essential guidance and support to future relevant studies [5,6]. In collaboration with Liu, their research extended the Divisia index decomposition method by providing analytical solutions to handle negative and zero values in the dataset, thereby offering greater potential for related studies [7]. Later, scholars further integrated IDA, widely used in energy and emission studies, into eight LMDI decomposition models and created summaries and comparisons [8]. In recent years, Ang's extensive research in the LMDI field has led to its widespread application in low-carbon and energy efficiency research [9–11]. The LMDI has been used in various research fields in later studies. Reviews such as summaries of Carbon Peak and Carbon Neutrality (CPCN), models for calculating and predicting building carbon emissions, theoretical underpinnings, methods and assessments of decomposition analysis, and thorough analyses of methods for assessing carbon emissions, including a description of the benefits and features of each method, have also been widely proposed by researchers. These evaluations provide more comprehensive and reliable references and explanations for future studies [12,13]. Zhao, Li, and Ma also conducted an IDA decomposition analysis on Residential Energy Consumption (REC) and highlighted that a high-quality and cleaner energy structure is crucial to achieving energy efficiency [14]. Moreover, Shen, Wu, and others studied the four stages of carbon emissions in Beijing's Low Carbon City policy [15].

However, in current research, there is still a lack of an extensive study of the driving factors in low-carbon city development. The previous related studies often focused on single factors or specific domains without an interdisciplinary understanding of the interactions between factors. Moreover, traditional decomposition methods, such as the LMDI, face challenges in handling large-scale data and highly depend on data quality. Together with the estimation of kernel density and spatial correlation analysis, the enhanced LMDI method overcomes these drawbacks by offering a more comprehensive review of the drivers of energy usage and carbon emissions. Integrating machine learning and big data technologies can enhance data-processing capabilities and analytical accuracy, offering scientific policy recommendations and practical tools for low-carbon city development [16]. Through particular case studies, this paper indicates the effectiveness of these approaches and proposes measures that include optimizing building design, enhancing energy efficiency, and refining energy-management procedures. These efforts aim to promote smart cities and achieve sustainable development goals.

This paper gathers and summarizes studies performed in the last 25 years on the LMDI, low-carbon development, and energy efficiency, including an overview of the LMDI analysis on building materials and urban energy and an analysis of the technical concepts related to the LMDI decomposition. It also further categorizes and analyzes building types, which are civil architecture, public architecture, and residential architecture. Additionally, the application of related methods within the building sector, such as the Impact, Population, Behaviour, Affluence, and Technology (I-PBAT) model, Life Cycle Assessment, and carbon emission analysis, are summarized.

Figure 1 provides a comprehensive framework, offering a conceptual statement of the overall review.

- The LMDI method has four advantages and two disadvantages, leading to four directions for future development.
- The LMDI is applied to examine the driving variances of urban REC, carbon emissions, and CO_2 emissions in China.
- The analysis of buildings using the LMDI covers three main categories: civil buildings, public buildings, and residential buildings. Public buildings are further subdivided into four categories. The analysis is conducted through the combination of the LMDI and other methods.
- The analysis of different aspects of building using various LMDI models and other methods.
- The LMDI method, combined with dynamic material flow analysis and index decomposition analysis, determines Domestic Material Consumption (DMC) and material footprint (MF) under the influence of material and residential intensity effects. This reflects the demand and consumption of materials in a country or region at different stages of development.

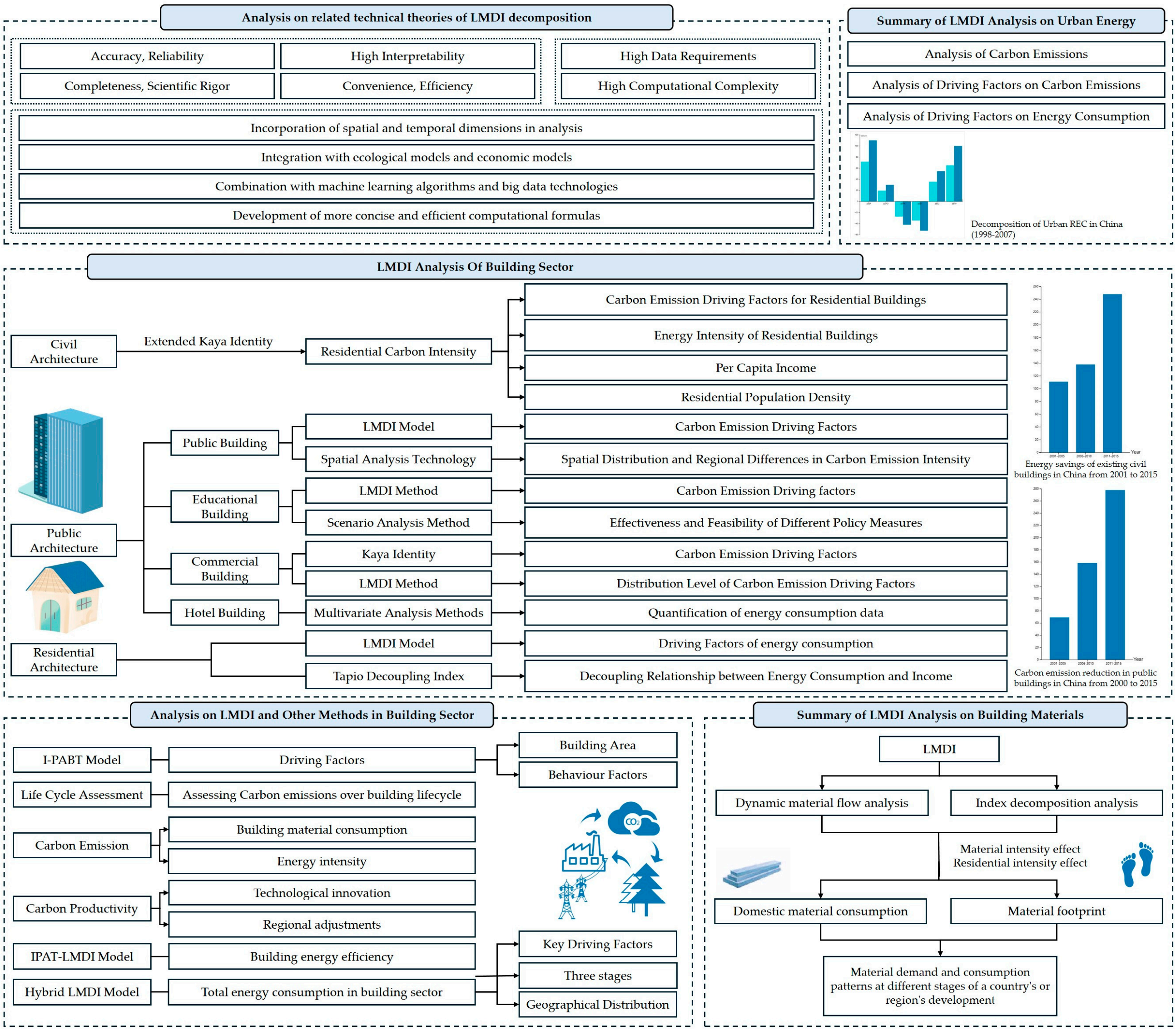

Figure 1. The structural framework of the literature review.

2. Methodology

This systematic review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a comprehensive and transparent review process. As shown in Figure 2, the process was conducted across multiple databases like CNKI, ScienceDirect, MDPI, ResearchGate, etc. to identify relevant studies. A total of 1116 records were initially retrieved through database searches, of which 465 records were repeated and later removed. Of the remaining 651 records, 462 records of studies that did not focus on urban energy planning or building design were excluded, leaving 189 records for screening, which assessed their relevance. Within the 189 records, 64 articles achieved the eligibility categories under the categories of Q1 and Q2 journals. From the final remaining records, 2 of the articles were determined to be qualitative research, while the other 64 articles were determined to be quantitative research.

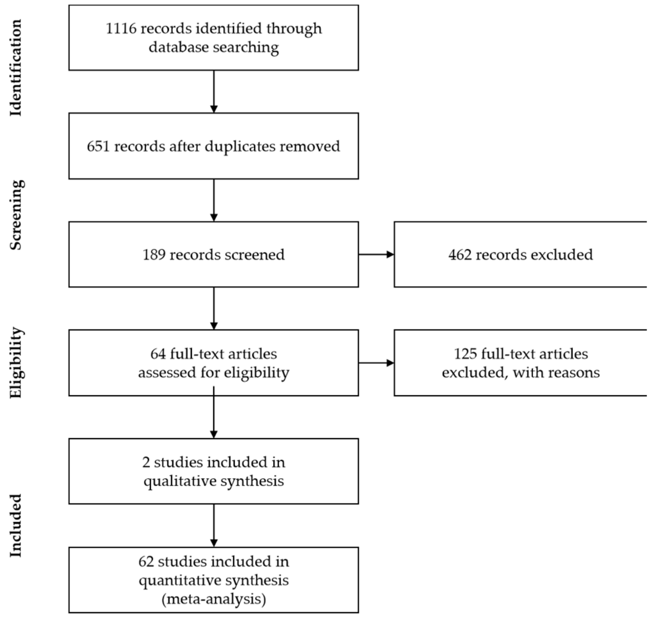

Figure 2. PRISMA framework of the research progress.

3. Analysis of Related Technical Theories of LMDI Decomposition

The theoretical basis of the LMDI method is mainly based on the index number theory. Scholars have proposed four criteria for evaluating decomposition methods, namely, theoretical foundation, adaptability, user-friendliness, and clarity of results. The LMDI approach performs well on these four criteria. Firstly, the robustness of the theoretical basis of the LMDI method is proved through the tests on time reversal, factor reversal, proportion, and polymerization. Secondly, the LMDI method can process data containing zero and negative values, which is very effective for analyzing time series and cross-section data. In addition, the calculation formula of the LMDI method is simple and easy for users to operate. The calculation process is relatively simple and does not require complex mathematical operations, so users can easily master and apply the method. Finally, the results of the LMDI method are highly interpretable, and the decomposition results are clear and direct. With the LMDI approach, researchers can clearly identify and quantify the contribution of individual drivers to the total change, thus providing a reliable basis for policy formulation.

Based on the concept of the logarithmic mean weight, the LMDI avoids the residual problem of traditional decomposition methods and has the property of complete decomposition. Its basic formula is shown below:

$$\Delta Y = \sum \Delta Yi$$

where ΔY represents the total change, and ΔYi represents the change in each driving factor [11].

The LMDI approach has been widely applied as research advances. By combining spatial correlation analysis and kernel density estimation, the method's potential for integrating spatial and temporal aspects has increased, leading to a more comprehensive and accurate study [11]. The LMDI, regarding energy usage and carbon emission decomposition analysis, is highly reliable and effective. It breaks down the total energy usage into various factors, allowing for the identification and quantification of each factor's contribution to changes in energy usage [12]. Additionally, compared to traditional Divisia decomposition methods, the LMDI offers several advantages. Firstly, the decomposition results are not influenced by the decomposition path, ensuring consistency and reliability. Secondly, the LMDI method effectively handles zero values in the data, avoiding decomposition biases caused by zero values [13].

4. Summary of LMDI Analysis of Urban Energy

This part of the study provides a detailed examination of key areas influencing carbon emissions and energy consumption. The analysis focuses on carbon emissions, driving factors on carbon emissions, and driving factors in energy consumption. Table 1 presents a summary of high quality academic researches related to urban energy.

Table 1. The statistical analysis of LMDI-related literature on urban energy.

Source	Year	Major Focus	Methodology
Zhao, X.L.; Li, N.; et al. [14]	2012	Factors Influencing REC	LMDI
Liu, Z.G.; Wang, S.S.; et al. [15]	2015	Factors Influencing Carbon Emissions in Urban Civil Architecture in China from 1997 to 2007	LMDI
Shen, L.Y.; Wu, Y.; et al. [17]	2018	EKC Analysis of Carbon Emissions in Beijing	EKC + LMDI
Gu, S.; Fu, B.Y.; et al. [18]	2019	Factors Influencing CO_2 Emissions in Shanghai from 1995 to 2016 and Forecast of the Decarbonization Potential from 2016 to 2030	LMDI + SD
Huang, Y.Z.; Matsumoto, K. [19]	2021	Influence of Urbanization on CO_2 Outputs in 30 of China's Provinces from 1990 to 2016	LMDI
Li, H.M., Qiu, P.; et al. [20]	2021	Estimation of CO_2 Emissions for Provincial-Level Building Industries and Different Building Types	LMDI
Zhang, Y.; Zhang, Y.X.; et al. [21]	2022	Research on Urban Carbon Footprint Drivers and LMDI Decomposition and Forecasting with Three Scenarios	LMDI
Gao, G.Y.; Jia, Q.; et al. [22]	2024	LMDI Decomposition of CO_2 Emission Factors, Tapio Decoupling Model Analysis, and LEAP Model Forecasting	LMDI

4.1. Analysis of Carbon Emissions

Global warming due to carbon emissions is a severe global issue, threatening both natural ecosystems and human development. Despite efforts by governments worldwide to reduce emissions over the years, carbon emissions have continued to rise. According to reports in 2011, global carbon emissions have experienced a 40 percent increase since 1750. This highlights the critical necessity for global action to regulate carbon emissions with a comprehensive and systematic method [17].

In the evaluation of carbon emission, the LMDI study is currently still limited at the regional level [17]. However, related research has been widely applied in many regions, especially China, the largest carbon emission country that is targeting achieving a low-carbon city. Using the LMDI, a related study mentioned that the decomposition and analysis of urban nonindustrial building carbon emissions involve factors including *POP*, *PCA*, *BS*, *EI*, and *EF*, of which *POP* and *PCA* are the key variances [15].

4.2. Analysis of Driving Factors on Carbon Emissions

In studying carbon emissions, CO_2 is used as the primary metric since it is the most important greenhouse emissions released by human activities [15]. A study analyzed CO_2 emissions in different regions and each region's statistical data, identifying six key factors driving CO_2 emissions, including *CI*, *EI*, *RC*, *CS*, *PU*, and *POP* [19]. Using those data and the LMDI method, the correlation between urbanization and CO_2 emissions can be evaluated.

Taking the Kaya Identity into account, CO_2 emissions are decomposed as follows:

$$CARB_i = \frac{CARB_i}{ENE_i} \times \frac{ENE_i}{GRP_i} \times \frac{GRP_i}{POP_i} \times POP_i$$

where *CARB* refers to CO_2 emissions, *ENE* refers to the total energy usage, *GRP* refers to the Gross Regional Product, and *POP* refers to population, with *i* referring to the number of provinces [19].

4.3. Analysis of Driving Factors in Energy Consumption

Scientific measurements of energy usage have been widely researched in relevant field studies. The factors influencing energy consumption included *EF*, *ES*, *EI*, *UC*, *AL*, *MCE*, and *M*. *EI* is a key factor of carbon reduction, followed by *ME*.

The data on energy usage can be decomposed into six transportation sectors: agriculture, industry, buildings, commercial, residential, and urban. Buildings are the key focus of this paper. Decomposing each sector in depth, the carbon emission can be standardized and classified into direct sources, such as burning fossil fuel, and indirect sources, such as electricity and heat.

With a more comprehensive dataset, the extended form of the LMDI method can be applied to explore the drivers of the growth of urban REC. This approach can examine the full structure of its energy usage, and its formula is commonly divided into four main categories, which are private transportation, household appliances, central heating, and other energy-use activities, alongside 17 energy-use products [14].

A relevant study suggests integrating the System Dynamics (SD) model, a tool for simulating complex system behaviors and feedback using mathematical modeling, with the LMDI method for carbon emission calculations. This simulation incorporates factors such as personal automobile ownership, urban transportation alternatives, and mean income levels into the traditional drivers of CO_2 emissions. Socio-economic scale effects, driven by PCGDP and P, emerged as the primary positive drivers of CO_2 growth [18].

Some studies have combined Kaya Identity and the LMDI model to decompose urban carbon emission driving variances. It is one of the carbon emission factorization models, and it includes economic growth, population, policy, and other variables with carbon emissions in the research. The driving factors of carbon outputs integrated into the model include *P*, *PCGDP*, *IS*, *EI*, and *ES*. In the research, based on a thorough evaluation of the factorization results of urban carbon emissions, *P* and *PCGDP* contribute the most to urban carbon emissions, while EI and CI inhibit carbon emissions significantly in most years [21]. On the other hand, using IDA to expand the Kaya Identity resulted in minor variations. E may rise as the key driving factor of CO_2 emission, and EI is the primary factor constraining the emission [22].

5. LMDI Analysis of Building

The application of the LMDI method has become a significant tool for understanding the factors driving energy consumption and carbon emissions in various building types. In the context of civil, public, educational, commercial, and residential architecture, the LMDI approach allows for a detailed decomposition of energy use drivers, offering insights into sector-specific challenges and opportunities. This section focuses on how LMDI has been applied to different architectural sectors, analyzing its effectiveness in identifying key factors influencing energy use and carbon emissions.

5.1. LDMI Analysis of Civil Architecture

Civil architecture plays a crucial role in shaping urban energy consumption, with its broad range of building types contributing significantly to overall carbon emissions. The application of the LMDI method in this area provides a detailed analysis of energy use drivers, offering a pathway toward improving energy efficiency. This section summarizes the key studies that have applied LMDI to civil buildings, identifying the most impactful factors and proposing relevant policies. Table 2 highlights the statistical analysis of LMDI-related literature on civil architecture.

Table 2. The statistical analysis of LMDI-related literature on civil architecture.

Source	Year	Major Focus	Methodology
Ma, M.; Shen, L.Y.; et al. [23]	2017	LMDI-I Decomposition of Carbon Emissions from Public Buildings in China and STIRPAT Drivers Model	STIRPAT + LMDI
Yang, S.H.; Liu, J.; et al. [24]	2021	Study on the Drivers of Carbon Emissions from Residential Buildings in Four Regions of China	LMDI
Ma, M.D.; Yan, R.; et al. [25]	2018	Contribution to Drivers of Energy Consumption in Public Buildings and Energy Usage Assessment During the 10th Five-Year Plan Period	LMDI

The LMDI model can study the drivers of civil buildings' carbon outputs in China. By comparing the carbon emissions of the regions, the key effects causing carbon emissions are revealed. Relevant policy proposals are presented to meet the carbon-reduction goal [24].

A method based on the LMDI method and Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, which is an advanced version of the Impact, Population, Affluence, and Technology (IPAT) model that examines how population, affluence, and technology influence environmental impact, is proposed to calculate the current civil buildings' energy efficiency in China from 2001 to 2015. China's energy usage has significantly reduced with the accelerated development of building energy conservation [25].

Enhancing building operational efficiency, improving energy efficiency, and promoting energy-saving lifestyles can significantly reduce energy usage in a building's operation. Reducing energy intensity is strongly negatively correlated with increased carbon productivity, indicating that energy-saving measures can also enhance carbon productivity [26,27]. This requires consideration throughout the building scheme life cycle, from planning to demolition and recycling [28]. For instance, energy reduction can be achieved by utilizing clean energy associated with the manufacturing, processing, and delivering of building materials [27]. Promoting green building technology and materials and implementing carbon-reduction strategies, such as applying low-carbon design in new buildings and low-carbon retrofitting on existing buildings, are also crucial [29,30]. The government is obligated to develop carbon-reduction technologies, such as optimizing the energy system using innovative scientific and technological approaches and boosting the usage of clean energy. The proportion of the expenditure on green research and development should also be increased [31]. In addition, different regions should develop corresponding energy-saving measures according to their specific energy needs. Relevant departments should formulate differentiated emission-reduction targets and policies for different regions to balance fairness and efficiency in green development [32,33], control the expansion of high-energy-consumption industries, and gradually phase out the obsolete capacity to reduce carbon emissions. To reduce total carbon emissions, governments should strictly regulate the expansion of industries that significantly contribute to energy usage and carbon emissions [34].

5.2. LMDI Analysis of Public Architecture

5.2.1. LMDI Analysis of Public Buildings

Public buildings, often characterized by their large size and high energy demands, represent a critical sector for carbon reduction efforts. Through the LMDI model, studies have effectively decomposed the drivers of energy use and carbon emissions in this sector, offering a comprehensive understanding of factors such as population growth, economic activity, and technological development. This analysis provides valuable insights into how public buildings can achieve greater energy efficiency. Table 3 presents the statistical analysis of LMDI-related literature on public buildings.

Table 3. A statistical analysis of the LMDI-related literature on public buildings.

Source	Year	Major Focus	Methodology
Ma, M.D.; Yan, R.; et al. [25]	2018	Analysis of Impact Factors on Public Building Energy Consumption and ESPB Evaluation during the 10th–12th Five-Year Plan Periods	LMDI
Gan, L.; Liu, Y.; et al. [26]	2022	Inequality Analysis of Carbon Output Intensity and Drivers in Public Buildings in China from 2010 to 2019	LMDI
Zhang, J.J.; Yan, Z.F.; et al. [27]	2023	Analysis of Factors Influencing Carbon Emissions in Public Buildings and the Impact of Economic Growth Level on Operational-Stage Carbon Emissions	LMDI
Zou, Q.; Zeng, G.P.; et al. [29]	2024	Major Drivers of Carbon Emissions in Public Buildings in Changsha	STIRPAT Model + Network Analysis + Spatial Durbin Model

The first model of the LMDI (LMDI-I) decomposition method and STIRPAT model were used in China to establish the driving factor equation for Carbon Emissions in Public Buildings (CPBCE) and evaluate carbon reduction (CERCPB) [35]. The technical approach involves using the STIRPAT model to determine the different drivers affecting carbon emissions and applying the LMDI-I decomposition analysis method.

The research methods include using the STIRPAT model to determine the decoupling of population, wealth, technology, and environmental pressure, as well as using the LMDI-I decomposition analysis to break down explanatory variables into a set of driving factors and quantify their contributions. Carbon-reduction amounts are calculated using the formula, treating CPBCE intensity as a result of public building energy efficiency and service levels.

This study reveals an extensive reduction in carbon outputs in the public building sector. The findings suggest that from 2001 to 2015, there was a negative effect of equivalent CPBCE intensity, and the carbon reduction increased significantly. The CERCPB values were 69.29 million tons of CO_2 for 2001–2005, 158.53 million tons for 2006-2010, and 277.86 million tons for 2011–2015. The actual CERCPB values exceeded the official targets, indicating significant achievements in public building energy efficiency during this period [36]. Therefore, implementing energy-efficient policies and goals for public buildings is crucial for achieving carbon reduction.

China's public buildings exhibit substantial regional disparities in the intensity of carbon outputs. Due to their advanced economic growth and high building density, the carbon emissions intensity of the coastal regions in the east is higher than the central and western parts of the country. Additionally, factors such as the economic growth level, energy structure, and climate conditions notably affect carbon emission intensity. It is suggested to formulate decarbonization policies tailored to the local context, encourage the development of the central and western regions, improve energy efficiency, optimize the energy structure, and achieve a balanced carbon emission reduction across the country.

The researchers used the STIRPAT and Long-range Energy Alternatives Planning System (LEAP) models to audit and predict the carbon emissions of public buildings in Xi'an. In their studies, various scenarios were evaluated, including baseline, energy-saving retrofit, renewable energy substitution, and comprehensive scenarios. This study proposed specific energy-saving and emission-reduction policy recommendations, including enhanced policy support, boosted investment in technology research and advancement, and the promotion of energy-efficient and renewable energy applications.

In another case in Changsha, the carbon emission paths of public buildings were monitored during their operational phase using the LEAP model for the prediction and scenario analysis from 2021 to 2035. The study focused on the key factors influencing public building carbon emissions and set up a baseline and green scenarios for energy usage scenarios [37].

5.2.2. LMDI Analysis of Educational Buildings

Educational buildings, including schools and universities, offer unique challenges and opportunities in energy management due to their operational patterns and diverse energy needs. Applying LMDI to this sector has revealed key drivers of energy use, such as occupancy rates and technological upgrades, offering insights into how educational institutions can improve energy efficiency. Table 4 presents a statistical analysis of LMDI-related literature on educational buildings.

Table 4. A statistical analysis of the LMDI-related literature on educational buildings.

Source	Year	Major Focus	Methodology
Zhou, X.; Xu, Z.X.; et al. [30]	2023	Analysis of Drivers of Carbon Emissions in Educational Buildings and Definition of Three Typical Scenarios	Scenario Analysis + LMDI
Laporte, J.P.; Román-Collado, R.; et al. [38]	2024	Assessment of Energy Consumption Changes in Chilean Universities from 2017 to 2022	STIRPAT

Educational buildings have complex and diverse factors influencing urban carbon emissions. A systematic analysis of these factors provides scientific evidence and specific policy recommendations for carbon neutrality in educational buildings.

The technical approach involves several steps. Collecting and organizing energy usage and carbon emissions-related data is the initial step for educational buildings. The second step is applying the LMDI method to decompose the drivers of carbon emissions, followed by scenario analysis to estimate the changes in carbon outputs under different policy scenarios. The last step involves proposing corresponding carbon-reduction strategies and policy recommendations [39,40].

The LMDI method is utilized to decompose the drivers of carbon emissions, such as *EI*, *EA*, *P*, and *TL*. Scenario analysis is used to predict carbon emission changes under different policy scenarios by setting baselines, policies, and intensified scenarios to evaluate the effectiveness and feasibility of various policy measures. By decomposing time series data on energy use, the effects of different factors, such as adjusted *EI*, *IR*, *CL*, and *SEN*, on energy usage are analyzed. Data sources include consumption figures for electricity, diesel, natural gas, and liquefied gas, as well as building area and student enrollment numbers.

The LMDI research provides a scientific foundation for developing reasonable carbon-reduction policies and emphasizes the importance of multi-sectoral collaboration. The recommendations include encouraging energy-saving technologies, optimizing energy use, and improving energy efficiency management. Furthermore, the research emphasizes the importance of considering climate impacts and energy management in higher education institutions. Suggested measures include behavior-change programs, energy audits, building management systems, and upgrades to Heating, Ventilation, and Air Conditioning (HVAC) systems to achieve energy efficiency.

5.2.3. LMDI Analysis of Commercial Building

The commercial building sector, driven by economic growth and urban development, has seen rapid increases in energy consumption. The LMDI model has been instrumental in analyzing the contributing factors behind this trend, revealing opportunities for enhancing energy efficiency through technological innovation and policy intervention. Table 5 presents a statistical analysis of LMDI-related literature on commercial buildings.

Table 5. A statistical analysis of the LMDI-related literature on commercial buildings.

Source	Year	Major Focus	Methodology
Zhang, M.; Yan, S.; et al. [27]	2015	Study on Factors Influencing Energy Consumption in Commercial Buildings and Decoupling Relationship with Economic Development	LMDI
Ma, M.D.; Cai, W.; et al. [33]	2018	Measurement of Decarbonization of Commercial Buildings in China	LMDI
Ma, M.D.; Cai, W.G. [34]	2018	Kaya Identity Drivers Decomposition of Carbon Footprint in Commercial Buildings in China and Evaluation of CMCCB Values from 2001 to 2015	LMDI
Xiang, X.W.; Ma, M.D.; et al. [35]	2022	Assessment of Decarbonization Progress in Commercial Buildings Across 16 Countries	LMDI
Ma, M.D.; Feng, W.; et al. [41]	2022	Estimation of Decarbonization Levels in Commercial Buildings of China's Five Major Urban Centers	GDI method

The economic growth in China has led to a remarkable elevation in the energy usage of commercial buildings. Studies on the variables impacting the energy consumption of commercial buildings and the gap between building energy usage and the growth of the commercial industry's economy reveal that *EI* in the commercial sector decreased from 61.78 percent in 1991 to 36.70 percent in 2011, representing a 40.59 percent reduction. As of 2003, electricity has emerged as the dominant energy source, overtaking coal products [42].

By analyzing the energy usage and carbon emission data on commercial buildings from multiple countries, a study revealed that global decarbonization trends are driven by various factors, including policies, technology, and economics [32]. Following the reform and opening-up policy in 1978, the mean annual rate of China's economy has increased by about 10 percent, with rapid growth in GDP in the commercial industry. Concurrently, commercial buildings' energy use has increased significantly, representing a substantial portion of the overall energy usage in China [43].

The research methods are presented as follows:

A: LMDI Method

This decomposition technique is applied to analyze the drivers in the commercial building sector.

B: Data Collection

The statistics on the commercial building industry in China have been collected, including *P*, *GDP*, *EC*, and *CE* [43].

C: Model Construction

The decomposition model for carbon emission drivers is established by using the extended Kaya Identity [43].

D: Empirical Analysis

The LMDI method on carbon decomposition quantifies the driving factor contribution to carbon emissions [43].

E: Case Analysis

This section examines multiple countries and regions, gaining detailed insights into the carbon-reduction measures and outcomes in the commercial building industry. The analysis involves collecting energy usage and carbon emission data for commercial buildings from major global economies, drawing from government reports, academic studies, and data established by the International Energy Agency [44].

F: Decarbonization Path Analysis

Through the analysis of carbon emission data from various countries during different periods, the primary decarbonization paths and drivers have been identified.

The rise in carbon emissions in China's commercial building industry is mainly driven by the growth of *POP* and *EA*. By enhancing energy efficiency and regulating the energy mix, carbon emissions can be significantly reduced. Worldwide, commercial building management experienced significant decarbonization in the early 21st century, primarily due to policy initiatives, technological advancements, and economic development. Decarbonization paths and outcomes vary across countries and regions; the United States and the European Union have seen significant reductions in commercial building carbon emissions while developing countries like China and India still face considerable pressure to reduce emissions [44,45].

5.2.4. LMDI Analysis of Hotel Building

Hotel buildings, due to their high energy consumption and specific operational requirements, represent a significant area for energy-saving measures. This section aims to uncover the primary drivers of energy use in this sector, including occupancy rates and operational efficiency, suggesting strategies for improving energy performance. Table 6 presents a summary of the major focus and methodology of LMDI-related literature on hotel buildings from the past year.

Table 6. A statistical analysis of the LMDI-related literature on hotel buildings.

Source	Year	Major Focus	Methodology
Du, Z.J.; Jiang, X.Y.; et al. [36]	2019	Assessment of Energy Consumption in Business Hotel Buildings	STIRPAT + LMDI

This section explores methods for assessing the energy usage of hotel buildings and aims to provide scientific evidence for formulating energy-saving policies. Due to their unique operational modes and high-energy-usage characteristics, hotel buildings have a high potential for achieving energy conservation and emission reduction [46]. Initially, energy consumption data for hotel buildings, including electricity, gas, and water usage, were collected and organized. Subsequently, statistical analysis tools were used to examine the relationships between energy consumption data, building characteristics, climatic conditions, and operational modes. Finally, energy consumption models were developed to predict variations under different conditions and propose corresponding energy-saving measures.

According to this study, business hotels' energy usage is influenced by various factors, including the building area, number of guest rooms, occupancy rates, and air conditioning usage. By optimizing building design, improving operational management, and adopting energy-efficient technologies, significant reductions in energy usage can be achieved. This article proposes energy-saving recommendations, such as improving air conditioning systems, enhancing insulation, and promoting energy-efficient lighting. These measures are crucial for enhancing the energy utilization efficiency of hotels.

5.3. LMDI Analysis of Residential Architecture

Residential buildings, both urban and rural, have a profound impact on energy consumption patterns due to their scale and diversity. The LMDI method has been effectively applied to explore the key factors driving energy use in residential architecture, from building design to household behaviors. This analysis offers a foundation for developing targeted policies to reduce carbon emissions in residential areas. Table 7 presents a statistical analysis of LMDI-related literature on residential architecture.

Table 7. A statistical analysis of the LMDI-related literature on residential architecture.

Source	Year	Major Focus	Methodology
Lin, B.Q.; Liu, H.X. [37]	2015	Identification of Factors Influencing REC and Tapio Decoupling Method for Describing the Decoupling Correlation between REC and Residential Income	3D LMDI model
Zhang, M.; Bai, C.Y. [39]	2018	Decomposition Analysis of CO_2 Intensity Factors and Assessment of Energy Service Demand for Residential Buildings in China Based on Household Size	LMDI
Ma, M.D.; Ma, X.; et al. [40]	2019	Drivers of CO_2 Emissions Under IDA	LMDI
Balezentis, T. [42]	2020	Decoupling Relationships between Drivers of Carbon Footprints in 30 Provinces of China from 2000 to 2015	LMDI
Huo, T.F.; Ma, Y.L.; et al. [47]	2021	Bottom-Up Analysis of Identifying the Contribution of Energy-Saving Policies to Mesoscale Change	LMDI
Reuter, M. Narula, K.; et al. [43]	2021	Exploration of the Spatiotemporal Rhythm and Driving Mechanisms of Urban Residential Building Carbon Footprints in 30 Provinces of China from 2000 to 2019	LMDI
Chen, H.D.; Du, Q.X.; et al. [44]	2023	Evaluation of Decarbonization in Residential Buildings in Henan from 2010 to 2020 and Forecast of Carbon Emission Trends and Peak Timing from 2020 to 2050	LMDI
Yang, X.; Sima, Y.F.; et al. [45]	2023	Research on the Peaks of Carbon Footprints and Decarbonization Path for Residential Buildings in Fujian Province	Kaya-LMDI
Lin, C.X.; Li, X.J. [46]	2024	Comprehensive Assessment Model for CPSIAM and Evaluation of Provincial Total Carbon Emission Peaks	Kaya-LMDI
Huo, T.F.; Du, Q.X.; et al. [48]	2024	Comprehensive Assessment of Carbon Emissions from Lighting and Electrical Appliances in Residential Buildings	LMDI + TD + LEAP
Li, X.J.; Lin, C.X.; et al. [16]	2024	Quantification of Factors Influencing Residential Carbon Emissions in Yunnan Province, China	LMDI + LEAP
Li, W.Y.; Li, Q.Y.; et al. [49]	2024	Identification of Factors Influencing REC and Tapio Decoupling Method for Describing the Decoupling Correlation Between REC and Residential Income	LMDI

Between 2000 and 2020, CO_2 emission data for commercial and residential architecture in China indicate an overall upward trend in CO_2 emissions, particularly in first-tier cities, where increased economic activities and accelerated urbanization have significantly raised building energy usage and associated emissions. There are substantial regional disparities in emissions, with coastal developed areas in the east exhibiting much higher emissions compared to central and western regions, reflecting regional economic development levels and energy structures. Major sources of emissions during building operation include heating, air conditioning, lighting, and the use of electrical appliances, with heating in northern regions being a significant carbon emission source, especially in winter. Additionally, the manufacturing and delivery of building materials, particularly cement and steel, are significant indirect emission sources [48].

The LMDI method is used in the research on the energy usage of residential urban and rural areas of Shandong to explore the drivers of energy usage. To explore the relationship between the REC and residential income, the Tapio decoupling index was employed, focusing specifically on the decoupling aspect. This study found that the REC of both areas has risen rapidly, following the residential income. The total REC in Shandong has shown an upward trend, but the gap in energy usage between urban and rural areas has narrowed. Since 2000, the decoupling index for both areas' residents has constantly decreased, indicating a reduced dependency of income on REC [16].

By comparing different building types and energy usage patterns, improvement measures have been proposed, such as selecting more environmentally friendly building materials, optimizing building design, and implementing energy-management systems. The goal is to provide feasible decarbonization strategies for the residential building sector to deal with global climate change. LCA and energy usage simulation can quantitatively assess the energy usage and carbon outputs of residential projects throughout their life cycle, focusing on selecting building materials that impact the carbon footprint and reducing the energy usage with technological innovation and design optimization [49].

In the extended Kaya Identity in the LMDI model, the carbon intensity of residential areas has been decomposed into four key elements, including *EF*, *SEN*, *PCI*, and *P*. From 2000 to 2015, there was an improvement in the decoupling state of *CI* and *PCI* in most of China's provinces, especially in the shift from weak to strong decoupling [50]. The data can be utilized by policymakers to develop focused energy-conservation and decarbonization programs in order to balance the management of the *PCI* and *EF*. Energy-saving policies have a direct influence on carbon intensity. For example, assessments of policies adopted in Germany and Switzerland in 2000 indicate that the energy efficiency metrics and policy evaluation methods used in both countries have led to significant reductions in energy usage [28].

6. Analysis of LMDI and Other Methods in Building Sector

The analysis of LMDI in the building sector reveals significant insights into the factors influencing energy usage and carbon emissions. Referring to Table 8, the analyse highlights key studies related to the application of LMDI in the building sector, emphasizing the impact of factors such as building area expansion and technological advancements.

Table 8. A statistical analysis of the LMDI-related literature in the building sector.

Source	Year	Major Focus	Methodology
Gong, Y.Y.; Song, D.Y. [50]	2015	Calculation of Full-Life Energy Usage and Carbon Footprints in the Construction Industry of Wuhan City	LCA + LMDI
Lu, Y.J.; Cui, P.; et al. [51]	2016	Decomposition Analysis of Incremental Emission Changes and Evaluation of Building Carbon Footprints in China from 1994 to 2012	LMDI

Table 8. *Cont.*

Source	Year	Major Focus	Methodology
Hu, X.C.; Liu, C.L. [52]	2016	Factors Influencing Carbon Productivity and a Carbon Productivity Survey of the Australian Building Industry	LMDI
Ma, M.D.; Yan, R.; et al. [53]	2017	Evaluation of Energy Consumption per Unit Area and Building Energy Savings in China	IPAT-LMDI
Lu, Y.J.; Cui, P.; et al. [28]	2018	Three-Dimensional Decomposition of the Total Energy Consumption Changes in the Building Industry	LMDI
Wang, M.; Feng, C. [31]	2018	Exploration of the Drivers of Energy-Related CO_2 Emissions in the Building Industry	LMDI
Du, Q.; Lu, X.R.; et al. [54]	2018	Analysis of the Industrial Carbon Emissions Characteristics in 30 Provinces of China	LMDI
Chen, X.; Shuai, C.Y.; et al. [55]	2020	Forecasting Peak Emissions and Investigating the Driving Factors of Carbon Footprints in the Industrial, Building, Transportation, and Agricultural Sectors	CKC + LMDI
Li, D.Z.; Huang, G.Y.; et al. [56]	2020	Exploring the Factors Influencing Total Carbon Emissions in the Building Industry at the Provincial Level	LMDI
He, J.H.; Yue, Q.; et al. [57]	2020	Analysis of the Factors Influencing Carbon Emissions in Three Types of Buildings in China from 2000 to 2005	Factor decomposition analysis + LMDI
Zhong, X.Y.; Hu, M.M.; et al. [58]	2021	Analysis of the Evolution of Building Energy Consumption Intensity from 1971 to 2014 and Correlation with Economic Growth and the Future Impact of Energy Conservation in 21 Global Territories by 2060	LMDI + IAM
Yan, S.H.; Chen, W.G. [59]	2022	Decoupling Status and Factors Influencing the Decomposition of CO_2 Emissions under the Construction of the LMDI Model	LMDI
Sun, Z.H.; Ma, Z.L.; et al. [60]	2022	Literature Review on Building Carbon Peaks and Carbon Neutrality	Bibliometric Methods
Jiang, B.Y.; Sun, L.; et al. [61]	2023	Introduction of Technological Factors in the Building Sector and and Reconstruction of Impact Variables for CO_2 Emission Fluctuations in Jiangsu Province from 2011 to 2019	LMDI
Huo, T.F.; Cong, X.B.; et al. [62]	2023	Establishment of an Integrated DEMATEL-ISM Model	DEMATEL-ISM
Shi, Q.W.; Liang, Q.Q.; et al. [63]	2023	Simulation of CE Trends Under Economic Dynamics and Building Demand Perspectives, and Exploration of CO_2 Influencing Factors for the Overall and Provincial Building Sector in China	LMDI

Table 8. *Cont.*

Source	Year	Major Focus	Methodology
Zhang, S.X.; Wang, M.P.; et al. [64]	2024	Development of a Dynamic Comprehensive Building Carbon Footprint Forecasting Model and Prediction of Building Sector Carbon Emission Trajectories and Probability Distributions for Shandong Province from 2020 to 2050	LMDI + SD Model
Zheng, S.M.; He, X.R.; et al. [65]	2024	Decoupling Model Study of the Correlation between Building Sector Carbon Emissions and Economic Growth in the Core Economic Region of East China	LMDI
Zhao, Q.F.; Wang, T.; et al. [66]	2024	Framework Development, Carbon Intensity Methods, and Exploration of CEMP	CPSIAM

6.1. Analysis of LMDI in Building Sector

6.1.1. Application of I-PBAT Model

A As one of the IDA methods, the LMDI is applied to examine the drivers. The extended I-PBAT model was adopted to analyze the driving factors. *B* was added based on the IPAT model to more fully consider the variances driving building energy usage and carbon emissions [27,67].

6.1.2. Key Drivers of Carbon Emissions in Building Sector

This study employed the LMDI method to determine the long-term effects of seven key variances by quantifying the gradual contributions of each major driving element to the alterations in carbon footprints. According to the research, *MC* contributes 63 percent of total carbon emissions, while *SEN* contributes 54 percent of the total carbon reduction [51]. Decomposition analyses also reveal that an increase in building area is the main factor influencing rising energy usage and carbon emissions, with human behavior factors following closely behind. In particular, the primary cause of the energy usage and carbon emissions growth is the expansion of *BA*. *B* is the second largest contributor. There is a direct correlation between rising living standards and rising energy use. The growth of the population and urbanization have also caused an increase in building energy usage to some degree [27]. Technological innovation substantially enhances carbon productivity, whereas regional adjustments have a minimal effect. Additionally, there has been no notable change in the structural adjustments within the building sector across different regions [52]. Building-related carbon emissions are predominantly influenced by two factors: *EO* and *SEN*. To effectively mitigate carbon emissions in the building industry, policymakers should emphasize these factors and develop strategies to adjust economic structures and reduce reliance on the construction industry [33,53].

6.2. Analysis of Other Methods in Building Sector

In exploring other analytical methods, this section covers a range of approaches including the Tapio decoupling model, bibliometric methods, system dynamics models, and dynamic integrated forecasting models, providing a comprehensive look at how different methodologies contribute to the understanding and management of emissions in the building industry. Table 9 presents a statistical summary of literature related to these methods, offering insights into their applications and findings in the context of building sector carbon emissions and energy use.

Table 9. A statistical analysis of the literature related to other methods in the building sector.

Source	Year	Major Focus	Methodology
Huo, T.F.; Du, Q.X.; et al. [68]	2023	STIRPAT-PLS Model Framework Construction and Analysis of Key Factors Affecting Cross-Sector Building Carbon Emissions	STIRPAT-PLS
Li, Y.; Wang, J.F.; et al. [69]	2023	Exploration of Emission Influencing Factors and Future Peak Emission Predictions for China and Its Provinces	GDIM + scenario analysis + Monte Carlo simulation
Xu, F.; Li, X.D.; et al. [70]	2024	2011–2020 Building Sector Emissions Calculation and Innovative Factor Analysis Model Development for 29 Chinese Provinces	LMDI

6.2.1. Analysis of Tapio Decoupling Model

By employing the Tapio decoupling model, this study analyzes the decoupling relationship between economic growth and CO_2 outputs within the building sector. This study finds that, in most provinces, the development of the industry is highly related to CO_2 emissions, and Beijing and Jiangsu have achieved a strong decoupling status. *EO* is identified as the main factor driving both CO_2 emissions and decoupling [30].

6.2.2. Bibliometric Method

The bibliometric method is useful in providing a comprehensive overview of studies related to current conditions and future trends in the development of carbon reduction. It is also good at revealing the research gaps in the field of building sectors [60].

6.2.3. Analysis of System Dynamics Model and Scenario

This study uses the SD model and scenario analysis to forecast the future trajectory of carbon footprints in Shandong Province's construction industry from 2020 to 2050. It includes three scenarios: baseline, low-carbon, and high-carbon. Monte Carlo simulation is employed to examine the uncertainty effects of various variances on the future carbon emission peak and its timing [64].

6.2.4. Dynamic Integrated Building Carbon Emission-Forecasting Model

The SD model is designed to forecast carbon footprints in the building industry. The model can handle complex nonlinear systems and thoroughly accounts for multiple factors influencing carbon emissions. In the model, the variances of carbon emissions are analyzed in three dimensions: *P*, *SEN*, and *SA*.

The connection between macro and micro variances of carbon emissions can be explored through such an approach [64].

6.2.5. Assessment of Synergistic Emission-Reduction Potential

Carbon emissions from the building-materialization process are assessed using a fundamental framework incorporating the SD model and carbon intensity methods. The construction industry's potential to reduce emissions through synergy is also predicted. This study forecasts that with collaborative efforts, carbon outputs in the building sector could be reduced to 23 percent by 2060; however, achieving carbon neutrality still presents significant challenges [66].

7. LMDI Analysis of Building Materials

This section delves into the application of the LMDI method in studying building materials. Referring to Table 10 which provides a statistical overview of past studies, the analysis offers insights into how factors such as material intensity and economic output influence building material demand and how regional characteristics affect material selection.

Table 10. A statistical analysis of the LMDI-related literature on building materials.

Source	Year	Major Focus	Methodology
He, H.; Myers, R.J. [71]	2021	Building Materials' Demand Decomposition	LMDI
Karakaya, E.; Sarı, E.; et al. [72]	2021	Identification of the Primary Factors Influencing the Alterations in DMC and MF	LMDI

When using the LMDI method to study building material, dynamic material flow analysis concepts and IDA are integration methods commonly used to examine the influencing variances of physical flow. To digitalize the data, the building material demand can be defined into six effects, including *MI*, *FAS*, *RT*, *RI*, and *EO* [71]. By combining IPAT and LMDI methods, the driving factors of building material demand can be analyzed [71,72].

In the analysis of the LMDI method and dynamic material flow analysis concepts, integrating the physical and monetary flows, *MI*—a measure of the quantity of material utilized per unit of economic or production output, which refers to the amount of material that is employed, stocked, and flowed through the social–economic system at various levels—is marked as the key parameter to be included. This combination aids in understanding how social, economic, and technological factors drive changes in resource demand, thereby enhancing the ability to perform reliable, quantitative modeling of material use in the built environment [71].

However, in another case study, research revealed that, in European Union countries, the key building material demand is *I*, followed by *P*. DMC and MF were employed by researchers and policymakers in the measurements. These indicators reflect the demand for and consumption of materials in a country or region at different stages of development [72].

By incorporating the LMDI method in the research, these studies consistently highlighted that the selection and utilization of building materials are highly influenced by regional characteristics and development. The integration of the LMDI method provides a macro-level view of building demand trends while also enabling micro-level analyses of influencing factors. This approach has significant potential to enhance future development.

8. Conclusions and Discussion

This study systematically reviews the technical and theoretical basis, applications, and evaluations of the LMDI (Log Mean Divisia Index) decomposition analysis method. By thoroughly exploring the theoretical background, application cases, and advantages and limitations of the LMDI method, this review aims to provide comprehensive and detailed reference materials for researchers in related fields and offer scientific decision-making support for policymakers.

Because the LMDI method can handle zero and negative values and provides path-independent decomposition results, researchers have widely used it in the decomposition analysis of energy consumption and carbon emissions. This study reviews the application of LMDI decomposition in public buildings, residential buildings, and building materials, systematically summarizing the development status of the LMDI in building industry analysis. Additionally, this study introduces other related methods, such as the Generalized Divisia Index Method (GDIM), an extension of the traditional Divisia index, which is used for decomposing changes in an aggregate indicator into contributions from various factors; the Decision Making Trial and Evaluation Laboratory (DEMATEL) method for analyzing and modeling causal relationships among complex factors; and Interpretive Structural Modeling (ISM), which is a technique for identifying and visualizing relationships among specific elements to create a hierarchical model. In the research, these methods are mainly discussed regarding their advantages and disadvantages compared to the LMDI and their respective applications in the building industry.

Despite the significant advantages of the LMDI method in building carbon emission analysis, it still needs work in handling large-scale data. Furthermore, it is highly dependent on data quality. Integrating spatial autocorrelation analysis and kernel density estimation methods can compensate for the limitations of traditional LMDI methods, providing a more comprehensive analysis of energy consumption and carbon emission drivers. Moreover, applying machine learning and big data technologies enhances data-processing capabilities and analysis accuracy, offering scientific policy recommendations and practical tools for low-carbon city construction (Table 11).

Table 11. Pros and cons of LMDI application and evaluation.

Application and Evaluation	Pros	Cons
Analyzes urban energy use and carbon emissions trends.	Handles zero and negative values, provides path-independent results.	Requires high-quality data, can be complex to implement at large scales.
Analyzes regional emissions, policy effectiveness, and energy-saving measures.	Identifies key drivers of emissions, useful for policy formulation.	Limited by data quality, may not capture all local factors.
Evaluates emission reductions, efficiency improvements, and regional disparities.	Provides detailed emission reduction insights, supports targeted policy recommendations.	May require extensive data for accurate modeling, regional differences can complicate analysis.
Analyzes energy use impacts, policy effectiveness, and technological advancements.	Helps in developing specific policies, emphasizes multi-sectoral collaboration.	May oversimplify complex interactions, relies on quality data for accurate predictions.
Analyzes global and regional carbon-reduction measures, energy usage patterns.	Highlights key factors in emission reductions, supports global and regional comparisons.	Different regions and countries have varying decarbonization paths, making comparisons challenging.
Evaluates factors influencing energy use, suggests efficiency improvements.	Provides specific recommendations for energy-saving measures, useful for operational improvements.	Limited to specific building types, may not account for all operational variations.
Evaluates impacts of material selection, regional characteristics, and development levels.	Integrates physical and monetary flows, enhances understanding of material demand drivers.	Regional variations can affect analysis, data integration can be complex.
Evaluates decoupling status and effectiveness of policies.	Useful for understanding decoupling trends, supports policy evaluation.	May not capture all drivers of emissions, focused on economic growth vs. emissions only.
Provides an overview of current research, identifies gaps.	Offers comprehensive literature analysis, helps identify future research directions.	Limited to existing literature, may miss emerging trends.
Projects emissions under various scenarios, assesses impacts of different policies.	Accounts for complex interactions, useful for scenario planning.	Can be complex to implement, requires detailed data and modeling expertise.
Forecasts emissions considering various drivers, provides detailed insights.	Handles complex systems, integrates multiple factors influencing emissions.	High computational demands, data quality issues can affect results.
Forecasts emission reduction potential through collaborative efforts.	Identifies potential for significant emission reductions, supports collaborative approaches.	Achieving carbon neutrality remains challenging, forecasts may be uncertain.

Referring to the pros and cons of the past articles aiming for a more comprehensive and advanced simulation, this review contributes to advancing the LMDI method by critically examining the driving factors in various aspects of architecture. For example, while some studies highlight the strength of the LMDI method in handling zero values and negative growth, there is a need to reexamine its mathematical treatment of zero values and improve its ability to handle more complex simulations. By comparing the

LMDI with other methods such as IPAT, this review identifies strengths from multiple studies, offering insights into improving the LMDI's computational capabilities to handle complexity in energy consumption analysis, thereby contributing to green and energy-efficient development and also improving decision-making in sustainable architecture and urban planning in order to combat climate change.

Future research can further combine emerging computational methods, such as artificial intelligence, to improve the usability of the LMDI model and address its high dependence on data quality and computational complexity. As global attention to sustainable development continues to increase, a deeper understanding and application of the LMDI decomposition analysis method will help better address energy and environmental challenges, promoting the achievement of global carbon-reduction goals and sustainable development strategies.

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Abbreviations

AL	automation level by area
B	behavioral
BA	building area
BS	building structure
CERCPB	carbon reduction
CI	carbon intensity
CL	climate
CO_2	carbon dioxide
CPBCE	Carbon Emissions in Public Buildings
CS	consumption suppression
DEMATEL	Decision Making Trial and Evaluation Laboratory
DMC	Domestic Material Consumption
E	economic
EA	economic activity
EC	energy consumption
EF	carbon emission
EI	energy intensity
EO	economic output
ES	energy structure
FAR	floor area shape
GDIM	Generalized Divisia Index Method
I	income
IDA	index decomposition analysis
IPAT	Impact, Population, Affluence, and Technology
I-PBAT	Impact, Population, Behaviour, Affluence, and Technology
IR	infrastructure ratio
IS	industrial structure
ISM	Interpretive Structural Modeling
LEAP	Long-range Energy Alternatives Planning System
LMDI	Logarithmic Mean Divisia Index
M	building material
MC	building material consumption
MCE	machinery efficiency
ME	building material efficiency
MF	material footprint
MI	building material intensity
POP	population
PCA	per capita area
PCI	per capita income

PCGDP	per capita GDP
PU	population urbanization
RC	residential consumption
REC	residential energy consumption
RT	residential type
RI	residential intensity
SA	social affluence
SD	System Dynamics
SDA	structural decomposition analysis
SEN	student enrollment numbers
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
TL	technological level
UC	unit cost

References

1. Qian, F.; Sun, H.; Yang, L. Integrating Smart City Principles in the Numerical Simulation Analysis on Passive Energy Saving of Small and Medium Gymnasiums. *Smart Cities* **2024**, *7*, 1971–1991. [CrossRef]
2. Yang, L.; Liu, X.; Qian, F. Research on water thermal effect on surrounding environment in summer. *Energy Build.* **2020**, *207*, 109613. [CrossRef]
3. Sun, D.C.; Xu, J.H.; Zhao, J.J.; Zhang, D.F.; Chen, K.M. Study on a new model for urban residential quarter of 21st century. *J. Shanghai Sci. Technol.* **2000**, *22*, 347–351. [CrossRef]
4. Li, Y.; Chen, L. A study on database of modular façade retrofitting building envelope. *Energy Build.* **2020**, *214*, 109826. [CrossRef]
5. Ang, B.W. Decomposition analysis for policymaking in energy: Which is the preferred method? *Energy Policy* **2004**, *32*, 1131–1139. [CrossRef]
6. Ang, B.W. The LMDI approach to Decomposition Analysis: A practical guide. *Energy Policy* **2005**, *33*, 867–871. [CrossRef]
7. Ang, B.W.; Liu, N. Negative-value problems of the logarithmic mean Divisia index decomposition approach. *Energy Policy* **2007**, *35*, 739–742. [CrossRef]
8. Ang, B.W. LMDI decomposition approach: A guide for implementation. *Energy Policy* **2015**, *86*, 233–238. [CrossRef]
9. Kaltenegger, O. What drives total real unit energy costs globally? A novel LMDI decomposition approach. *Appl. Energy* **2020**, *261*, 114340. [CrossRef]
10. Li, X.D.; Zhu, C. A Review of Carbon Emission Accounting and Influencing Factors in China's Construction Industry. *J. Saf. Environ.* **2020**, *20*, 317–327.
11. Li, Y.; Wang, Z.; Wang, F.; Dong, S.C.; Li, Z.H. A Review of Assessment Methods, Influencing Factors and Process on Urban Carbon Emissions. *J. Nat. Resour.* **2013**, *28*, 1637–1648. [CrossRef]
12. Qu, S.N. The decomposition analysis of carbon emissions: Theoretical basis, methods and their evaluations. *Chin. J. Urban Environ. Stud.* **2020**, *8*, 2050020. [CrossRef]
13. Gao, H.; Wang, X.K.; Wu, K.; Zheng, Y.R.; Wang, Q.Z.; Shi, W.; He, M. A Review of Building Carbon Emission Accounting and Prediction Models. *Buildings* **2023**, *13*, 1617. [CrossRef]
14. Zhao, X.L.; Li, N.; Ma, C.B. Residential energy consumption in urban China: A decomposition analysis. *Energy Policy* **2012**, *41*, 644–653. [CrossRef]
15. Liu, Z.G.; Wang, S.S.; Liu, J.Y.; Liu, F.; Fu, X.L. Analysis of factors affecting CO_2 emissions by civil building in China's urban areas. *Int. J. Low-Carbon Technol.* **2013**, *10*, 460–463. [CrossRef]
16. Li, X.J.; Lin, C.X.; Lin, M.C.; Jim, C.Y. Drivers and spatial patterns of carbon emissions from residential building: An empirical analysis of Fuzhou city (China). *Build. Environ.* **2024**, *257*, 111534. [CrossRef]
17. Shen, L.Y.; Wu, Y.; Lou, Y.L.; Zeng, D.H.; Shuai, C.Y.; Song, X.N. What drives the carbon emission in the Chinese cities?—A case of pilot low carbon city of Beijing. *J. Clean. Prod.* **2018**, *174*, 343–354. [CrossRef]
18. Gu, S.; Fu, B.Y.; Thriveni, T.; Fujita, T.; Ahn, J.W. Coupled LMDI and system dynamics model for estimating urban CO_2 emission mitigation potential in Shanghai, China. *J. Clean. Prod.* **2019**, *240*, 118034. [CrossRef]
19. Huang, Y.Z.; Matsumoto, K. Drivers of the change in carbon dioxide emissions under the progress of urbanization in 30 provinces in China: A decomposition analysis. *J. Clean. Prod.* **2021**, *322*, 129000. [CrossRef]
20. Li, H.M.; Qiu, P.; Wu, T. The regional disparity of per-capita CO_2 emissions in China's building sector: An analysis of macroeconomic drivers and policy implications. *Energy Build.* **2021**, *244*, 111011. [CrossRef]
21. Zhang, Y.; Zhang, Y.X.; Zhang, Y.J.; Gong, C.; Kong, Y.Q. Analysis of the carbon emission driving factors and prediction of a carbon peak scenario—A case study of Xi'an city. *Heliyon* **2022**, *8*, e11753. [CrossRef]
22. Gao, G.Y.; Jia, Q.; Wang, Y.; Ding, Y.H.; Xu, Z.C.; Li, F.T. Research framework for low-carbon urban development: A case study of Shanghai, China. *J. Clean. Prod.* **2024**, *455*, 142372. [CrossRef]
23. Ma, M.; Shen, L.Y.; Ren, H.; Cai, W.G.; Ma, Z.L. How to measure carbon emission reduction in China's public building sector: Retrospective decomposition analysis based on STIRPAT model in 2000–2015. *Sustainability* **2017**, *9*, 1744. [CrossRef]

24. Yang, S.H.; Liu, J.; Wang, M.J. Study on influencing factors of carbon emission of civil building based on regional differences. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *647*, 012194. [CrossRef]
25. Ma, M.D.; Yan, R.; Cai, W.G. A STIRPAT model-based methodology for calculating energy savings in China's existing civil building from 2001 to 2015. *Nat. Hazards* **2017**, *87*, 1765–1781. [CrossRef]
26. Gan, L.; Liu, Y.; Shi, Q.W.; Cai, W.G.; Ren, H. Regional inequality in the carbon emission intensity of public buildings in China. *Build. Environ.* **2022**, *225*, 109657. [CrossRef]
27. Zhang, J.J.; Yan, Z.F.; Bi, W.B.; Ni, P.A.; Lei, F.M.; Yao, S.S.; Lang, J.C. Prediction and scenario simulation of the carbon emissions of public buildings in the operation stage based on an energy audit in Xi'an, China. *Energy Policy* **2023**, *173*, 113396. [CrossRef]
28. Lu, Y.J.; Cui, P.; Li, D.Z. Which activities contribute most to building energy consumption in China? A hybrid LMDI decomposition analysis from year 2007 to 2015. *Energy Build.* **2018**, *165*, 259–269. [CrossRef]
29. Zou, Q.; Zeng, G.P.; Zou, F.; Zhou, S.F. Carbon emissions path of public buildings based on LEAP model in Changsha city (China). *Sustain. Futures* **2024**, *8*, 100231. [CrossRef]
30. Zhou, X.; Xu, Z.X.; Yan, J.W.; Liang, L.Q.; Pan, D.M. Carbon emission peak forecasting and scenario analysis: A case study of educational buildings in Shanghai city. *J. Build. Eng.* **2023**, *76*, 107256. [CrossRef]
31. Wang, M.; Feng, C. Exploring the driving forces of energy-related CO_2 emissions in China's construction industry by utilizing production-theoretical decomposition analysis. *J. Clean. Prod.* **2018**, *202*, 710–719. [CrossRef]
32. Zhang, M.; Song, Y.; Yao, L.X. Exploring commercial sector building energy consumption in China. *Nat. Hazards* **2015**, *75*, 2673–2682. [CrossRef]
33. Ma, M.D.; Cai, W.; Cai, W.G. Carbon abatement in China's commercial building sector: A bottom-up measurement model based on Kaya-LMDI methods. *Energy* **2018**, *165*, 350–368. [CrossRef]
34. Ma, M.D.; Cai, W.G. What drives the carbon mitigation in Chinese Commercial Building Sector? Evidence from decomposing an extended Kaya Identity. *Sci. Total Environ.* **2018**, *634*, 884–899. [CrossRef] [PubMed]
35. Xiang, X.W.; Ma, M.D.; Ma, X.; Chen, L.M.; Cai, W.G.; Feng, W.; Ma, Z.L. Historical decarbonization of global commercial building operations in the 21st century. *Appl. Energy* **2022**, *322*, 119401. [CrossRef]
36. Du, Z.J.; Jiang, X.Y.; Song, W.C. A manner to assess the energy consumption of business hotel building. In Proceedings of the 2019 Chinese Control and Decision Conference (CCDC), Nanchang, China, 3–5 June 2019. [CrossRef]
37. Lin, B.Q.; Liu, H.X. CO_2 emissions of China's commercial and residential buildings: Evidence and reduction policy. *Build. Environ.* **2015**, *92*, 418–431. [CrossRef]
38. Laporte, J.P.; Román-Collado, R.; Cansino, J.M. Key driving forces of energy consumption in a higher education institution using the LMDI approach: The case of the Universidad Autónoma de Chile. *Appl. Energy* **2024**, *372*, 123797. [CrossRef]
39. Zhang, M.; Bai, C.Y. Exploring the influencing factors and decoupling state of residential energy consumption in Shandong. *J. Clean. Prod.* **2018**, *194*, 253–262. [CrossRef]
40. Ma, M.; Ma, X.; Cai, W.G.; Cai, W. Carbon-dioxide mitigation in the residential building sector: A household scale-based assessment. *Energy Convers. Manag.* **2019**, *198*, 111915. [CrossRef]
41. Ma, M.D.; Feng, W.; Huo, J.W.; Xiang, X.W. Operational carbon transition in the megalopolises' commercial buildings. *Build. Environ.* **2022**, *226*, 109705. [CrossRef]
42. Balezentis, T. Shrinking ageing population and other drivers of energy consumption and CO_2 emission in the residential sector: A case from Eastern Europe. *Energy Policy* **2020**, *140*, 111433. [CrossRef]
43. Reuter, M.; Narula, K.; Patel, M.K.; Eichhammer, W. Linking energy efficiency indicators with policy evaluation—A combined top-down and bottom-up analysis of space heating consumption in residential buildings. *Energy Build.* **2021**, *244*, 110987. [CrossRef]
44. Chen, H.D.; Du, Q.X.; Huo, T.F.; Liu, P.R.; Cai, W.G.; Liu, B.S. Spatiotemporal patterns and driving mechanism of carbon emissions in China's Urban Residential Building Sector. *Energy* **2023**, *263*, 126102. [CrossRef]
45. Yang, X.; Sima, Y.F.; Lv, Y.B.; Li, M.W. Research on influencing factors of residential building carbon emissions and Carbon Peak: A case of Henan Province in China. *Sustainability* **2023**, *15*, 10243. [CrossRef]
46. Lin, C.X.; Li, X.J. Carbon peak prediction and emission reduction pathways exploration for provincial residential buildings: Evidence from Fujian Province. *Sustain. Cities Soc.* **2024**, *102*, 105239. [CrossRef]
47. Huo, T.F.; Ma, Y.L.; Yu, T.; Cai, W.G.; Liu, B.S.; Ren, H. Decoupling and decomposition analysis of residential building carbon emissions from residential income: Evidence from the provincial level in China. *Environ. Impact Assess. Rev.* **2021**, *86*, 106487. [CrossRef]
48. Huo, T.F.; Du, Q.X.; Yuan, T.; Cai, W.G.; Zhang, W.S. Has the provincial-level residential building sector reached the carbon peak? An integrated assessment model. *Environ. Impact Assess. Rev.* **2024**, *105*, 107374. [CrossRef]
49. Li, W.Y.; Li, Q.Y.; Zhang, C.B.; Jin, S.K.; Wang, Z.H.; Huang, S.; Deng, S.H. The Quantification of Carbon Emission Factors for Residential buildings in Yunnan Province. *Buildings* **2024**, *14*, 880. [CrossRef]
50. Gong, Y.Y.; Song, D.Y. Life cycle building carbon emissions assessment and driving factors decomposition analysis based on LMDI—A case study of Wuhan City in China. *Sustainability* **2015**, *7*, 16670–16686. [CrossRef]
51. Lu, Y.J.; Cui, P.; Li, D.Z. Carbon emissions and policies in China's building and construction industry: Evidence from 1994 to 2012. *Build. Environ.* **2016**, *95*, 94–103. [CrossRef]

52. Hu, X.C.; Liu, C.L. Carbon productivity: A case study in the Australian construction industry. *J. Clean. Prod.* **2016**, *112*, 2354–2362. [CrossRef]
53. Ma, M.D.; Yan, R.; Du, Y.J.; Ma, X.R.; Cai, W.G.; Xu, P.P. A methodology to assess China's building energy savings at the national level: An IPAT–LMDI model approach. *J. Clean. Prod.* **2017**, *143*, 784–793. [CrossRef]
54. Du, Q.; Lu, X.R.; Li, Y.; Wu, M.; Bai, L.B.; Yu, M. Carbon emissions in China's construction industry: Calculations, factors and regions. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1220. [CrossRef]
55. Chen, X.; Shuai, C.Y.; Wu, Y.; Zhang, Y. Analysis on the carbon emission peaks of China's industrial, building, transport, and agricultural sectors. *Sci. Total Environ.* **2020**, *709*, 135768. [CrossRef]
56. Li, D.Z.; Huang, G.Y.; Zhang, G.M.; Wang, J.B. Driving factors of total carbon emissions from the construction industry in Jiangsu Province, China. *J. Clean. Prod.* **2020**, *276*, 123179. [CrossRef]
57. He, J.H.; Yue, Q.; Li, Y.; Zhao, F.; Wang, H.M. Driving force analysis of carbon emissions in China's building industry: 2000–2015. *Sustain. Cities Soc.* **2020**, *60*, 102268. [CrossRef]
58. Zhong, X.Y.; Hu, M.M.; Deetman, S.; Rodrigues, J.F.D.; Lin, H.X.; Tukker, A.; Behrens, P. The evolution and future perspectives of energy intensity in the global building sector 1971–2060. *J. Clean. Prod.* **2021**, *305*, 127098. [CrossRef]
59. Yan, S.H.; Chen, W.G. Analysis of the decoupling state and driving forces of China's construction industry under the carbon neutrality target. *Environ. Sci. Pollut. Res.* **2022**, *29*, 78457–78471. [CrossRef]
60. Sun, Z.H.; Ma, Z.L.; Ma, M.D.; Cai, W.G.; Xiang, X.W.; Zhang, S.F.; Chen, M.X.; Chen, L.M. Carbon peak and carbon neutrality in the building sector: A bibliometric review. *Buildings* **2022**, *12*, 128. [CrossRef]
61. Jiang, B.Y.; Sun, L.; Zhang, X.X.; Li, H.X.; Huang, B.L. The impacts of driving variables on energy-related carbon emissions reduction in the building sector based on an extended LMDI model: A case study in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 124139–124154. [CrossRef]
62. Huo, T.F.; Cong, X.B.; Cheng, C.; Cai, W.G.; Zuo, J. What is the driving mechanism for the carbon emissions in the building sector? An integrated DEMATEL-ISM model. *Energy* **2023**, *274*, 127399. [CrossRef]
63. Shi, Q.W.; Liang, Q.Q.; Wang, J.L.; Huo, T.F.; Gao, J.X.; You, K.R.; Cai, W.G. Dynamic scenario simulations of phased carbon peaking in China's building sector through 2030–2050. *Sustain. Prod. Consum.* **2023**, *35*, 724–734. [CrossRef]
64. Zhang, S.X.; Wang, M.P.; Zhu, H.Y.; Jiang, H.Z.; Liu, J.Z. Impact factors and peaking simulation of carbon emissions in the building sector in Shandong Province. *J. Build. Eng.* **2024**, *87*, 109141. [CrossRef]
65. Zheng, S.M.; He, X.R.; Liang, X.; Yu, L.Y. Research on the Decoupling Relationship and Driving Factors of Carbon Emissions in the Construction Industry of the East China Core Economic Zone. *Building* **2024**, *14*, 1476. [CrossRef]
66. Zhao, Q.F.; Wang, T.; Gao, W.J.; Su, Y.; Wang, J.M.; Dai, J.L. The synergistic decarbonization potential from construction industry and upstream sectors with a city-scale: A case study of Hangzhou, China. *J. Clean. Prod.* **2024**, *460*, 142572. [CrossRef]
67. Ma, M.D.; Yan, R.; Cai, W.G. Energy savings evaluation in public building sector during the 10th–12th FYP periods of China: An extended LMDI model approach. *Nat. Hazards* **2018**, *92*, 429–441. [CrossRef]
68. Huo, T.F.; Du, Q.X.; Xu, L.B.; Shi, Q.W.; Cong, X.B.; Cai, W.G. Timetable and roadmap for achieving carbon peak and carbon neutrality of China's building sector. *Energy* **2023**, *274*, 127330. [CrossRef]
69. Li, Y.; Wang, J.F.; Deng, B.H.; Liu, B.; Zhang, L.; Zhao, P. Emission reduction analysis of China's building operations from provincial perspective: Factor decomposition and peak prediction. *Energy Build.* **2023**, *296*, 113366. [CrossRef]
70. Xu, F.; Li, X.D.; Yang, Z.H.; Zhu, C. Spatiotemporal characteristics and driving factor analysis of embodied CO_2 emissions in China's building sector. *Energy Policy* **2024**, *188*, 114085. [CrossRef]
71. He, H.; Myers, R.J. Log Mean Divisia Index decomposition analysis of the demand for building materials: Application to concrete, dwellings, and the UK. *Environ. Sci. Technol.* **2021**, *55*, 2767–2778. [CrossRef]
72. Karakaya, E.; Sarı, E.; Alataş, S. What drives material use in the EU? Evidence from club convergence and decomposition analysis on domestic material consumption and material footprint. *Resour. Policy* **2021**, *70*, 101904. [CrossRef]