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Review of non-domestic building stock modelling studies under socio-technical system framework

Jingfeng Zhou [a,*], Pamela Fennell [b], Ivan Korolija [a], Zigeng Fang [c], Rui Tang [a], Paul Ruyssevelt [b]

[a] Institute for Environmental Design and Engineering, University College London, London, United Kingdom
[b] Energy Institute, University College London, London, United Kingdom
[c] Department of Civil Engineering, University of Nottingham, Nottingham, United Kingdom

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ABSTRACT

The construction industry contributes to approximately 30% of global energy consumption and carbon dioxide emissions, necessitating urgent measures to mitigate carbon emissions and address climate problems. This study focuses on the underexplored realm of Non-domestic Building Stock (NDBS), which constitutes 8% of global energy consumption and 11% of worldwide carbon emissions. Due to the long lifecycle of buildings, a comprehensive assessment of the NDBS is imperative to achieve the goal of net-zero carbon buildings by 2050. The current NDBS studies can be categorised into two groups based on the geographic location and type of building being studied. Each of these two different building stocks demonstrates different research and analysis tools, but specific comparisons have not yet been made between them. In addition, existing literature reviews of NDBS have mainly emphasised the technical aspects and neglected their social aspects. This study aims to critically review the energy and carbon footprint related efforts in NDBS research, assess the current state of research, and propose potential research trends. Based on inclusion and exclusion criteria, 99 out of 906 articles are fully reviewed. Utilising and adapting the Social-Technical Systems (STS) approach, this study analyses the data requirements, research methods, and research objectives of NDBS studies concerning energy consumption and carbon footprint from five perspectives, namely infrastructure, technology, processes, goals, and people. Results demonstrate that geo-stock and type-stock approaches, while focusing on different aspects of building stock, can share data and analysis methods to improve research efficiency and model accuracy. Additionally, findings highlight that incorporating socio-economic factors into technical models can enhance model robustness and output reliability, thereby supporting effective policy-making and energy management strategies. This study provides a new multidimensional approach to evaluate the development of NDBS energy and carbon footprint research, and helps to incorporate socio-economic analysis into NDBS physics-based models to improve the efficiency and reliability of such models for future research and practice.

* Corresponding author. 14 Upper Woburn Place, London, WC1H 0NN, United Kingdom.
E-mail address: jingfeng.zhou.20@ucl.ac.uk (J. Zhou).

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Nomenclature

BIM	Building Information Modelling
DBS	Domestic Building Stock
GIS	Geographic Information System
HVAC	Heating, Ventilation and Air-conditioning
MPC	Model Predictive Control
NDBS	Non-domestic Building Stocks
SLR	Systematic Literature Review
SQL	Structured Query Language
STS	Socio-technical System
TBL	Triple Bottom Lines

1. Introduction

The scarcity of resources and global warming are widely recognised issues that require urgent solutions, necessitating proactive measures across various industries. The global building industry, which accounts for 30 % of energy consumption and directly and indirectly contributes to 26 % of carbon dioxide emissions [1], demands in-depth research and the formulation of corresponding strategies to facilitate energy efficiency and emission reduction on a substantial scale. Developing the existing building stock physics-based models and conducting comprehensive performance analyses is one of the evidence-based approaches that can support the development of effective strategies. Based on the physics-based models, it is possible to estimate the energy consumption, carbon emissions, cost-effectiveness retrofit and other important information about the building stock, providing solid evidence to support policy decisions

Existing buildings can be broadly classified into two categories based on usage scenarios and primary functions, namely domestic building stock (DBS) and non-domestic building stock (NDBS). Domestic buildings exhibit relative homogeneity in physical features and usage purposes, with a lower degree of complexity in information gathering compared to non-domestic buildings. In contrast to DBS, NDBS encompasses a broader spectrum of economic and social activities, leading to the collection of more extensive data for in-depth analysis. However, the diversity of data poses challenges and complexities to the study of NDBS. Therefore, among the existing building stock studies, NDBS research has not been carried out extensively, and the building stock models established are still mainly focused on DBS [2]. The contribution of NDBS to global energy consumption and carbon emissions underscores the significant omission in its research. Given that NDBS constitutes an energy-intensive subset within the field of construction, it significantly contributes to energy consumption and emissions, harbouring substantial energy-saving potential [3]. For instance, NDBS constitutes approximately 8% of global energy consumption, contributing both directly and indirectly to around 11% of worldwide carbon emissions [4]. Within Europe, NDBS commands a substantial portion, accounting for 25% of the total energy consumption within the building sector [5]. Similarly, in the United States, NDBS encompasses approximately 19% of the total energy consumption within the entire construction landscape [6]. To achieve the efficient and net-zero carbon building stock envisaged by the Paris Agreement by 2050 [7], a thorough analysis of the existing NDBS is imperative, considering that a significant portion of the current building stock will continue to be in use until 2050 [8].

It is necessary to review the current research on NDBS to understand the latest developments in the field. The review of building stock research has covered several aspects to date, encompassing summaries of modelling techniques [8,9], applications in retrofitting [10], the impact of energy regulations on buildings [11] and more. In the case of NDBS, the current reviews have already covered several aspects. Fu et al. [12] reviewed statistical models aimed at predicting energy consumption in non-domestic buildings, pointing out significant gaps in current whole-building energy modelling methods. Ruparathna et al. [13] critically examined energy efficiency retrofitting practices in commercial buildings, stressing the importance of adopting more systematic decision-making processes. Bischof and Duffy [2] conducted a meta-analysis of life-cycle assessment models, underscoring the importance of comprehensive life-cycle coverage for non-domestic buildings. Borgsteina et al. [14] reviewed end-use energy consumption patterns, discussing benchmarking methodologies and the challenges associated with data collection in this sector. Rockett and Hathway [15] provided a critical review of model predictive control (MPC) applications in non-domestic buildings, identifying current challenges and outlining future research directions to enhance the effectiveness of MPC in optimising energy use and indoor environmental quality. These reviews on NDBS research predominantly focus on modelling methods and the technical aspects of the research subjects. Meanwhile, current stock studies have long been based on standardised input for building performance simulations to establish models [16], which has resulted in insufficient consideration of social elements such as culture and people in the research. Evaluating the outcomes and significance of NDBS studies solely from a technical perspective is limited and lacks a comprehensive understanding when viewed from a social standpoint. This derives the first research gap of this study, which is the lack of evaluation of NDBS research from a social perspective. In this context, the social perspective pertains to analysing the human components that play a role in the development, execution, and utilisation of NDBS. The emergence of such research gaps primarily stems from the lack of consideration for the compliance of the data involved in NDBS models, the impact of the social attributes on the NDBS physics-based models, as well as the rationality of utilising research findings for resource allocation and policy formulation purposes.

In terms of the research objects, NDBS studies can be broadly clustered into two categories. Heterogeneous building assemblages constituted by geographical boundaries are classified as geo-building stock, hereafter referred to as geo-stock, and homogenous building assemblages categorised by similar usage but located in different areas are classified as type-building stock, hereafter referred to as type-stock [17]. Geo-stock allows the exploration of interdependencies among neighbouring buildings, facilitating regional-level policy formulation. Conversely, type-stock assists in benchmark testing and operational optimisation of buildings with similar functions. Both geo-stock and type-stock research involve profound investigations into NDBS performance. Due to their distinct boundary conditions, their modelling processes and methods differ. The absence of a comparison of the two research objects underlies the second research gap of this study, which is the lack of a comprehensive comparison of the differences between type-stock and geo-stock studies. This research gap exists because previous research has not delineated studies based on the definitions of these two diverse objects, and the differences between the two have not been discussed in detail.

To address the two research gaps mentioned above, this work aims to review NDBS research from a societal perspective based on two research objects, type-stock and geo-stock, with a focus on studies related to reducing energy consumption or carbon emission. Since research on NDBS can be viewed as a complex system that involves abstract interactions between people, processes, and technology [18], conducting a relevant review requires a framework that incorporates social elements and is capable of handling complex relationships. Due to the technical nature of NDBS research, socio-technical systems (STS) have been introduced to consider the synergies between social and technological elements and to improve the relevance and applicability of the model to real-world problems [19]. STS represent a system composed of independent yet interdependent technological and social subsystems, including a technological subsystem comprising hardware, software, and other technical components, as well as a social subsystem consisting of individuals, work environments, and organisations involved in the system [20]. Using an integrated STS framework at the social and technological levels, a comprehensive review of NDBS research is undertaken to investigate the intricacies of modelling techniques, data content, and the complex relationships among various stakeholders. To address the identified two research gaps, and assist in the development of NDBS-related research, three research questions are developed accordingly.

- How can energy and carbon footprint related NDBS studies be evaluated with different STS dimensions?
- What are the differences between geo-stock and type-stock NDBS objects in different STS dimensions?
- What are the potential ways in which NDBS studies could enhance the robustness of the physics-based models and the reliability of the model outputs?

By addressing these research questions, this paper could provide insights into the means and trends of the current NDBS research. The rest of the paper is structured as follows. Section 2 introduces the primary modelling approaches for NDBS and the development of the STS framework used for NDBS reviews. Section 3 outlines the criteria for the literature included in this paper. Section 4 provides a technical and societal analysis of NDBS type-stock and geo-stock research from the infrastructure, technology, process, goal, and people perspective of the STS framework. Section 5 details the societal considerations of the existing non-domestic stock, the current state of the research on energy efficiency and conservation, and the future challenges of the NDBS studies. Section 6 summarises the current status of NDBS studies and proposes the potential technological means to improve the reliability of the NDBS models.

2. Preliminary

2.1. NDBS modelling approaches

The analysis of the energy consumption and carbon emissions of NDBS is mainly done through physics-based modelling methods. Depending on the specific research objectives, physics-based modelling methods can be further delineated into top-down and bottom-up approaches [21]. The top-down modelling approach operates at an aggregated level, assessing energy consumption by buildings based on the relationship between their energy use and macro-level variables such as aggregated economic data or generalised climatic conditions. The top-down approach avoids complex technical requirements, enabling the modelling of diverse socio-economic cost-benefit impacts of energy and emission policies; nevertheless, its reliance on historical energy-economic interactions for predicting future trends lacks technical granularity and is less adept at assessing specific technology effects on the entire stock [22]. Especially when unprecedented phenomena occur, such as significant technological changes, the top-down approach fails to simulate their specific impacts on the stock. Conversely, the bottom-up approach operates at a disaggregated level, encompassing methods based on statistical analysis utilising empirical or measured data, or physics calculations and simulations estimating individual building energy consumption, and then aggregating the outputs to the stock level.

Within the realm of the bottom-up approach, based on the granularity of the model, the physics-based modelling can be further refined to archetype-based modelling or building-by-building modelling approaches. Due to the individual heterogeneity of buildings, archetype-based methods considerably alleviate modelling efforts and find extensive application for stock-level studies. This approach can be defined as taking a representative set of buildings, each of the buildings is given a different weighting to collectively represent the entire stock, analysing the performance of each representative building and then weighting and aggregating to the stock level. Currently, there are several widely adopted building archetype frameworks available for stock-level analysis, for example, TABULA, a building typology database covering European countries [23], or ComStock, using archetypes to represent the entire US non-domestic building stock [24]. Building-by-building modelling approach has gained prominence in recent years, largely driven by significant advancements in geographic information system (GIS) and computational capabilities [25]. This approach can be defined as a method of physics-based modelling of individual buildings on a large scale based on the respective characteristics of each building in the stockpile, such as geometry, structure, occupancy and detailed data on equipment. Building-by-building modelling enables more precise stock analysis, facilitating targeted investigations of individual buildings while still aggregating their impacts to the stock level.

Compared with archetypal modelling, the building-by-building approach enables a more sophisticated per-building modelling analysis of the stock. A few example projects of building-by-building modelling are here. In the US, Chen et al. [26] developed a web-based platform, the City Building Energy Saver (CityBES), to automatically generate separate office and retail building models at the regional level. Similarly, an urban energy simulation platform, SimStadt, was applied to the city of Rotterdam, Netherlands, to automatically model individual buildings at several scales [27]. Table 1 below shows some released projects on bottom-up stock modelling so far and their cross-sectional comparisons. These urban energy modelling tools excel in large-scale energy analysis, ranging from individual buildings to entire cities. They offer powerful, customisable, and often open-source capabilities but generally require high-quality data, complex setups, and significant computational resources. While these tools are versatile, they often present steep learning curves and may have limited applicability across different regions.

For the bottom-up approach, its advantage lies in the capability to determine end-use energy consumption at an individual level, thereby enhancing the precision of energy policy formulation. Nonetheless, a drawback lies in the extensive data requirements, particularly for the granular bottom-up building-by-building physics-based analysis, alongside the necessity for advanced expertise. To wrap up, both top-down and bottom-up approaches possess their own merits and limitations, offering diverse insights into stock-level building modelling. However, since this study is more concerned with exploration at the disaggregated level of building stock, only bottom-up studies are reviewed.

2.2. Development of socio-technical theory framework for NDBS studies

The origins of STS thinking can be traced back to research on coal mining operations at the Tavistock Institute in the United Kingdom, which conceptualised it as a complex interaction between people (the social component), machines (the technological component), and the environmental context [32]. Based on this core thinking, Leavitt [33] proposed a socio-technical model, which initially encompassed four interacting and coordinating dimensions, namely people, tasks, structure, and technology, as vital components of organisational work systems. This four-dimensional model was subsequently evolved by Davis et al. [34] into a hexagonal interconnected structure, encompassing people, buildings/infrastructure, technology, culture, processes, and goals, embedded within an external environment constituted by various stakeholders, economic contexts, and regulatory frameworks. Regardless of the evolution of the model, the key insight in the STS system is that the system's effectiveness is enhanced only when the social and technical dimensions are integrated and seen as interdependent facets within a broader system [35]. Following this insight, the application scenarios of the STS systems have evolved, spanning from the initial focus on heavy industry [32] to the exploration of advanced manufacturing technologies [36], extending to office work and services [37], and even the design and operation of future open data cities [38]. STS framework could also be applied to building-related studies.

Numerous endeavours have been undertaken to assess building performance through the STS framework. For instance, Lachhab et al. [39] treated energy-efficient buildings as complex socio-technical systems, integrated technologies such as intelligent event processing, predictive analytics, and information and communication technologies tools to optimise energy efficiency, occupant comfort, and building performance. This approach can be extrapolated to a cohort of buildings within a stock, where technological integration and optimisation can lead to collective enhancement in energy efficiency. Lowe et al. [40] employed a socio-technical approach to investigate building performance evaluation, revealing buildings as complex socio-technical systems and emphasising the significance of comprehending the interplay between social and technical elements for effective performance assessment, aiding in dynamic modelling of energy consumption and efficiency within building stock. Savvidou and Nykvist [41] utilised a socio-technical

Table 1
Summaries of physics-based bottom-up NDBS studies.

Project Name	Model Granularity	Project Objective	Advantages	Disadvantages	Developer	Reference
TABULA	Archetype	Provides typical building energy consumption models	Easily extensible, detailed building classification	Primarily applicable in Europe, limited non-domestic application	TABULA Project	[23]
ComStock	Archetype	Simulates US non-domestic building energy consumption, supports national policy-making	Detailed classification, applicable across the US	Limited international use	National Renewable Energy Laboratory (NREL)	[24]
CityBES	Building-by-building	Supports urban building energy simulation and energy-saving strategy assessment	Utilises EnergyPlus, 3D city models, suitable for detailed analysis	High data requirements, primarily for US cities	Lawrence Berkeley National Laboratory (LBNL)	[26]
SimStadt	Building-by-building	Urban energy simulation, assessing energy demand and saving potential	Suitable for large-scale urban analysis	Complex initial setup and high data requirements	HFT Stuttgart	[28]
SimStock	Building-by-building	Large-scale building energy consumption analysis	Emphasises building interaction, suitable for large-scale analysis	High data requirements	University College London (UCL)	[29]
UMI	Building-by-building	Comprehensive building performance analysis for urban planning and design	Multi-domain integrated analysis and ideal for the design stage	Primarily used for design	Massachusetts Institute of Technology (MIT)	[30]
UrbanOPT	Building-by-building	Urban-scale energy system optimisation for distributed energy resources	Open-source and highly customisable	Requires technical expertise	National Renewable Energy Laboratory (NREL)	[31]

systems approach, integrating behavioural, structural, and technological driving factors, to analyse and estimate the potential for reducing the heat energy demand of Swedish domestic building stock, thus assessing barriers and driving factors for enhancing energy efficiency, aiming towards a comprehensive stock modelling endeavour to elevate energy efficiency across the board.

Reviewing NDBS research as a form of STS allows for a comprehensive understanding from both social and technical perspectives, considering behavioural aspects in technology development and implementation [42]. Here the concept of the "social perspective" is broadly construed as the inclusion of factors such as users, businesses, cognitive categories, etc., in causal analysis [43]. The social perspective analysis of NDBS research could be defined in this context as an examination of the human factors involved in the design, implementation, and utilisation of stock-level analysis systems. This examination includes scrutinising the social relationships, behaviours, motivations, and expectations of all relevant stakeholders. The exploration of the social aspect aims to ensure that NDBS analysis aligns with human and societal needs, as well as the goals of organisations and their environments.

Based on the hexagonal STS model proposed by Davis et al. [34], this study tailored a new quintuple STS framework for reviewing NDBS research. This is done by excluding the external environmental factors and simplifying one corner of the hexagonal interconnected structure namely culture. Using this STS framework, a systematic literature review (SLR) of NDBS studies from a socio-technical perspective is conducted to understand the simultaneous effects of NDBS research in assessing energy consumption and carbon emissions across the five selected dimensions, which are infrastructure, technology, process, goal and people. The innovations of this study's new quintuple framework compared to previous frameworks are fourfold. Firstly, the new framework demonstrates a more focused approach, particularly in adapting to the specific characteristics of building stock models. Geels [44] underscored the importance of STS being specifically tailored to the distinct attributes of the sectors they encompass, thus justifying the redefinition of dimensions to better accommodate building stock models. In light of this, the cultural dimension is excluded, considering the inherent physics properties pertinent to building stock research. Secondly, this study places emphasis on the adaptability of technology, a concept also elaborated upon by Foxon et al. [45], in relation to how technological innovations can be effectively integrated and utilised within existing buildings. This adjustment is crucial for addressing challenges such as technological compatibility that arise

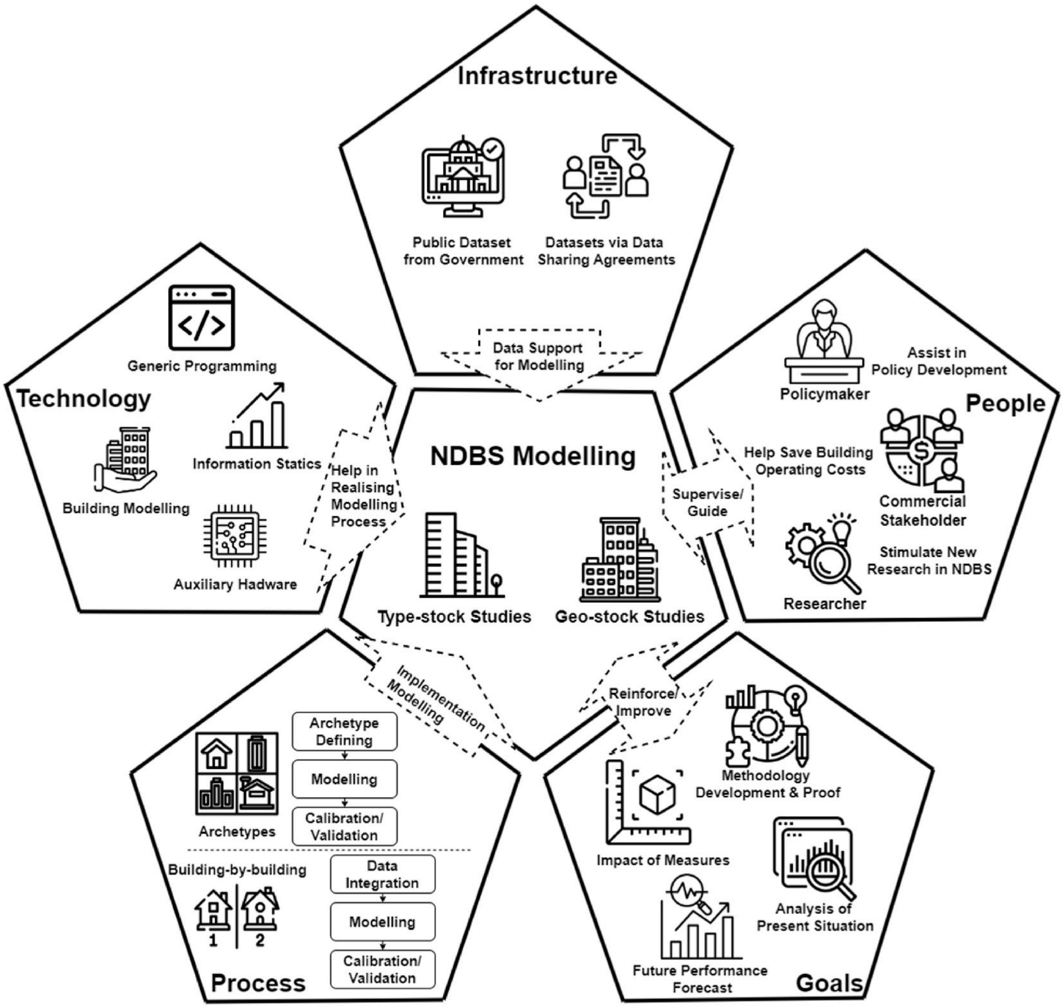

Fig. 1. Reviewing NDBS studies from five dimensions under STS framework.

during the upgrading processes of building stock. Furthermore, the goal dimension within the new framework is reoriented to concurrently address both short-term efficiency gains and the achievement of long-term sustainability objectives. This dual focus is particularly relevant in the context of building stock, where the integration of technological and societal factors is essential for sustaining improvements in energy efficiency and carbon emissions reduction, as supported by the findings of Verbong and Geels [46]. Finally, the framework broadens the definition of relevant stakeholders, incorporating a wider array of social groups that are directly or indirectly associated with building stock, such as business stakeholders, academic researchers, and local governmental bodies. This expansion is in alignment with the perspective offered by Baxter and Sommerville [20], who advocate for the inclusion of a diverse range of stakeholders within socio-technical systems to enhance their effectiveness. Through these innovations, the new framework not only preserves the interdependence of societal and technical dimensions inherent in the STS system but also better aligns with the unique requirements of NDBS models. This alignment provides a more precise and systematic analytical tool for the application of NDBS research in the assessment of energy consumption and carbon emissions. The overall STS framework adapted for NDBS studies in this paper is shown in Fig. 1 below. Detailed contents are elaborated upon in subsequent sections.

3. Literature scanning methodology

This study mostly employs the SLR methodology, following the latest 2020 PRISMA guidelines [47], to comprehensively review engineering-related research on NDBS modelling published in mainstream journals, including all type-stock NDBS studies as well as geo-stock studies involving NDBS, with particular attention to energy and carbon aspects. Scoups database is selected as it provides good coverage of NDBS literature. As the focus of this study is on NDBS research within two distinct stock classifications, the search keywords have been selected accordingly to align with these two categorisations, as shown in Table 2. For the type-stock subcategory, the initial four keywords "Retail", "Office", "Industry" and "Warehouse" correspond to the four categories of NDBS defined by the Valuation Office Agency of the United Kingdom [48], while the selection of the remaining keywords under the type-stock subcategory includes other NDBS types known to all the authors for which relevant studies have been conducted. Within each category or between subcategories, use the OR operator to search for keywords. And between categories, use the AND operator to concatenate search queries.

The SLR of this paper is conducted in two phases, the first phase being the selection of articles and the second phase being the content analysis. During the article selection stage, considering the varying quality of research related to building stock, all authors jointly decided to focus on peer-reviewed journals and conference proceedings within the field to ensure the validity and credibility of the findings, excluding book chapters and other sources. The reason conference proceedings are addressed here is because they often precede or complement journal publications, allowing the review to capture the latest state of the field. The literature included in the study covers research up to 2024. Following this approach for the initial selection, a total of 906 papers are included for the preliminary review. The title and abstract sections of these articles are initially screened with the help of Rayyan [49], a web-based SLR software using machine learning algorithms such as Support Vector Machine classifiers to simplify the process of literature selection. After the initial screening phase, duplicate articles and those unrelated to the topic of NDBS research are further excluded. Then, a full-text review is conducted on the remaining articles to filter out further studies that focused on the effectiveness of a particular technology at the stock level unrelated to building stock modelling, studies that focused on individual buildings, studies on domestic building stock, studies related to stock-related policies, and articles where the full text could not be located. The workflow of the selection process is shown in Fig. 2. Information on the peer-reviewed journals and conference proceedings selected and the number of research articles that are included in this review are summarised in Fig. 3. Overall, the papers reviewed in this paper focus on the application of engineering methods to the modelling of the building stock and their use in analysing the performance of building stocks in terms of energy consumption and carbon emissions. During the content analysis phase, after identifying and selecting relevant articles, the existing research on NDBS in the engineering aspect is examined from the perspectives of the five different dimensions of the STS. Subsequently, a summary of the mutual influence between the two stock classifications, type-stock and geo-stock models, as well as the trends and challenges in existing NDBS research, is provided. It is hoped that this study can offer diverse perspectives for researchers and policymakers to assess and utilise insights generated by NDBS models.

The latitudinal analysis results are shown in Figs. 4 and 5, indicating that research in the energy and carbon aspect of NDBS is generally on an upward trajectory. The United Kingdom and the United States have the highest number of NDBS research studies, indicating that researchers in these countries have a clear understanding of the importance of NDBS in energy conservation and emissions reduction in the construction industry. Overall, European countries hold six out of the top ten positions in terms of relevant research quantity, suggesting that compared to other continents, NDBS research has received relatively more attention in Europe. Also, based on the findings from papers and research outcomes, several institutions are at the forefront of relevant studies worldwide. These

Table 2
Keywords searched for in the SLR.

Category	Sub-category	Keywords
Objective	/	"Building Stock" OR "Existing Stock" OR "Current Stock" OR "Stock Model"
AND Classification	Overall Classification	"Non-domestic" OR "Non-residential" OR" Commercial"
	Type-stock	"Retail" OR "Office" OR "Industry" OR "Warehouse" OR "Hotel" OR "Public Buildings" OR "Shop" OR "School" OR "Factory"
	Geo-Stock	"City" OR "Urban" OR "National" OR "Regional"

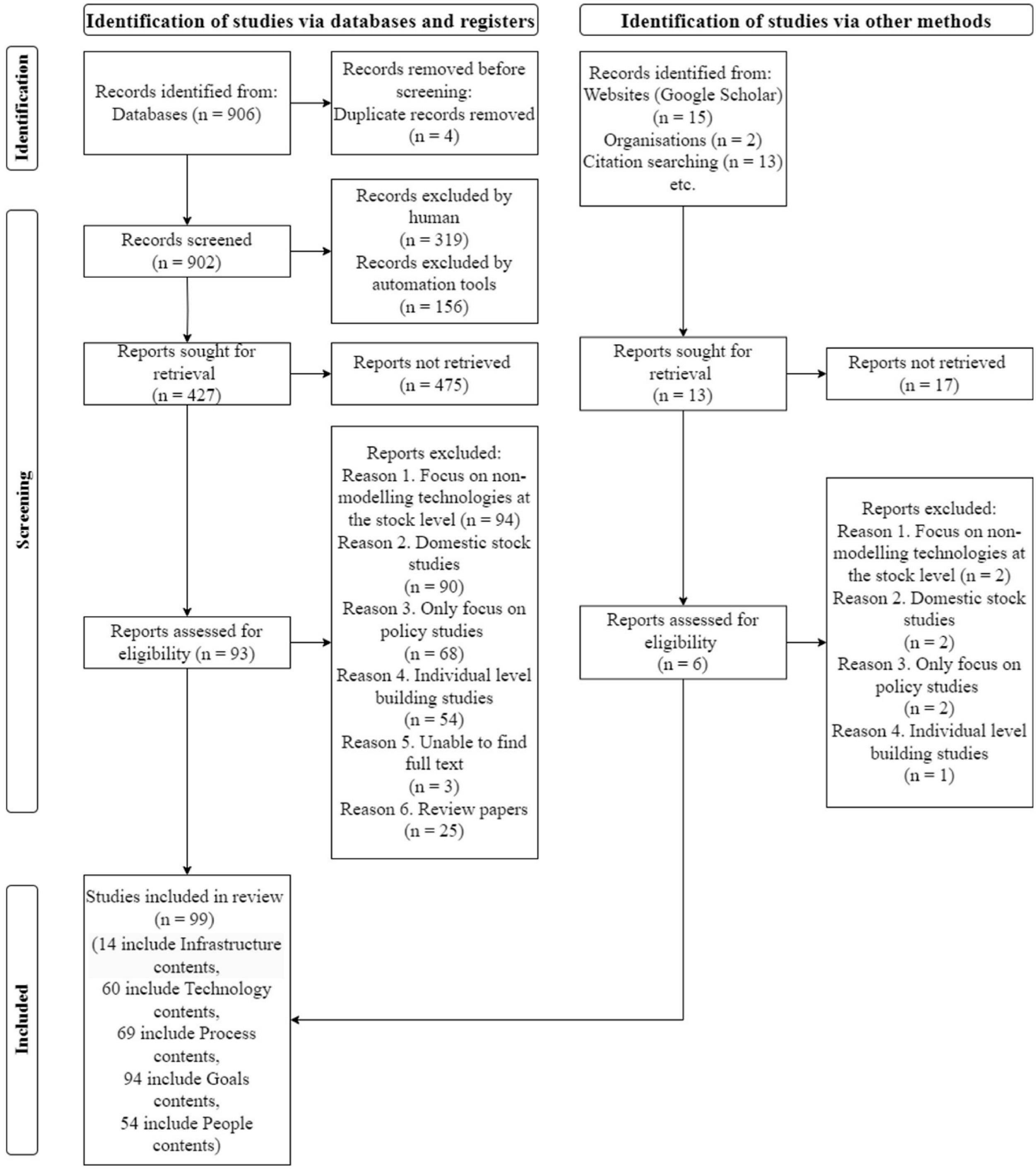

Fig. 2. Workflow of the literature selection process.

include the Massachusetts Institute of Technology and Lawrence Berkeley National Laboratory in the United States, University College London in the United Kingdom, the ETH Zurich in Switzerland, RWTH Aachen University in Germany, and Tsinghua University and Hunan University in mainland China, among others. The choice to base the summary on research institutions, rather than individuals, is intended to avoid a focus on personal contributions. This approach provides a more comprehensive representation of the academic strength and contributions of research teams within the field, offering a broader and more representative perspective.

A summary of information for all reviewed papers is presented in Table 3. For the classification of building stock, if a study mentions a specific type of building while also discussing geographic regions, it is still categorised as type-stock. Here the spatial scales

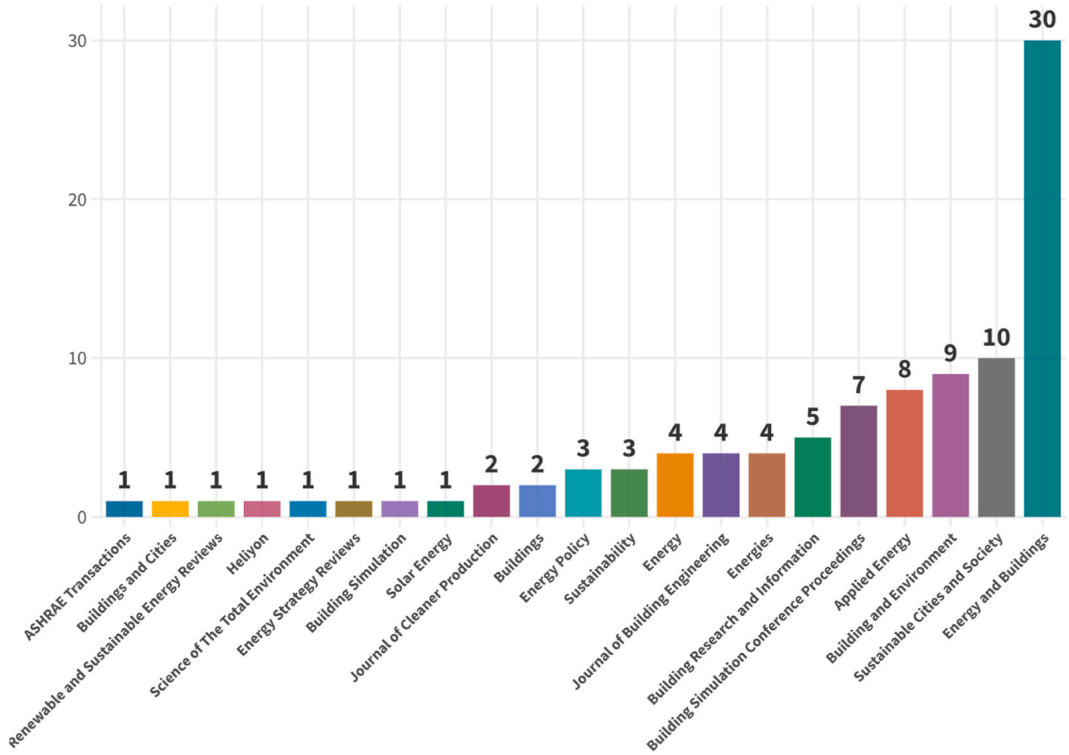

Fig. 3. Summary of sources and the number of studies reviewed in this study.

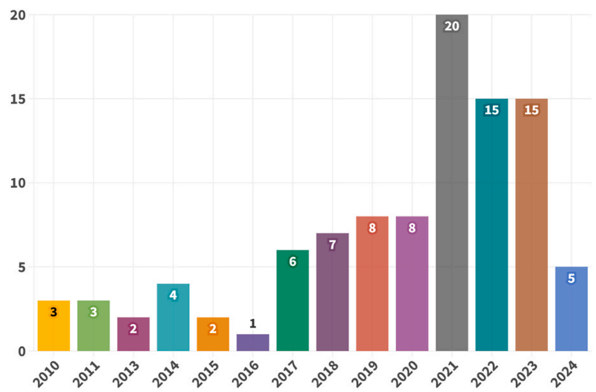

Fig. 4. Summary of the year of selected articles published.

are divided into four categories, district, city, regional, and national. City and national are levels according to administrative division, and scales in between are classified as regional. Studies with a scale smaller than city level, but beyond the single-building analysis, are classified as the district level. From the collected literature as a whole, it appears that researchers have a higher interest in geo-type models, and their studies often culminate at the national level. A potential reason for this could be that many studies rely on data sources derived from national-level statistics, which provide comprehensive coverage of an entire country. Therefore, focusing research at this level undoubtedly maximises the utilisation of information sources.

Clarification of what is covered in each section of the STS is necessary prior to the review. First is the examination of buildings and infrastructure, wherein a summary of databases across various nations is presented. This encompasses the summary of digitalised infrastructure databases which could support stock-level modelling. The second dimension, technology, involves a thorough exploration of the preliminary preparations and auxiliary tools employed in establishing physics-based models within the NDBS framework. The third dimension, process, delves into the specifics of modelling through physics-based methods, elucidating the concrete parameters involved. Moving on to the fourth dimension, goals, the focus shifts to the immediate objectives of the research and their corresponding policy implications. Lastly, the fifth dimension, people, examines the research outcomes and their direct benefits to

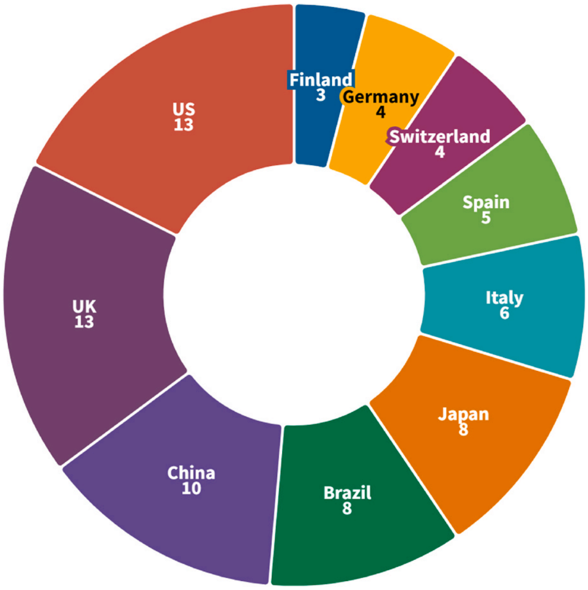

Fig. 5. Top 10 countries/regions with the highest number of relevant studies in selected articles.

Table 3
Overview of selected article research content.

Stock Category	Detailed Stock	Spatial Scale	Reference
Type-Stock	School Building Stock	City	[50,51]
		Regional	[52–54]
		National	[55–62]
	Office Building Stock	District	[63,64]
		Regional	[65]
		National	[66–75]
	Hotel Building Stock	City	[76]
		National	[77]
	Bank Building Stock	City	[78]
	Retail Building Stock	City	[79]
Geo-Stock	Entire Stock	District	[80–88]
		City	[89–112]
		Regional	[113–119]
		National	[120–141]
	Non-domestic Building Stock	City	[111]
		National	[142–147]
	Public Service Building Stock	National	[148]

diverse stakeholder groups. This analysis employs the Triple Bottom Line (TBL) approach, evaluating the social, economic, and environmental impacts of the research beneficiaries, thereby providing a comprehensive perspective on the NDBS research within the broader context of science, technology, and society. The following provides an example to illustrate how this framework performs in practice. Consider a modelling project aimed at reducing the energy consumption and carbon emissions of the existing NDBS. In this scenario, detailed information about the building stock, including age, type, and energy performance, is provided from building and infrastructure databases. Relevant tools are then selected from the technology perspective to model the current state of the building stock and the potential impact of various retrofit scenarios, taking into account factors such as energy efficiency improvements and the integration of renewable energy. The process perspective involves specific steps in modelling, careful selection of parameters, and detailed application of the model to simulate outcomes under different conditions. The goal perspective is to achieve specific reductions in energy use and carbon emissions, aligning with national climate targets. Finally, the people dimension assesses the broader impacts, ensuring the project achieves economic savings, enhances social equity by providing energy-efficient retrofits to all income groups, and contributes to environmental sustainability. A comprehensive analysis of each dimension would ensure that in practice the project is not only successfully implemented and meets its established objectives but also ensures the economic and social benefits of the project, demonstrating the practical utility of the STS framework in real-world applications.

4. Assessments of non-domestic stock studies under socio-technical theory frameworks

4.1. Digitalised infrastructure supported NDBS research

NDBS STS framework's infrastructure dimension is about examining the public digital databases supporting the physics-based modelling of NDBS in city and national infrastructures. Based on existing literature, the scale of digital formats supporting NDBS research in infrastructure mainly falls into two categories: national-scale building information datasets and city-level building surveys supported by municipal governments. The data sources pertaining to these two categories reviewed in the literature are summarised in the Table 4 below.

Stock-level analysis of buildings through physics-based means relies heavily on extensive input data， such as building geometry and location, internal systems, enclosure information, and indoor occupancy schedules [163]. The demand for complex input data makes the openness and availability of data a primary challenge that researchers worldwide must confront. In the reviewed literature, research utilising open national-level big data predominates. Databases with broader geographical coverage tend to be favoured by researchers, as they can offer higher generalisation performance based on the same modelling methodology and assess the performance of more buildings. Two attributes, which appear with high frequency in these national-level databases, are building construction year [149,152,155,157] and building type [151,153,154,156,157]. While all national-level databases in the papers reviewed are listed, some regularly updated statistical databases are still not covered in this study. These databases also hold potential for NDBS modelling and analysis. Examples include the Commercial Buildings Energy Consumption Survey (CBECS) in the USA [164] and the Commercial and Industrial Consumption of Energy Survey (CICES) in Canada [165]. Moreover, the UK government's Valuation Office Agency (VOA) dataset [166], while primarily intended for taxation statistics related to building area and purpose, still holds relevance for NDBS research and has already been utilised in stock level studies [167]. For the current national-level databases, the object of geo-stock is still more targeted. Compared to type-stock, geo-stock databases would be more involved in building energy efficient attributes, such as energy consumption in Refs. [154,158,159]. Type-stock databases are not widely used in NDBS studies, and the few that are still available are mostly used in service-oriented social infrastructures such as schools. Research on school buildings is popular due to their unique occupancy patterns, which often feature high intermittent use leading to elevated internal heat peaks, increased carbon dioxide levels, odours, and other indoor pollutants, making their design more complex and challenging compared to other building types [168]. However, regardless of the objects of the national datasets, inconsistencies in building statistical data, high data loss rates, and limited coverage are evident due to the heterogeneous nature of NDBS buildings [169]. In massive national-level databases, these issues manifest as data gaps, mismatches, and outliers.

In comparison to national-level databases, city-level databases can introduce new parameters for NDBS modelling, such as urban infrastructure and territorial information [161]. Broader coverage of input data increases the robustness of NDBS models. In terms of database objects, there is no type-stock city-level database. One potential explanation for this phenomenon lies in the relatively modest scale of urban centres in comparison to the national-level stock, rendering it economically unfeasible to exclusively undertake a specific category of NDBS survey within them. Whether at the national or city level, although these publicly available databases facilitate more detailed stages of NDBS research, enabling the construction of performance analysis models, it must be acknowledged that the primary purposes of most of these databases are not research-oriented. The data quality of non-research-orientated databases is typically low, mostly static snapshot data from a certain period of time, which requires significant time and effort for data cleaning and preprocessing. Care should be taken to ensure the alignment of disparate databases in preprocessing, maintaining consistent timestamps for snapshot data, such as ensuring consumption and geometric data correspond to the same period, thereby mitigating potential biases in results. In any case, the databases used for NDBS research require significant time and manpower, as well as economic costs, to obtain data streams that are sufficiently representative and have adequate sample sizes, with the result that building stock databases of sufficient volume are usually only available in developed countries. These current aggregated big data building repositories facilitate the assessment of the value of existing building assets [166], aid in achieving energy efficiency improvements [154,158,164], and serve various other functions. The advent of big data methodologies has spurred a transformation in how building stock is understood and managed through data streams [170]. However, an ideal and comprehensive building stock information database should not only encompass the mentioned functionalities but also enable targeted maintenance and management of buildings, identification of safety risks both within and outside structures, and ultimately contribute to sustainable development goals.

From the paper reviewed, type-stock analysis typically relies on national statistics data, such as school data from the education sector [149,151], while geo-stock analysis utilises more extensive databases. Therefore, type-stock studies can benefit by extracting relevant information about specific populations from general databases to supplement or validate the building information used in typical population NDBS research. Similarly, geo-stock NDBS research can enhance the accuracy of specific types of buildings by utilising data from specific building stocks. Additionally, privately owned data, such as commercially valuable data on bar and hotel occupancy rates, or data held by large real estate or facility management agencies, constitute potential data sources for both type-stock and geo-stock analyses. However, striking a balance between model accuracy and input time is crucial, as continually increasing the number of input parameters in NDBS models may lead to model convergence, where the ongoing addition of input parameters may not significantly contribute to the robustness of the model. In summary, the diversity and complexity of NDBS buildings, coupled with limited data availability, pose significant challenges to modelling this building category [2].

4.2. Technologies facilitating NDBS modelling

Due to the complexity of NDBS research, it's challenging to meet research needs using a single technology. Based on the application conditions and purposes of different technologies, they are categorised into four sections: Generic programming, Building Energy Modelling, Information statistics, and Auxiliary Hardware, as shown in Table 5.

Table 4
Summary of digitalised infrastructure supporting NDBS research.

Dataset Type	Dataset Name	Dataset Objectives	Country/City	Main Data Attributes	Public Availability	Stock Category	Detail Stock	Dataset Source
National Survey	National Register of School Buildings (SNAES)	Survey of the situation of school buildings and facilitate the implementation of school reconstruction projects	Italy	• Building Identification Key • Geographical Locations • Construction Years	Yes	Type-Stock	National School Building Stock	[149]
National Survey	Operational Energy Performance	Monitoring and optimising energy usage in operational building	Brazil	• Benchmark Values	Yes	Type-Stock	National Non-domestic Building	[150]
National Survey	Property Data Survey Programme	Gather accurate and up-to-date information on the building condition of the educational estate	UK	• Building Fabric • Building Type	Yes	Type-Stock	National School Building Stock	[151]
National Survey	Federal Building Registry (GWR)	Use for planning, research, and statistical reasons as well as for carrying out legal duties at the federal, cantonal, and commune levels	Switzerland	• Building Type • Construction year • Floor Level	Yes	Geo-Stock	National Building Stock	[152]
National Survey	Statistik der Unternehmensstruktur (STATENT)	Provide core information on the structure of the Swiss economy, thus providing an overview of the Swiss economic landscape	Switzerland	• Building Type	Yes	Geo-Stock	National Business Building Stock	[153]
National Survey	META Project	Enhance market efficiency in the Brazilian energy and mining sectors, taking into account climate adaptation, to strengthen institutional capacity	Brazil	• Energy consumptions • Building Type • Floor Plan • Weekly Operation	Yes	Geo-Stock	National Non-domestic Building Stock	[154]
National Survey	Ein Blick auf die Gemeinde	Provide an overview of the community as well as regional information and respond to the ongoing development of the municipality in relation to its political district or federal state	Austria	• Construction Year • Building Area • Main Occupants	Yes	Geo-Stock	National Building Stock	[155]
National Survey	The Swiss Federal Register of Buildings and Dwellings (RegBL)	Give an overview of Switzerland's present stock of structures and homes.	Switzerland	•Building Location • Building Dimensions • Heating system • Building Type	Yes	Geo-Stock	National Building Stock	[156]
National Survey	Le Certificat énergétique cantonal des bâtiments (CECB)	Focuses on energy certifications for buildings	Switzerland	• Construction Year • Heating system • Building Type	Yes	Geo-Stock	National Building Stock	[157]
National Survey	Energy Management System Open data	Monitor energy usage and indoor environment to help building operations managers use energy wisely and realise a sustainable society	Japan	• InfrastructureElectricity Consumptions	Yes	Geo-Stock	National Buildings with Building Energy Management System Stock	[158]
National Survey	Display energy certificate (DEC)	Reflect the energy performance of public buildings	UK	• HVAC systems • Main Heating Fuel • Occupancy levels • Energy consumptions	Yes	Geo-Stock	National Public Building Stock	[159]
National Survey	Energy Performance of Buildings Data: England and Wales (EPC)	Rating schemes to summarise the energy efficiency of buildings	UK	• Floor Area • HVAC System • Building Fabric	Yes	Geo-Stock	National Building Stock	[159]
National Survey	URBAN3R	Conduct urban analysis through remote sensing and social data	Spain	• Building Indicators • Building Current State • Building Energy Demands after Renovation	Yes	Geo-Stock	National Building Stock	[160]
Local Survey	SITG: Le système d'information du territoire à Genève	Coordinate, centralise and widely disseminate data relating to the territory of Geneva	Geneve, Switzerland	• Geographical Locations • Urban Infrastructure and Territorial Information	Yes	Geo-Stock	City Building Stock	[161]
Local Survey	San Francisco's open data portal	Public database to provide a comprehensive picture of the current situation in the city	San Francisco, USA	• Building Footprints • The Land Use	Yes	Geo-Stock	City Building Stock	[162]

Table 5
Summary of model breakdown functions and the implementation technologies in the paper reviewed.

Purpose of the Applied Technology	Stock Category	Model Breakdown Functions	Implementation Technologies	Requirements for Utilisation	Related Paper Reviewed
Generic programming	Both	• Retrieve and manipulate data from databases	Database Programming Language (PostgreSQL, Oracle)	• Ability to perform database administration tasks • Understanding of database architecture and optimisation • Proficiency in writing complex SQL queries	[65,86,90,107]
	Both	• Preprocess data, including removing outliers, completing missing values • Support for customised data processing, analysis and visualisation • Assist in building large-scale models and simulations	General-propose Programming Language (Python, R, MATLAB)	• Experience in building scalable and efficient code • Advanced knowledge of algorithms and data manipulation • Proficiency in utilising advanced data structures	[59,63,96,109,111,120,121,127,142]
	Geo-Stock	• Obtain geometric and typological data on building stocks • Link information from different databases based on building location	GIS (QGIS, ArcGIS, GrassGIS)	• Proficiency in spatial analysis and geospatial modelling • Integration of spatial data from various sources	[52,81,83,85,86,93,95,97,107,113,139]
Building Energy Modelling	Both	• Model and design complex architectural structures	Model Establishment (Revit, Sketchup, Grasshopper)	• Advanced understanding of architectural design principles • Proficiency in parametric modelling and scripting	[54,63,79,81,88,95,105,121,125]
	Both	• Obtain detailed energy performance and environmental comfort metrics of buildings • Conduct sensitivity analysis and optimisation	Dynamic Simulation (OpenStudio, EnergyPlus, DesignBuilder, TRNSYS, IDA-ICE, ESP-r, Dymola/Modelica)	• Advanced understanding of thermodynamics and heat transfer • Ability to handle complex simulation scenarios	[50,53,55–57,59,62,63,67,69]– [72,74,76,77,79]–[84,86,87,92,95,96,103]– [105,110,111,114,119,121,124,125,137,138,140,143,145,147]
Information statistics	Type-stock	• Collect and process survey data effectively	Microsoft Forms	• Proficiency in designing and deploying surveys • Familiarity with data validation and integrity checks	[56]
	Type-stock	• Analyse complex building-related data sets • Generate comprehensive statistical reports and insights	SPSS	• Advanced statistical modelling and analysis skills • Knowledge of advanced features and functionalities	[65]
	Geo-Stock	• Process and integrate diverse spatial and attribute data sets	Microsoft Excel	• Proficiency in data manipulation and analysis • Experience in building complex formulas and macros	[94,97,134]
Auxiliary Hardware	Both	• Process large-scale data sets and computational models efficiently	High-Performance Computer	• Access to parallel processing and distributed computing • Familiarity with cluster management and job scheduling • Ability to optimise algorithms for performance	[55,96,114]

The technologies in the generic programming category can broadly be classified into three main types: database programming language, general-propose programming language, and GIS. Database programming language primarily serves the purpose of data manipulation, especially when dealing with extensive datasets, enabling efficient data retrieval and consolidation from different databases within the NDBS framework. SQL and similar technologies are crucial for performing complex data operations, ensuring data integrity and accessibility. The general-propose programming language offers versatile capabilities within the NDBS research context, including data preprocessing, handling outliers and missing values, data analysis (e.g., clustering based on building attributes [120] or utilising machine learning algorithms [96]), and batch modelling (e.g., utilising the eppy package in Python for dynamic building model establishment [63]). GIS adds a spatial dimension to NDBS analysis, which is primarily used in the context of geo-stock analysis, allowing for the examination of the geographical distribution of buildings within a specific region and facilitating [85,97,113] the integration of disparate geographic databases [83,84,100]. Tools such as QGIS and ArcGIS enable researchers to map and analyse the geographical distribution of buildings, identifying regional trends and supporting spatial decision-making.

Building modelling tools play a crucial role in assessing NDBS performance. Tools like Revit, Sketchup and Grasshopper are utilised for creating 3D building models. Computational software such as OpenStudio, EnergyPlus, DesignBuilder, TRNSYS, IDA-ICE, and ESP-r is essential for dynamic thermal simulation, a common technique for evaluating NDBS energy usage. Notably, Dymola/Modelica is also utilised in NDBS energy performance analysis to accurately represent energy systems and control requirements [86], enabling co-simulations of buildings. Co-simulation involves the simultaneous operation of different simulation tools, data exchange during runtime, and has been applied in various research tasks, including optimising ventilation strategies, analysing control strategies, and evaluating building systems [171]. Employing co-simulation can enhance the detail and reliability of NDBS models.

Information statistics software aids in data collection and analysis for NDBS research. Microsoft Forms is a valuable tool for collecting survey-based NDBS information, while Microsoft Excel serves for data consolidation and computation. SPSS software enables in-depth statistical analysis of NDBS attribute performance patterns. Finally, hardware components such as high-performance computers can significantly increase efficiency and reduce the time costs associated with large-scale building model simulations. Collectively, their use accelerates the processing of complex NDBS simulations, thereby facilitating comprehensive analysis and informed decision-making in the field of building stock management and optimisation.

In summary, the technologies utilised in NDBS analysis encompass generic programming, building energy modelling, information statistics, and auxiliary hardware. Some technologies are currently employed exclusively for the single building stock category; for instance, GIS is mainly used for geo-stock in the reviewed literature, leaving untapped potential for its application in type-stock analysis. Moreover, there is a growing need for the development of a multifunctional, cross-platform framework tailored for NDBS energy performance analysis. Such a framework should encompass data preprocessing, dynamic building energy performance simulation, and statistical analysis of results, and ideally be an open-source platform.

4.3. Processes of NDBS modelling

As mentioned in the previous section, this paper focuses on the NDBS physics-based modelling at the disaggregation level. Two modelling approaches are classified under this scope, which are archetype-based and building-by-building modelling. Both of them are discussed in detail below.

4.3.1. Archetype-based modelling

NDBS buildings exhibit a high degree of heterogeneity, resulting in a very tedious modelling effort. The most popular method of reducing modelling work is to use archetype-based techniques, which choose sample structures to represent the complete building stock. There are two main points to discuss in the archetype-based approach, which are the selection of model attributes and the mechanism by which the model is built.

The input attributes of the model are the cornerstone for subsequent physics-based modelling. A basic set of building complex attributes includes geometric data (e.g., shape, orientation, height and footprint), structural data, and system data [172]. Developing and representing building representatives based on different input attributes is the most crucial part of the archetype-based approach. In this process, the initial step involves introducing the target NDBS into a standardised framework and categorising the buildings into several classes [173]. Additionally, the weights of each archetype within the building stock range are determined based on real-world conditions, which is a key aspect of archetype development. From the literature review, it can be seen that for both type-stock and geo-stock studies, the most commonly considered attributes are building year and HVAC system. Whereas building size parameters are more often considered in the categorisation criteria for type-stocks. Geo-stocks explore more the influence of building type parameters in building archetypes. Although the classification of building groups based on building attributes is crucial for NDBS analysis, the selection process is still mostly based on the determination of researchers based on their expertise and is considered arbitrary [174]. In recent years, with the development of machine learning techniques, some studies have started to use clustering technology for segmenting NDBS from a statistical perspective. Cluster analysis is an unsupervised machine learning technique employed to identify groups of similar data points within a given dataset [175]. In the context of NDBS, it is used to uncover hidden structures within the building attribute dataset based on similarity and representative elements for analysis [176]. The use of clustering technology can make the selection of archetype buildings more reliable and convincing.

The mechanism of modelling is a key point to be discussed. Based on the input attributes, archetype-building methods can be further divided into two subcategories: sample archetypes and theoretical archetypes. Sample archetypes are generally derived from real buildings and are based on statistical analysis, such as clustering methods, to determine the average geometric and structural characteristics of each specific category of building stock [177]. The issue with this approach is that it may not be able to consider buildings with outlier attribute values, as they may not fit into relevant clusters. Additionally, this approach requires relatively

Table 6
Summary of archetype-based NDBS studies.

Stock Category	Main Attributes	Minor Attributes	Related Paper Reviewed
Type-stock	Energy Modelling Approach	Dynamic modelling	[50,53–60,63,66,69–74,79]
		Qusai-steady modelling	[51,52,64,65,68,75,78]
	Approach for Selecting Archetypes	Sample archetypes	[50–52,54,65,68]
		Theoretical archetypes	[53,55,57–59,63,66,69–75,78]
	Calibration and Validation of Model Outputs	Compare with the relevant standard	[50,71]
		Compare the energy consumption of similar buildings with each other	[54]
		Compare with benchmark models	[53]
		Compare with other relevant literature	[52]
		Compare with real consumption data	[57,58]
		Compare with relevant government data	[55,59,66]
	Criteria for Defining Archetypes	Building size	[50,57,65,68,69,71]
		Building shape	[50,57,58,63,65]
		Construction year	[52,55,58,59,64,66,69,75,78,79]
		Surface-to-volume ratio	[52]
		Number of rooms	[53]
		Window-to-wall ratio	[53,56,64]
		Construction characteristics	[53,57,59,63,72,73]
		Building types	[54,55,74,78,79]
		Number of floors	[51,54,63,64,68]
		External wall area	[51]
		Geographical information	[55,66]
		Energy Consumption	[57]
		Climate region	[59,69,71]
		Building fabric	[54,65,72]
		Urban settings	[57]
		HVAC system	[55,59,65,66,69–72]
Geo-stock	Energy Modelling Approach	Dynamic modelling	[81,87,88,95,103–105,110,111,114,119,121,124,125,127,128,130,132,133,137–141,143,145,147]
		Qusai-steady modelling	[90,93,101,113,120,144,146,148]
	Approach for Selecting Archetypes	Sample archetypes	[101,148]
		Theoretical archetypes	[81,90,93,95,103–105,111,113,114,120,121,124,125,127,128,130,132,133,143–147]
	Calibration and Validation of Model Outputs	Compare with benchmark models	[101,148]
		Horizontal comparison of consumption data with other countries	[127]
		Compare with other relevant literature	[119,121]
		Compare with real consumption data	[105,120,130,143,147]
		Compare with relevant government data	[93,111,137,146]
		Compare with validated simulation results	[104]
		Empirically validated	[114]
	Criteria for Defining Archetypes	Building footprint	[93,101,146]
		Building fabric	[95,121,130]
		Number of floors	[101,104,127]
		Geographical information	[93,133,144]
		Building type	[81,90,95,105,110,111,113,120,124,125,128,130,132,133,137–139,141,144,145,147,148]
		Building structure	[125]
		Thermal condition	[81]
		Construction year	[90,95,105,110,111,113,119,120,124,128,132,133,141,144,145,147,148]
		Building shape	[93]
		Energy consumption	[93,101,139,146]
		Carbon emissions	[93]
		Occupancy schedule	[95,114]
		HVAC system	[95,114,121,124,128,130,132,143,145]
		Building zoning	[101,104,127]
		Urban settings	[113,138]
		Internal loads	[114,120]
		Climate condition	[119,120,132,145]
		Building size	[125,130,138,144]
		Construction characteristics	[143]
		Energy saving measurements	[111,143]

high-quality information about real buildings [176] and may have limited generalisability. The second approach, theoretical archetypes, involves creating a series of virtual building archetypes to represent NDBS stock. The attributes of virtual archetypes can be derived from collected building-related information or can be based on local building design manuals, standards, and regulations. In the context of highly heterogeneous NDBS, local building-related design manuals and regulations serve as primary data supplements for stock-level modelling when data is lacking. These virtual archetypes resemble parametric modelling, where the model's attributes are divided into several categories and then combined to cover the entire stock. Whether type-stock or geo-stock, though, most are still utility theoretical archetypes to conduct stock-level studies. However, corresponding issues may arise, such as virtual archetypes created by combining extreme values of different attributes may not be representative or may even not exist. Therefore, secondary screening is necessary to exclude non-representative archetypes and reduce the computational workload for subsequent analyses after the initial virtual archetype construction. The computational methods for model performance can be classified into two categories: quasi-steady state calculation methods using thermal balance models and dynamic thermal simulation methods using the simulation software previously mentioned in section 4.2. Based on the review of the literature, archetype-based research employing dynamic models predominates. Summaries could be found in the Table 6 below.

4.3.2. Building-by-building modelling

In recent years, with the iterative advancements in technology and expanded computational capacity, it has become feasible to model individual buildings on a large scale, known as building-by-building modelling. This modelling approach is primarily based on GIS technology and is typically used in NDBS models for geo-stock. All types of datasets are integrated into a unified format, which includes geometric information for real-world environmental 3D spatial visualisation and additional semantic and attribute data in 3D standardised formats such as CityGML, Shapefile, and GeoJSON, with CityGML being widely utilised [176]. For example, the aforementioned CityBES uses CityGML format files to represent and exchange 3D city models for subsequent EnergyPlus calculations [26]. The integration of data from different sources is a crucial factor that needs to be considered in building-by-building modelling. Generally, this can be achieved either by using GIS technology to integrate all information about a building into its corresponding 2D or 3D model or by utilising unique identifiers, akin to a building's ID card. For instance, in the case of 3Dstock modelling in the UK, the unique property reference number is employed to link various pieces of information together [98]. Based on the reviewed literature, research on building-by-building modelling is still in its infancy, with only a few scattered papers available. Detailed information on this is summarised in Table 7 below.

Compared to the archetype method, the building-by-building approach has the potential to consider coupling effects between buildings, taking into account the impact of urban microenvironments on building stocks. Although this method demands higher data precision, there is no doubt that improving simulation accuracy and level of detail can be the direction of improvement for researchers in stock modelling. In summary, the process of NDBS modelling primarily relies on bottom-up physics-based methods, especially archetype simulation methods. This is not to say that other methods are not valuable but given the current limitations in available data and computational capacity, archetype-based methods unquestionably dominate stock analysis at present.

4.4. Goals of NDBS studies

Research objectives in NDBS studies can be categorised based on their goals and the type of building stock under investigation. Four research objectives are identified, namely methodology development and proof, analysis of the present situation, impact of measures, and future performance forecast, which are shown in the Table 8. Policies related to building stock can be categorised into four categories, which are improvements to energy efficiency, increases in renewable energy increase, low carbon material uptake and climate change adaptation and resilience [178]. These four areas of policy echo the abovementioned four applications.

Methodology development and proof focus on assessing the feasibility of the methodology developed due to possible limitations in data sources and geographical constraints. As for NDBS, this application involves the development and testing of new methods, tools and models for measuring, monitoring and assessing the energy performance and environmental impacts of non-domestic buildings. A greater proportion of geo-stocks for such purposes are studied than type-stocks. The most common approach is the use of building energy modelling methods to assess the energy use, carbon emissions and environmental costs of non-domestic buildings [45,46,49,60,70,71,81,88], which can help to identify the potential for and barriers to improving energy efficiency, increasing renewable energy, reducing carbon footprints and enhancing climate resilience in non-domestic buildings. An example of a policy that supports this goal is the EU's Energy Performance of Buildings Directive, which requires member states to develop energy efficiency certificates, inspection programmes and long-term retrofit strategies for buildings.

Analysing the present situation involves evaluating various energy usage intensity indicators within the building stock. This application includes collecting and analysing current data on the energy efficiency and environmental impacts of non-domestic

Table 7
Summary of building-by-building NDBS studies.

Stock Category	Energy Modelling Approach	Integration among diverse data sources	Calibrated or Validated Model Outputs	Reference
Geo-stock	Dynamic modelling	Based on the GIS system	No	[83]
	Dynamic modelling	Based on the GIS system	Yes	[84]
	Dynamic modelling	Based on building identification keys	No	[85]
	Dynamic modelling	Based on the GIS system	No	[86]
	Dynamic modelling	Based on the GIS system	No	[87]
	Dynamic modelling	Based on building identification keys	No	[98]
	Dynamic modelling	Based on building identification keys	No	[99]
	Dynamic modelling	Based on the GIS system	No	[100]
	Dynamic modelling	Based on building identification keys	No	[102]

Table 8
Summary of the NDBS research goals.

Stock Category	Breakdown of applications	Expected Model Outputs	Limitation of Outputs	Related Studies
Geo-stock	Methodology development and proof	• Evaluation of the feasibility of developed methodologies, typically measured using parametric indicators such as energy efficiency and carbon intensity metrics relevant to specific geographic areas	• The accuracy and reliability of the methodology may be constrained by the quality and availability of data sources, potentially leading to errors • Results may only be applicable within the current geographic boundaries of the stock, limiting broader generalisation	[57,82,83,85,86,88,90,91,96,98,99,101,106,108–110,112,115–119,121,130,131,134,135,137–141]
	Analysis of the present situation	• Detailed analysis of energy usage intensity across building stocks, including metrics like heating and cooling demands, specific energy consumption, material stock levels, fuel use, and carbon emissions, offering a comprehensive overview of the energy status quo	• Inability to precisely capture the unique energy needs of individual buildings within a diverse stock • Findings may only be relevant to the specific geographic area studied, which limits the applicability of results to other regions	[58,84,93–95,100,103,105,113,120,127,129,132,143]
	Impact of measures	• Quantification of the impact of energy-saving or retrofit measures on the overall energy performance and carbon footprint of building stock, providing insights into potential energy savings and reductions in emissions	• Transparency and accuracy at the building granularity level cannot be ensured • Simplifications within the models may introduce bias, leading to potential inaccuracies in assessing the impact of measures	[72,80,81,87,97,102,104,107,111,114,122,124,128,133,136,144,145,147,148]
	Future performance forecast	• Projections of future energy consumption and carbon emissions for building stock, considering factors such as technology trends, policy changes, and demographic shifts	• Uncertainties in future data, such as unexpected changes in technology or policy, may affect the reliability of the forecasted results	[92,125,127,146]
Type-stock	Methodology development and proof	• Validation of methodologies developed for specific building types, assessing feasibility through indicators tailored to NDBS or other defined categories	• The applicability of these methodologies may be limited to specific building types, reducing the potential for generalisation to other categories	[65,73,75]
	Analysis of the present situation	•In-depth analysis of current energy usage intensity, focusing on specific building types to identify patterns in energy consumption and potential efficiency improvements	• Results may only be valid for the current specific stock • Data sources may introduce systematic errors • The process may require significant resources and effort, limiting the scope of the analysis	[50,53,59,60,63,66,76,78]
	Impact of measures	• Quantification of the impact of energy-saving or retrofit measures on energy consumption or indoor comfort indicators	• Oversimplification in modelling complex building dynamics might lead to incomplete or inaccurate assessments • Uncertainties in the models may influence the reliability of decision-making outputs • Limitations in data availability can restrict the depth and scope of research	[51,54–56,61,62,64,67–71,74,79]
	Future performance forecast	• Future energy consumption or carbon emissions of building stock	• Uncertainties in future data may impact the results	[72,77]

buildings, as well as the factors that influence these data. For example, several studies have investigated and analysed the energy consumption, carbon emissions and energy efficiency of non-domestic buildings in different countries, regions, sectors and types [58,103,120,127,143]. These analyses help to understand the baseline, trends and drivers of energy performance and environmental impacts of non-domestic buildings and benchmark them against policy targets and best practices. However, this application may not precisely capture individual building energy needs and is bound by the current geographic delineation. A relevant policy example is China's Green Building Action Plan, which aims to increase the share of green buildings in total floor area to 50 % by 2020.

The impact of measures objective quantifies the effects of energy-saving measures, though challenges exist in ensuring granularity and model simplification. This application involves assessing and quantifying the energy efficiency and environmental impacts of various measures on non-domestic buildings, such as technologies, policies, and behaviours. A number of studies have estimated and compared the impact of energy efficiency measures, renewable energy systems, low-carbon materials and climate change adaptation strategies on energy use, carbon emissions and environmental benefits of non-domestic buildings [111,122,144]. These assessments help to identify and prioritise the most efficient and cost-effective measures to improve the energy performance and environmental impacts of non-domestic buildings and assess their feasibility and acceptability. A relevant policy example is the new target set by the UK Government to achieve high energy efficiency, low carbon heating and zero carbon standards in all new buildings by 2025.

For future performance forecasting, this application refers to predicting and forecasting future energy performance and environmental impacts of NDBS under different scenarios, such as technological developments, policy interventions and climate change. For instance, some studies have used scenario analysis, optimisation models and system dynamics to predict the energy demand, carbon emissions and environmental impacts of non-domestic buildings in the short or long term [92,125,127,146]. These forecasts help to anticipate and plan for future challenges and opportunities to improve the energy performance and environmental impacts of NDBS, and to assess the potential and trade-offs of different policy options and pathways. One example of a policy that supports this goal is the Paris Agreement, which aims to reduce greenhouse gas emissions and limit the increase in global average temperature to 1.5 °C above pre-industrial levels.

Whilst all applications are designed to support relevant policies, there are several NDSB studies that have directly articulated their support for policies aimed at improving the design, implementation and evaluation of policies on energy efficiency and environmental impacts of non-domestic buildings. For example, some studies have contributed to the development and revision of building codes, standards, and regulations, as well as the provision of incentives, information, and guidance to owners, managers, and users of non-domestic buildings [72,104,147,148]. Such support has helped to promote and accelerate the adoption of and compliance with energy efficiency, renewable energy, low-carbon materials and climate change policies in NDBS as well as to monitor and verify their outcomes and impacts. The provision of financial subsidies, tax incentives, and preferential loans by the Chinese government to facilitate green building projects exemplifies policy measures aimed at fostering this objective.

In summary, the multifaceted approach of NDBS research objectives, encompassing both geo-stock and type-stock studies, provides a solid foundation for improving energy efficiency and informing policies related to increasing renewable energy, low-carbon materials, and climate change adaptation and resilience. These contributions are critical to achieving sustainable and resilient energy systems. While geo-stock studies aim to understand the present situation and measure impacts within certain geographical boundaries, type-stock studies focus on specific building types. Both types of research encounter challenges related to data quality, model simplifications, and policy trend assessments, which necessitate careful consideration when interpreting their results and implications for future energy systems and policies.

4.5. Beneficiaries of NDBS research

Reviewing NDBS research from the perspective of STS with a focus on the people allows for a detailed analysis of the beneficiaries of such research. The audiences for this research can be categorised into three main groups: researchers, commercial stakeholders, and policymakers. See the Table 9 below for details. Analysing the societal value of NDBS from the perspective of beneficiaries, the TBL analysis undoubtedly proves to be a highly appropriate approach. TBL is a sustainable development framework that assesses three crucial dimensions: economic, social, and environmental. It emphasises a comprehensive business approach, considering not only financial performance but also social and environmental impacts. Based on TBL allows for a more comprehensive review of NDBS research from an STS people perspective.

Table 9
Summary of the NDBS research beneficiaries.

Stock Category	Audiences	General Benefits of Target Audiences	General Limitations on Target Audiences	Related Studies
Geo-stock	Researchers	• Charting specific pathways to aid NDBS in achieving carbon neutrality and reducing energy consumption	• The consideration of socio-economic factors alongside achieving the objectives is necessary	[111,118,122,126]
		• Inspiring researchers with new perspectives on Geo-stock NDBS research	• The quality of data sources needs thorough exploration	[84,91,101,121,142,146]
	Commercial Stakeholders	• Assisting building owners in energy cost savings and creating more responsible, sustainable building environments	• Profitability may be low	[114,148]
	Policymakers/ City planners	• Crafting relevant policies/measures to aid geo-stock NDBS in achieving carbon neutrality and reducing energy consumption	• Socio-economic factors need to be considered while achieving the objectives • The impacts of policies/measures may take a long time to manifest • Research results are often confined to specific regions and are challenging to generalise	[79,81–83,87–89,92–96,100–102,104–108,111,113,116,117,119,124,125,127,135,137,140,143,144,147]
Type-stock	Researchers	• Using research outputs to support the formulation of relevant policies • Quantifying the general impact of different measures on specific type-stock NDBS	• Research methods and expected outcomes differ for policies targeting NDBS of different scopes	[53,59]
		• Inspiring researchers with new perspectives on type-stock in NDBS research	• Heterogeneity within the type-stock building on the results should be considered	[90]
	Commercial Stakeholders	• Assisting building owners in optimising building renovations to save energy and reduce expenditure	/	[51,57,64]
	Policymakers/ City planners	• Crafting relevant policies to aid type-stock NDBS in achieving carbon neutrality and reducing energy consumption	• Different criteria should be considered for multi-objective optimisation for making decisions	[55,63,67,76,79]

Researchers could undoubtedly be inspired by the research of their peers on NDBS. In the geo-stock, researchers play a pivotal role in developing pathways to promote non-domestic stock towards carbon neutrality and reduced energy consumption. This helps us to understand the socio-economic factors that are intertwined with these goals. It also provides researchers with new perspectives, despite the challenges associated with the quality of data sources. Type-stock studies enable researchers to support policy development and quantify the impact of measures on specific non-residential stock types. However, it is important to recognise that research methodologies and expected outcomes can vary considerably depending on the scope of non-domestic stock policies. Researchers can gain new insights from this, although attention should be paid to the inherent heterogeneity within the non-domestic stock of buildings in the type-stock to ensure the validity of the results. Incentivise researchers to gain new perspectives and knowledge on the geographic stock and type stock aspects of non-domestic stock research, thereby enhancing the intellectual capital within the community. Assisting homeowners in optimising building retrofits to save energy and reduce expenses has a direct economic impact on stakeholders, reflecting the profitability of TBL.

Commercial stakeholders have rarely been discussed as separate beneficiaries in previous studies. Geo-stock research can benefit from insights that help building owners save on energy costs and promote a sustainable environment. However, potentially lower profitability is also a limiting factor. Commercial stakeholders in type-stocks can benefit from studies that help optimise building retrofits, save energy and reduce expenses. Yet, the limitations of non-domestic stock studies for commercial stakeholders have not been articulated. Reviewing the TBL methodology, non-domestic stock contributes directly to the economic side of the equation by implementing specific measures to achieve carbon neutrality and reduce energy consumption, resulting in cost savings for building owners.

Policymakers and urban planners can benefit from NDBS research that contributes to the development of relevant policies. For geo-stocks, it is important that these decision-makers understand the complexity of socio-economic factors and recognise that policy impacts can take considerable time to realise. In addition, the limited generalisability of research results to specific areas is a noteworthy constraint. Using the results of the type-stock study, policymakers and urban planners can develop policies to achieve carbon neutrality and reduce energy consumption. However, they must consider different criteria for multi-objective optimisation in their decision-making. The development of policies and measures related to non-domestic stock is consistent with the environmental aspects of TBL, quantifying the overall impact of various measures on non-domestic stock for specific types of stock. This not only helps to improve the economic efficiency of buildings but also stimulates researchers to explore new perspectives on non-domestic stock research and contributes to social progress through knowledge sharing.

NDBS research offers numerous benefits to researchers, commercial stakeholders, and policymakers in the pursuit of carbon neutrality and reduced energy consumption. Using the TBL framework, the interconnections between economic prosperity, social well-being and environmental sustainability are highlighted, demonstrating how non-domestic stock research can contribute holistically across these dimensions by providing energy-saving or decarbonisation pathways, inspiring new perspectives, supporting policy formulation, and quantifying policy impacts. However, limitations encompass data quality concerns, potential lower profitability, socio-economic complexities, delayed policy impacts, and regional-specific research results. Overall, NDBS research is a valuable endeavour, although stakeholders must remain aware of these benefits and limitations as they engage in this field.

5. Discussion

This section provides reflections and conversations on a few of the societal concerns that have been addressed during the literature review. Additionally, a summary of the state of NDBS research is provided, and possible approaches to improve the robustness and reliabilities of NDBS physics-based models are explored.

5.1. Societal concerns associated with NDBS studies

The societal implications of the physics-based models in NDBS are often overlooked due to their technical nature. This encompasses aspects such as data politics involved in the process of NDBS physics-based modelling supported by digitalised infrastructure, and the societal significance of the parameters during the modelling process. In-depth discussions regarding these aspects can facilitate decision-making and resource optimisation within NDBS, while ensuring the economic and social benefits of NDBS research.

5.1.1. Data politics in digitalised infrastructure

The emergence of big data has undoubtedly facilitated research related to non-domestic stock, especially the digitalised infrastructure. However, it simultaneously raises concerns about digital justice, with the potential for instances where individual and collective interests may be sacrificed for the sake of data [179]. For instance, databases involving information about building users [154,155] must consider the specific means of data acquisition. In the process of collecting data on building stock, it is essential to study how data is generated, metabolised, and collected, as well as the motivations behind data collection, the identity of collectors, the voluntariness of participants in the digitalisation process, and the impact on data sources post-collection. The term "data politics" has emerged in this context. In the realm of digitalised building stock, data politics can be defined as the power relations and decision-making processes regarding the collection, processing, transmission, and use of architectural data in the digital age. This includes power struggles, conflicts, and cooperation among governments, businesses, organisations, and individuals in the management and use of data. For the NDBS, decisions about data inevitably become a political process, granting privileges to some while offending others. Owners or users of buildings, when providing information such as building usage, energy consumption, building footprint, or architectural system details, should be mindful of their privacy to avoid surveillance by "smart" systems [180]. Data politics not only addresses the political struggles related to data production and deployment but also examines how data creates new power relations and politics at different and interconnected scales [181]. These dynamics have significant implications for democratic norms and ideals, social fairness, and NDBS-related studies, which furthermore have a significant impact on the living conditions of building users [170]. Therefore, a careful examination of how data flows shape today's cities and architectural stock is necessary, to rethink and reshape data flows to simultaneously accommodate democratic norms and social fairness while achieving the goals of the digitalised building stock.

5.1.2. Social parameters within NDBS studies

In the establishment of NDBS physics-based models, different parameters used for model construction can be approached from various perspectives in building the social context of the model. Indicators in the physics-based models of architecture used to describe and analyse quantifiable or qualitative attributes related to social factors can be defined as social parameters of architectural models. Commonly utilised social parameters frequently found in reviews include building type, geographical information, building footprint, and energy consumption. Building type can reflect social functions, cultural influences, and considerations for environmental sustainability. The diversity of building types, such as schools, hospitals, industrial structures, and retail centres, serves different social purposes, closely tied to the social nature and purposes of the city, reflecting societal needs and development trends, particularly in geo-stock NDBS. Understanding building types as social parameters and employing them in NDBS modelling contributes to a comprehensive assessment of their roles and impacts in society, aiding sustainable social development and planning. Geographical information becomes another crucial social parameter by providing a nuanced understanding of spatial backgrounds and their social impacts. Barnes and Wilson [182] emphasise the historical antecedents of geographical information in the field of social physics, tracing its roots back to the scientific revolution. Liu et al. [183] underscore the importance of integrating Building Information Modelling (BIM) and GIS for comprehensive spatial analysis, revealing complex relationships between physical structures and geographical environments. Geographical information contributes to social parameters by modelling multi-scale building data based on GIS, addressing complex information challenges, and promoting a bottom-up approach. Bill et al. [184] further highlight the expertise of geographic information science in data collection, interpretation, and management, positioning it as a valuable resource for understanding dynamic social and environmental trends. The integration of geographical information as a social parameter provides a solid foundation for spatial analysis and modelling in NDBS, allowing for a more comprehensive examination of social interactions and environmental factors. Building footprint, observed as the physical outline of structures from above, also holds the potential of being a social parameter, reflecting societal values and contributing to a broader cultural narrative. In the context of environmental sustainability, building footprints showcase how architectural design and density influence social behaviour and resource consumption. Unique features of building footprints, including size, shape, and layout, contribute to enhancing the aesthetic and functionality of urban spaces, impacting residents' quality of life. Viewing building footprints as social parameters in NDBS provides a valuable perspective for analysing and enhancing the social-cultural structure of communities. Energy consumption emerges as a key parameter in archetype modelling, surpassing its technical implications and embodying essential social dimensions within the community. Liu and Qian [185] emphasise the interconnectivity between energy usage and social sustainability, highlighting the need to consider the societal impacts of energy consumption patterns. This understanding prompts a paradigm shift in energy modelling, urging researchers and planners to delve into the societal aspects supporting and influenced by energy consumption behaviour. Additionally, research by Heidelberger and Rakha [16] advocates for a comprehensive approach in urban building energy modelling, emphasising the importance of integrating population and socio-economic factors to capture the societal complexity related to energy usage. By considering energy consumption as a social parameter, the modelling process gains depth, enabling a more comprehensive understanding of the societal impacts of energy-related decisions. Incorporating energy consumption as a social parameter into NDBS archetype models provides a nuanced perspective, aligning with the growing recognition of the intertwined nature of energy dynamics and social structures. Defining and refining these social parameters allows for a more comprehensive and in-depth analysis of the societal impact of building systems in the context of NDBS. Considering the societal angle in the analysis of social parameters supports sustainable development and social responsibility.

5.2. Current conditions of NDBS studies

The proposed comprehensive approach in this paper for non-domestic stock research within the STS framework emphasises its social significance, highlighting the symbiotic relationship between infrastructure, process, technology, goals, and people from start to finish. As the STS-based overview of non-domestic stock research shown in Fig. 1 above, the infrastructure component provides data support for the NDBS. The technology component aids in the modelling of the NDBS. The process reflects the modelling implementation of the NDBS. Goals present a mutually reinforcing/improving relationship with NDBS studies. And the people perspective, supervise and guide the orientation of the NDBS research. The detailed analysis from these perspectives is as follows.

Analysing the development of NDBS physics-based modelling from five perspectives within the STS framework allows for evaluating the latest modelling technologies while exploring the research's societal value. Current NDBS-related studies have made significant progress in data sourcing, technological means, and application scenarios. From the infrastructure perspective, the digitisation of infrastructure and building stock databases has garnered attention in many countries, as shown in Table 4. Without these databases, subsequent stock physics-based models cannot be established [186]. The openness and accessibility of data shape the technological landscape by influencing the choice of data sources and stock modelling methods. Cities' openness in publicly disclosing their inventory data through open portals has gradually become a trend [187]. However, more cities and countries need to collect and disclose their building data to help advance local building stock modelling and energy analysis. The data collection process often requires integrating various sensitive information, such as building usage data. Attention must be paid to protecting the interests of building stakeholders and maintaining digital justice [179]. The inherent diversity of global building structures rooted in culture demands the adoption of various technologies, thus impacting the tools used for data processing, simulation, and analysis. From the technology perspective, the integration demand of various building big data information flows has led to database management approaches being introduced into NDBS research [65,86,90]. Meanwhile, EnergyPlus remains the mainstream physics-based simulation engine. The main challenges in technology are establishing seamless workflows, and the coupling between different tools needs further optimisation. Technological means shape the process of non-domestic stock modelling by providing analysis and simulation tools. From a process perspective, archetype modelling is still the mainstream research method, but the building-by-building method is also increasingly prevalent. The classification of archetypes is gradually introducing more data, not limited to the field of architecture, such as urban condition [66,113] that can reflect the interaction between buildings, used to form more comprehensive representative NDBS archetypes. At the same time, the introduction of social parameters allows for the consideration of the complexity of population and socio-economic factors in developing NDBS archetypes and subsequent evaluation of energy use [16]. More parameters can be introduced fundamentally due to the strengthening of simulation computing capabilities. However, the classification of building archetypes still needs to strike a balance between the number and representativeness of archetypes and try to describe the building groups as completely as possible with as few models as possible, reducing wasted computing power [176]. With the advancement of computing power and the iteration of geographic information systems [25], the use of building-by-building modelling methods makes it possible to create physics-based substitutes for each building on a large scale and visualise their information on maps. However, attempting to simulate all buildings in a city requires a large amount of computing resources [187]. At the same time, the reliability of building-by-building analysis models also needs to be strengthened. However, since there is still no single database that can independently support NDBS modelling, the different granularity of different databases may potentially lead to additional uncertainty during integration. A verification method suggests calibrating models based on actual building consumption data [6]. In terms of NDBS objective, there is a slight imbalance between geo-stock and type-stock studies. For geo-stock, especially at the regional or city level, research has advanced to the point of being able to produce results on an hourly basis with the assistance of GIS [83,84,86,98,100]. However, type-stock models often rely on archetypes for an approximate analysis of stock energy consumption. Therefore, it is advocated that type-stocks adopt a more granular analytical approach to dig deeper into the unique building attributes of a specific category of NDBS to provide more robust energy efficiency recommendations to relevant commercial stakeholders. From the goal perspective, the most studied goal is still methodology development and validation. Overall, all modelling is more or less aimed at assisting policy decisions. Various studies covering multiple scenarios can provide insights into enhancing climate change adaptation and resilience goals [178]. However, if non-technical considerations such as psychological, social, and economic barriers are not adequately addressed, pushing policy implementation may encounter strong resistance [188]. For formulating comprehensive multi-objective policies, there are inevitably trade-offs between different objectives, so understanding the complex and dynamic interactions between technical and social aspects that affect policy decisions is crucial. As stakeholders, people promote goal-oriented practices by influencing policy outcomes and cultivating a culture of responsible and sustainable building practices. From the people perspective, researchers and policymakers have always been the primary audience for NDBS research, and relevant studies by commercial stakeholders have not been widely promoted. It is suggested to include cost-benefit assessments in retrofit analysis, as investment costs and payback periods drive the efficiency of energy measures implemented by local authorities and building owners in NDBS research [176].

5.3. Challenges of developing robust and reliable NDBS physics-based models

The challenges of NDBS research primarily stem from two aspects, data availability and model accuracy. The data availability challenge can be further decomposed into two smaller adversities, namely data scarcity and data quality issues. Data scarcity has long been a problem in the NDBS field. Due to the nature of stock-level studies, without the support of big data, it is impossible to conduct corresponding physics-based modelling. Non-research datasets are one potential solution, such as estimating the internal facility consumption by using service descriptions from hotel booking pages. Alternatively, attempting to couple NDBS models, especially geo-stock models, with other urban systems such as urban atmosphere, urban transportation and mobility, and regional-scale energy systems, is used to establish high-fidelity models [187]. Data quality is also a challenge that must be addressed in NDBS research. Inferring and completing missing data based on existing data are the primary data augmentation techniques for addressing data gaps. Traditional statistical methods, regression models, and deep learning methods have all been attempted for data imputation in the building domain and have demonstrated their effectiveness [189].

Model accuracy has been a persistent pain point in NDBS research. Research on NDBS calibration is limited. Broad-scale stock analyses require making certain assumptions about input data, leading to systemic errors in stock analysis. Annual building consumption data is often used for calibrating building stock energy models [187]. Obtaining more granular energy consumption data is generally difficult. Furthermore, for studies on stock building energy measures, the performance of specific energy measures is compared based on their absolute performance without quantifying uncertainty [190]. The difficulty in obtaining historical building energy consumption data and the challenge of quantifying building energy measures collectively contribute to the challenging verification of NDBS research results. Therefore, the validation of NDBS research results is crucial. It is recommended to use non-user-driven, mathematics-based automatic calibration, such as Bayesian validation which can explain uncertainty and risks in the modelling process [190].

5.4. Future research directions of NDBS

In the current global environmental context, advancing research on NDBS has become increasingly urgent. These research efforts are driven not only by the need to enhance building performance to meet increasingly stringent energy use standards and sustainability requirements, but also by goals related to environmental protection and carbon neutrality. In the face of climate change, reducing carbon emissions from buildings has become a critical measure for countries aiming to achieve their climate targets. Therefore, it is essential to improve NDBS models to provide policymakers with more accurate data support, effectively facilitating the achievement of carbon reduction objectives.

Simultaneously, with the rapid development of technology and the accelerated pace of urbanisation, the complexity and diversity of buildings continue to increase. The ultimate ideal state of future research is to develop a comprehensive, real-time digital twin model, which is a dynamic system capable of reflecting building performance in real-time and predicting future changes. However, due to technological limitations and ethical concerns, this ideal state can currently only be simulated through models to assess the potential of different scenarios. These models not only require continuous improvements in accuracy but also need the capability to handle complex dynamic data to ensure that they fully reflect the operational state of buildings in practical applications.

Given these drivers, four key areas of future research could advance the understanding and modelling of NDBS. One crucial direction is the integration of socio-economic factors, as discussed in this paper, into existing physics-based NDBS models. Incorporating parameters such as occupant behaviour, cultural influences, and economic incentives would provide a more holistic understanding of energy use in non-domestic buildings, thereby enhancing the accuracy and effectiveness of these models. Secondly, advancements in data acquisition technologies, including Internet of Things devices and AI-driven analytics, offer opportunities to enhance the real-time data collection and processing capabilities of NDBS models, making them more dynamic and responsive to changes in building use and environmental conditions. Thirdly, an important area is the long-term impact of energy-saving measures and policy implementations. Conducting longitudinal studies that track the performance of NDBS over extended periods could provide valuable insights into the sustainability of interventions and their effectiveness in achieving long-term carbon reduction goals. Finally, the development of open-source modelling platforms that integrate various techniques and data sources is critical, as such platforms would encourage greater collaboration among researchers and practitioners, fostering innovation and improving the accessibility of advanced NDBS modelling tools.

6. Conclusion

This study systematically reviewed previous achievements in NDBS research related to energy and carbon footprint and addressed three research questions in the NDBS research domain. To address the first and second research questions, five perspectives of socio-technical systems are examined, including infrastructure, technology, processes, goals, and people. In response to the first research question, i.e. how can energy and carbon footprint-related NDBS studies be evaluated across different STS dimensions, key findings can be summarised as follows: (1) Findings revealed that from the infrastructure perspective, digitalised infrastructure supports the establishment of physics-based models for NDBS but faces challenges of data gaps and inconsistencies. Uneven development is also a current issue, with digitalised infrastructures more common in developed countries. Compliance with data collection processes also requires attention. (2) Regarding technology, tools for NDBS encompass general programming, information statistics, model building, and auxiliary hardware to facilitate dynamic thermal simulation, statistical analysis, and data collection. However, integrating GIS into type-stock analysis and developing comprehensive cross-platform frameworks for NDBS energy performance assessment still holds potential. (3) From the process perspective, bottom-up archetype modelling relying on attributes and clustering techniques dominates NDBS, while building-by-building models integrating GIS data for spatial visualisation remain in the early stages compared to archetype-based methods. (4) In terms of purpose, NDBS research objectives include method development, present situation analysis, measures impact assessment, and future performance prediction, aiming to support policies related to energy efficiency, renewable energy, low-carbon materials, and climate adaptation. (5) From the people perspective, NDBS research benefits researchers, commercial stakeholders, and policymakers economically, socially, and environmentally by providing energy-saving pathways, inspiring new viewpoints, supporting policy formulation, and quantifying policy impacts.

Regarding the second research question, the differences between geo-stock and type-stock NDBS objects when viewed through different STS dimensions, while geo-stock and type-stock research focus on different subjects, they offer cross-fertilised opportunities. They can share data and analysis methods to enhance research efficiency and accuracy. Building energy models can be improved and applied across both types of research to enhance model reliability and applicability. Furthermore, policymakers can obtain comprehensive data support from both types of research to develop energy management policies and measures tailored to different geographical regions and building types. Through collaboration and cross-fertilisation, geo-stock and type-stock research can collectively drive the construction industry towards sustainability and efficiency.

For the third research question, the potential strategies for strengthening the robustness of physics-based models and the reliability of the outputs in NDBS studies, challenges in NDBS research primarily revolve around data availability, encompassing data scarcity, quality issues, and model accuracy concerns. Overcoming these challenges involves leveraging non-research datasets, coupling NDBS models with urban systems, and employing techniques like data augmentation and advanced statistical methods for data imputation. Enhancing model accuracy requires calibration efforts and result validation through rigorous methods like Bayesian validation to mitigate uncertainties in the modelling process.

This study provides a new multidimensional approach to evaluate the development of NDBS energy and carbon footprint research and helps to incorporate socio-economic analysis into NDBS physics-based models to improve the efficiency and reliability of such models for future research and practice.

CRediT authorship contribution statement

Jingfeng Zhou: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Pamela Fennell:** Writing – review & editing, Supervision. **Ivan Korolija:** Writing – review & editing, Supervision. **Zigeng Fang:**

Writing – review & editing, Methodology, Conceptualization. **Rui Tang:** Writing – review & editing. **Paul Ruyssevelt:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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