Energy & Buildings 346 (2025) 116157

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Energy flexibility at multi-building scales: A review of the dominant factors and their uncertainties☆

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A R T I C L E I N F O

Keywords:
Energy flexibility
Dominant factors
Uncertainty mitigation
Building-grid interaction
Building energy systems

A B S T R A C T

Energy flexibility from buildings is a key enabler of the flexible energy system required to integrate intermittent renewable energy sources. This systematic literature review investigates the factors influencing energy flexibility from the built environment and the uncertainties associated with its exploitation. It employed a structured methodology using over 140 relevant studies to identify and categorise the sources of uncertainty into aleatory and epistemic sources.

Stochastic elements, like weather and occupant behaviour, introduce aleatory uncertainty which challenges prediction capabilities. This can be managed through probabilistic modelling and adaptive controls. Epistemic uncertainty, driven by incomplete data, lack of knowledge and modelling assumptions, remains a barrier to accurate forecasting. The identified dominant factors were determined iteratively and comprise occupant behaviour, building characteristics, energy systems and controls, and externalities.

A framework was proposed in which uncertainties arising from the dominant factors can be categorised and mitigated for different stakeholders. Uncertainty can propagate through systems and controls, causing poor realisation of building energy flexibility. This can be managed via implementation of robust optimisation methods and real-time (15 min or shorter) data integration. Externalities such as market volatility and complex policy frameworks also pose risks to the economic viability of flexibility services. This review emphasises the need for improved data collection and advanced control as methods to mitigate uncertainty in flexibility quantification. Additionally, it highlights the critical role of diversity in mitigating uncertainty, and the importance of increasing building populations (i.e., 100 or more domestic dwellings) to enable scalable flexibility solutions.

☆ This article is part of a special issue entitled: 'Decarbonising Built Env' published in Energy & Buildings.

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https://doi.org/10.1016/j.enbuild.2025.116157
Received 28 March 2025; Received in revised form 30 June 2025; Accepted 14 July 2025
Available online 15 July 2025

Nomenclature

B2DN	Building-to-Distribution Network
BEMS	Building Energy Management System
BGI	Building Grid Interaction
DER	Distributed Energy Resources
EV	Electrical Vehicle
ESCO	Energy Service Company
GHG	Greenhouse-gas
HVAC	Heating, Ventilation and Air-conditioning
MPC	Model Predictive Control
MW	Megawatt
PV	Solar Photovoltaic
RBC	Rule-Based Control
SSSS	Sub-keyword Synonym Subtopics Searching
TDR	Thermal Demand Response

1. Introduction

1.1. Background

The pursuit of decarbonisation and achieving net-zero targets through widespread renewable energy integration into the energy mix has led to a growing interest in the use of building energy flexibility to balance supply and demand mismatches which pose risks to grid operability and congestion. As defined by [1], a building's energy flexibility is "*its ability to manage its demand and generation according to local climate conditions, user needs and grid requirements*". Considering energy flexibility during the design, development or operation of a building's lifetime provides many benefits, including enabling occupants to contribute to national net-zero targets [2], providing grid management services by reducing the need for expensive and invasive network upgrades [3] and contributing towards peak demand management [4].

Building energy flexibility involves leveraging a variety of technologies and strategies to achieve single, or multiple objectives. To appropriately mitigate risks and maximise energy flexibility potential it is necessary to consider what the dominant factors affecting energy flexibility are. The dominant factors of energy flexibility in this research were determined iteratively and qualitatively defined as "the variables or conditions that most significantly influence a building's ability to provide building energy flexibility". The factors can be classified by the thermophysical characteristics of the building's materials and structure (building characteristics), utilisation and control of building technologies and services (energy systems & controls), the behaviour of occupants within the building and with the services (occupant behaviour), and the impacts of externalities such as weather, building-grid interactions and energy markets. Understanding and addressing these factors is essential for designing effective flexibility strategies and realising the full potential of energy flexibility in the built environment. However, despite the growing interest in energy flexibility, there are significant uncertainties related to these factors that can hinder the exploitable energy flexibility potential of a building – these uncertainties need to be explored.

1.2. Categorising uncertainty for building energy flexibility

Providing a qualitative definition of uncertainty for energy flexibility at multi-building scales, including connecting infrastructure (i.e., power, heating, cooling and gas networks) is important. Prior research considered four sources of uncertainty for building stock energy modelling (Aleatory, Epistemic, heterogeneity and model uncertainty) [5], which, after further development by [6], does not clarify uncertainty sources for energy flexibility in the real world. A more holistic and widely adopted approach by [7], notes that most uncertainties are categorised as **epistemic** if the uncertainty can be reduced by gathering more data or refining models, or as **aleatory** if they cannot be reduced. Therefore, this paper proposes two broad descriptions of uncertainty sources for building energy flexibility – Fig. 1 illustrates the interrelationships between the uncertainty categories:

1. Aleatory uncertainty – (or stochastic uncertainty), stems from inherent variability and randomness in a system or process. For building energy flexibility, aleatory uncertainty is related to unpredictable variations in occupant behaviour, and externalities such as weather conditions and energy prices. These fluctuations are intrinsic to the system and cannot be eliminated, only managed. For instance, daily changes in temperature, sudden shifts in occupancy, and market-driven energy price volatility represent aleatory uncertainty. While these uncertainties cannot be reduced through additional information, methods that incorporate adaptive control systems or probabilistic modelling can help manage and accommodate the inherent variability.
2. Epistemic uncertainty – also known as systematic uncertainty, arises from a lack of knowledge about a system or process. In the context of building energy flexibility, epistemic uncertainty can be attributed to incomplete or imprecise information about building characteristics, occupant behaviour, and system performance. For example, lack of knowledge for the thermal properties of building materials, lack of detail in energy consumption data, or limited time series data on occupant behaviour contribute to epistemic uncertainty. This type of uncertainty can potentially be reduced through improved data collection, more accurate modelling, and a better understanding of the system.

There are additional sources of uncertainty which may be relevant for specific use cases. However, these can be categorised into epistemic sources due to the origins based on lack of knowledge or understanding:

- Heterogeneity – uncertainty resultant from the variation between parameters which have been assigned to the same group/classification/population. For example, buildings assigned to a particular archetype will not exhibit the exact same characteristics.
- Model uncertainty – uncertainty about how to model the true processes of systems due to lack of knowledge, simplification, assumption or omission. An example includes different methods of modelling heat and mass transfer in building energy simulations.

1.3. Previous reviews

To date, most studies have focused on the single-building scale. However, the real-world operation and market execution of energy flexibility programmes are likely to occur at multi-building scales – requiring aggregation of multiple buildings to provide energy network solutions at local (<1Megawatt (MW) [8]), distribution (1–100 Megawatt [8]) and transmission (>100 Megawatt) scales to provide a meaningful service [8]. Understanding how dominant factors and their uncertainties can affect the exploitable energy flexibility of buildings is crucial for optimising energy management strategies in building clusters to deliver energy flexibility. Existing reviews in the field explore several aspects pertaining to the energy flexibility of buildings and are summarised in Table 1.

Further, [19] highlighted the complexities associated with competing interests amongst stakeholder groups which makes it arduous to devise suitable incentives for participation in flexibility services xx. Such stakeholders include homeowners, aggregators, network operators, and energy providers. This review refines this list into four stakeholder groups (non-exhaustive), each broadly representing a distinct part of the energy system.

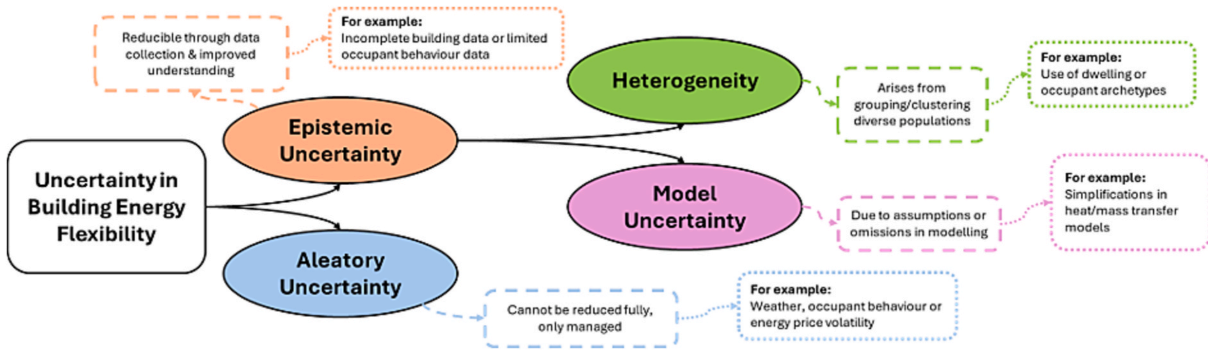

Fig. 1. A hierarchical diagram illustrating the relationship between four sources of uncertainty for building energy flexibility.

Table 1
A summary table of existing review articles detailing their considerations of the focal points of this paper and limitations which this current research addresses.

Reference	Dominant Factors Identified	Stakeholder Risk and/or Mitigation	Sources of Uncertainty or Categorisation	Review Limitations
C. Silva et al. (2022) [9]	Consumer participation and awareness, signal appropriateness, information sharing	System reliability, consumer discomfort – context aware signals can mitigate these	Consumer response levels, appliance interdependence, uninformed consumers, stochastic load profiles	Limited generalisability, assumed "perfect agents" not realistic for contextual signals
A. Kathirgamanathan et al. (2021) [10]	Data-driven MPC, building physics and dynamics, occupant behaviours, weather conditions	Inaccurate controls from poor data inputs and consumer discomfort – mitigated by high quality data and adaptive controls	Epistemic model inaccuracies, aleatory weather variability and occupant behaviour	Limited discussion of scalability and no consideration for non-data-driven methods
J. Le Dréau et al. (2023) [11]	Energy system integration, and occupant diversity/ variability	Risks of coordination failure, system inefficiency, low occupant participation. Mitigation via standardised planning, real-time monitoring, and stakeholder collaboration	Epistemic data gaps in planning stages	Limited practical implementation details and limited focus for stakeholders
H. Li et al. (2023) [12]	Building characteristics and data integration/quality	Misalignment of performance indicators and data inaccessibility across stakeholders	Building performance variability, data incompleteness, poor responses in low-data scenarios	Limited focus on operational aspects of energy flexibility
J. Langevin et al. (2024) [13]	Customer enrolment, participation and behaviours	Low uptake/engagement with services and poor programme design, mitigated by targeted incentives, energy education and user-friendly programme design	Participation unpredictability	Behavioural focus may overlook technical barriers and other factors
H. Li et al. (2021) [14]	Residential building characteristics, energy system controls and occupant behaviour	Disparity between design and realised flexibility potentials, and lack of occupant engagement	Errors in measurement and aleatory behavioural variability	Residential focus limits broader applicability and method diversity may confuse practical use
J. R. Vázquez-Canteli and Z. Nagy (2019) [15]	DR controls and algorithms, modelling techniques	Algorithm failure leading to sub-optimal realised flexibility responses, could be mitigated by reinforcement learning and real-time data integration	Weather/environmental variability	RL complexity limits adoption and dating of the review may miss most recent advances in computation
X. Jin et al. (2020) [16]	Multi-scale flexibility markets and models, stakeholder coordination	Market inefficiencies and low participation from occupants, mitigated by more transparent pricing	Aleatory market dynamics and epistemic modelling assumptions	The theoretical approach lacks practical validation. A limited consideration of consumers and the built environment
M. L. Lu et al. (2024) [17]	Building characteristics and building energy systems	System underperformance, mitigated by uncertainty-aware design	Inter-system performance responding to variable weather conditions	No strong consideration of building characteristics or control algorithms
C. Rae et al. (2020) [18]	Local-scale energy systems	Failure to achieve scalability and poor standardisation of technologies	Aleatory demand variability	Broad scope of the review lacks specificity, alongside a shallow depth of solutions proposed to problems

1. Occupants (including both domestic and non-domestic energy consumers, and billpayers) who wish to reduce energy bills or improve operating carbon emissions;
2. Service providers (including energy companies and aggregators) who aim to enable small-scale demand-side flexibility and support large-scale system operations;
3. System operators (including local or larger grid/system operators and power generators) who seek grid stability and resilience;

A further group of decision makers – (including local or national governments, policy makers and regulators) who wish to achieve fair, balanced and transparent operations for other stakeholders – was also identified. To keep the focus of this review on the operational side of delivering energy flexibility this group is not mentioned in as much detail as other groups.

1.4. *Research aims & objectives*

Existing literature has shown this is an established topic, but current research lacks the necessary links between dominant factors, their uncertainties and mitigation for different stakeholders. The primary aim was, therefore, to identify the dominant factors and uncertainties of energy flexibility in the built environment and subsequently analyse their impacts on varying stakeholder groups. The purpose of this paper is to provide a detailed review of the dominant factors but also highlight how their uncertainties can be categorised and mitigated by stakeholder groups to help achieve energy flexibility at multi-building scales. To do this several research objectives were proposed:

1. Assess the current state-of-the-art research regarding the dominant factors of exploitable energy flexibility.
2. Identify and categorise sources of uncertainty regarding energy flexibility in the built environment, specifically noting the challenges or barriers they create.
3. Provide recommendations for future research and stakeholders, including suggestions for improving uncertainty management for energy flexibility in the built environment (i.e., buildings are their connected energy networks) and addressing the challenges identified in the literature.

In this section an overview of the scope of the research is provided, identifying the issues created due to uncertainty and gaps in knowledge surrounding the dominant factors of energy flexibility in the built environment. Section 2 discusses the novel systematic review methodology employed to explore the state-of-the-art. Section 3 presents results of the review analysis by categorising sources of uncertainty for each dominant factor. In Section 4, a discussion of the dominant factors and sources of uncertainty is provided alongside proposal of a framework to categorise and manage uncertainties for different stakeholders. Section 5 then concludes with a cross-examination between the dominant factors, uncertainties and how they might hinder exploiting energy flexibility.

2. Review methodology and metadata analysis

2.1. Literature review methodology

The dominant factors explored in this research were derived from existing review literature, as per Table 1, which were either mentioned factors impacting building energy flexibility directly or its uncertainty. This study expands these findings by categorising findings across the four dominant factors: occupant behaviour (Section 3.1), building characteristics (Section 3.2), building energy systems and controls (Section 3.3) and, externalities and interactions (Section 3.4).

The Sub-keyword Synonym Subtopics Searching (SSSS) Python package was used to conduct a comprehensive literature review that

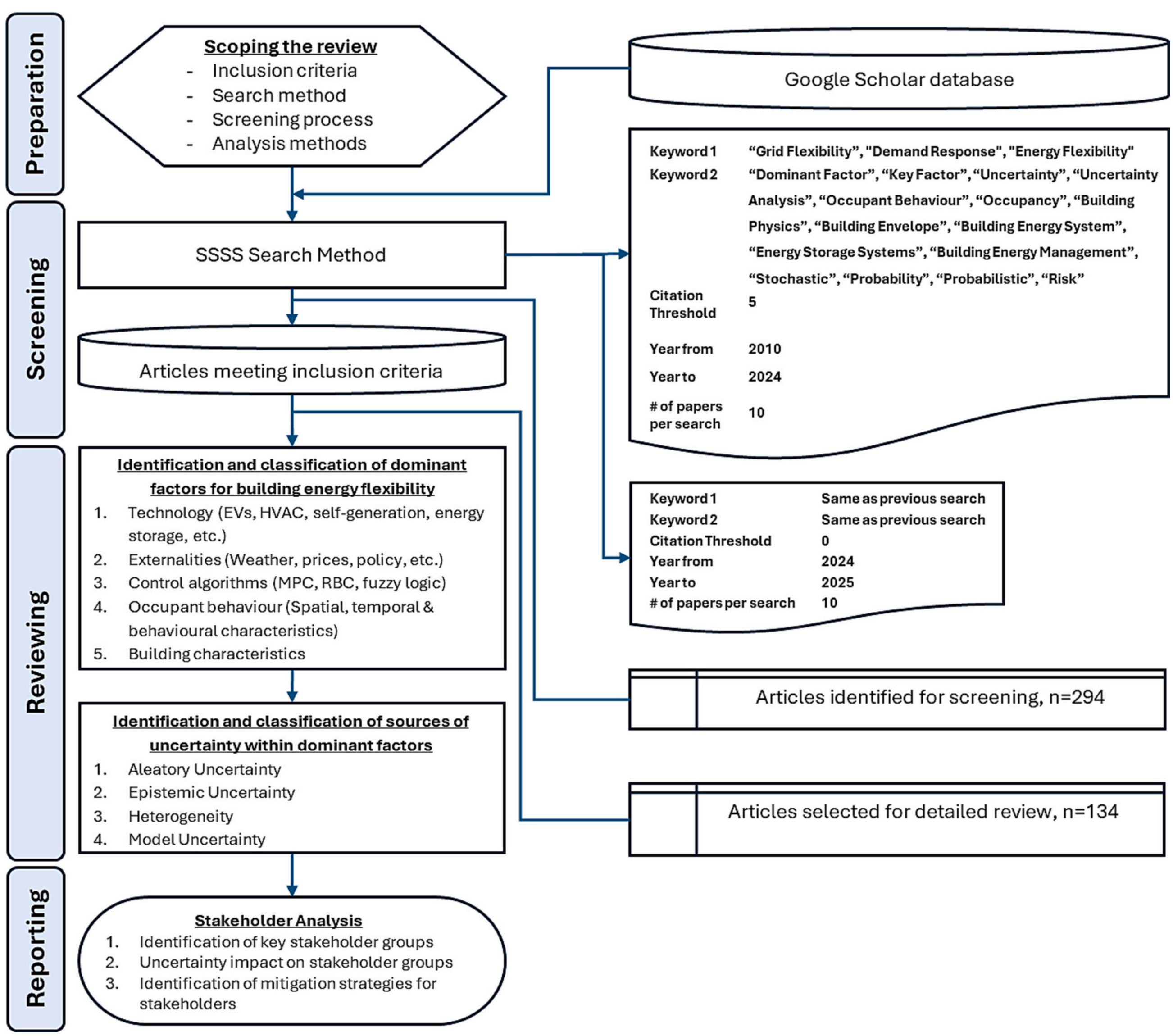

Fig. 2. A flow chart of the review process conducted in this systematic literature review, including input parameters of SSSS for the literature search.

captures the most relevant and important articles. The methodology used follows that of [20]. In this study, the search list consists of two sub-keywords listed in Fig. 2. The first sub-keyword narrows the paper to focus on energy flexibility, whilst the second sub-keyword defines the specific topic; 45 keyword search combinations were used in this paper. Inclusion/exclusion criteria were considered to improve the quality of the papers considered. Firstly, a citation threshold of five was used, then papers were ranked by citation number of which the 10 most cited papers were selected. The use of the SSSS methodology yielded 472 unique papers over two searches which, after a first screening by checking titles to ensure adequate relevance, yielded 294 papers. Following a second screening via abstract review, 121 papers were selected for a detailed review, of which 92 were referenced in this paper. Conference papers that did not undergo a peer-review process were omitted – book chapters were also omitted from the analysis as they do not provide original research.

2.2. Metadata analysis

The reviewed literature metadata is summarised in Fig. 3, illustrating the case-study location, year of study, journal publication and flexibility objective (where possible). The metadata suggest that the geographic location of case studies is heavily biased towards nations where energy flexibility is already noted as a key integrator of future energy system operations.

3. Review results

3.1. Occupant behaviour

This section focuses on 40 papers identified to have relevance to the occupant stakeholder group. The date range of the papers was between 2010 and 2025, which helps base these findings in more modern energy use patterns and behaviours. The research in this area was mainly mixed quantitative–qualitative or quantitative, with many articles based on modelling of flexible assets and occupants. In many of the reviewed studies, occupant modelling was treated as a secondary analysis, rather than the central focus. This trend likely reflects the methodological challenges and data limitations associated with capturing occupant behaviour and the interactions with energy systems in a detailed and realistic manner. In this paper, we define occupant behaviour in three broad dimensions which aligns with other studies in the field, similarly to [21]:

- Spatial occupancy: identification of where occupants/consumers are in (or out of) the building;
- Temporal occupancy: understanding when occupants are in the building and the types of activities and when equipment is used, and;
- Behavioural occupancy: exploring how occupants will interact with the building and energy system

Addressing uncertainties from occupant behaviour requires both probabilistic approaches to handle variability (aleatory) and improved data collection, modelling, and understanding of human behaviour (epistemic). A summary of the uncertainty categorisation for occupant behaviour can be found in Table 2.

Integrating subsystems such as EVs, heat pumps, and self-generation complicates predicting occupant interactions, making real-time energy flexibility management challenging. This is especially the case for scenarios when these systems are not controlled by the same entity. As noted in [22], advanced tracking and predictive technologies are required to adjust energy usage dynamically – such as their use of a robust framework to handle uncertainties due to intermittent renewable energy sources and occupant behaviour in day-ahead energy scheduling

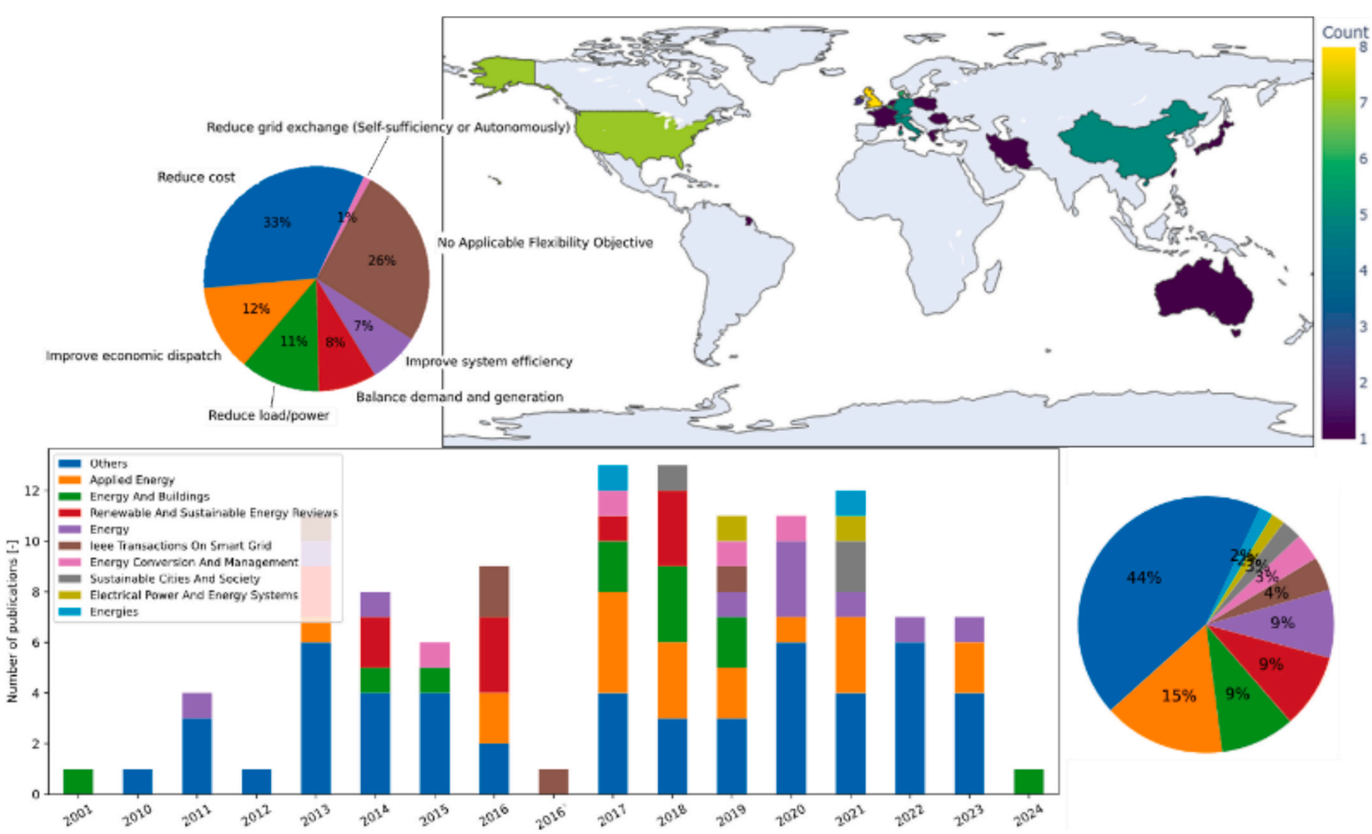

Fig. 3. A series of figures illustrating (clockwise from top left) the flexibility objectives employed by the reviewed studies, the geographical location of studies considering modelled or real-world case-studies, the percentage of articles from varying journals and the number of publications each year by journal source.

Table 2
A table of findings from the review which categorises the main sources of uncertainty for occupant behaviour between aleatory and epistemic uncertainty types.

Aleatory Uncertainty Stems from the inherent randomness of human behaviour.	Epistemic Uncertainty Arises from incomplete knowledge or gaps in data and models.	Reference
Variability in appliance use due to differing schedules and preferences introduces stochastic changes in energy demand.	Limited or incomplete data on how occupants use energy (e.g., spatial, temporal, and behavioural patterns).	[22,23,24]
Intermittent and periodic behaviours (e.g., daily routines, turning devices on/off) cause fluctuations in consumption.	Use of generalised models or assumptions that fail to capture the complexity of human activities.	[23,25–27]
Socio-technical factors, such as external influences and personal preferences (e.g., heating, cooling), add unpredictability.	Lack of understanding of decision-making drivers, such as attitudes toward energy conservation and smart tech.	[24,26,28]
Externalities like weather or dynamic pricing impact behaviour unpredictably.	Limited granularity and quality of data can hinder accurate modelling and prediction of energy demand.	[29,30]
Engagement with energy flexibility services (e.g., time-of-use pricing) varies; some respond to signals, others do not.	Simplifying behaviour into fixed schedules fails to reflect the dynamic and stochastic nature of occupant actions.	[28–31]

for a residential microgrid. However, modelling human-technology interactions incurs high development and computational costs [32]. This unpredictability in occupant-behaviour creates challenges for development of building control strategies, especially for systems that rely on accurate predictions such as MPC. Although MPCs may be trained using real-world data, it is often difficult to initially acquire such data [33] – this is discussed in more detail in Section 3.3.

Behavioural heterogeneity further complicates energy flexibility potential as variations in behaviour due to building type, socio-economic factors (incomes, ownership, lifestyle), technological (type of systems, perceived interaction), and regulatory contexts influence occupant participation [20,21,22]. Occupants' awareness of their energy use is also a significant factor, but many remain unaware of how their routines impact flexibility, limiting engagement with such services [31,34] – without acceptance of occupants and energy service companies (ESCOs), achieving scalable energy flexibility is limited. [27] identifies occupant behaviour as a critical and highly uncertain driver of residential flexibility, where comfort constraints and user adaptability often limit the real-world impact of advanced control strategies. This extends to uncertainty in occupant engagement and service uptake which can pose issues across the value chain, causing risks for aggregators due to lack of participation, and for network operators due to lack of sufficient balancing reserve. Lack of awareness or understanding, can further inhibit engagement with energy flexibility technologies [30], as occupants (domestic or non-domestic) may be reluctant to invest in assets without clear financial incentives or guaranteed returns [9,13].

3.2. Building characteristics

This section focuses on 10 papers, published between 2014 and 2023, which considered the importance of building characteristics to deliver energy flexibility. These nine journal articles and one conference paper, all originate from Europe; they focus primarily on theoretical modelling and simulation studies. A summary of the uncertainty categorisation for building characteristics can be found in Table 3.

As per Table 3, the uncertainty associated with building characteristics is mainly categorised into epistemic sources. The literature presents several challenges with the existence and quantification of

Table 3
A table of findings from the review which categorises the main sources of uncertainty for building characteristics between aleatory and epistemic uncertainty types.

Aleatory Uncertainty Stems from the time-varying thermophysical properties of building materials and surfaces.	Epistemic Uncertainty Arises from incomplete knowledge or gaps in understanding building materials, structures and facades.	Reference
Inherent variability in interactions between weather patterns and built form affecting building thermal performance, including solar gains.	Incomplete knowledge about building characteristics, such as material variability, insulation levels, and thermal capacity.	[28,29,33]
	Simplifications in thermal models that fail to capture real-world conditions.	[35–37]
Dynamic building conditions, including fluctuations in heating or cooling performance due to externalities like weather and solar radiation.	Use of averaged building archetypes or limited monitoring that overlook heterogeneity in building types and thermal performance.	[37]
Sensitivity of thermal energy storage potential due to fluctuations in internal and external ambient conditions.	Poor material-level understanding of interactions between thermal mass, insulation, and other design parameters (e.g., window size, thermal environments).	[31,33,38,39]
	Assumptions about space conditions (e.g., treating internal spaces as empty) that fail to reflect actual building usage.	[32,38]
	Lack of quantitative assessments in studies, with most providing qualitative evaluations of building energy flexibility due to thermophysical interactions.	[38,40]

uncertainty which can be categorised, by lack of detail (i.e., mismatch between theory and real-world – such as the performance gap of buildings), lack of understanding fundamental thermophysical interactions (i.e., underlying building physics of the building materials and components) and other epistemic uncertainties (including heterogeneity due to simplifications). It is important to note that a theoretical "flexibility potential" could be considered using well-established building and product standards as a reference case. In practice the real-world performance of building materials and energy systems produces a significant performance gap [41] – producing further uncertainties for measurements [42].

Predicting the ensuing post-retrofit impacts on changing fabric thermal performance remains a significant challenge due to the diverse range of outcomes buildings can have [43]. Many buildings, particularly older ones, lack the infrastructure to support energy flexibility solutions, and retrofitting to improve insulation or thermal inertia can be both complex and costly [44]. Epistemic uncertainties, at multi-building scales arise due to lack of detailed knowledge of building's thermal inertia and, by extension, its thermal demand response (TDR) capacity. [45,46]. For example, variability in thermal mass across buildings introduces both aleatory and epistemic uncertainties, as demonstrated by [47], where retrofitting impacts vary by building type. Building characteristics such as thermal inertia can also have an impact on how occupant behaviour influences the energy flexibility, e.g., as discussed in Section 3.1, occupant-driven thermostat adjustments can cause unpredictable load profiles. Buildings with high thermal mass minimises the uncertainty of thermostat adjustments from occupants as sharp temperature changes are avoided. As [38] highlights, incomplete understanding of these interactions complicates accurate predictions of energy flexibility potential across different building types and thermal performance capacities.

3.3. Building energy systems & controls

This section focuses on 61 papers published between 2011 and 2024 that investigate how building energy systems contribute to building energy flexibility, and the importance and intricacy of the controls used to manage these systems. Of the 61 papers, 13 were review papers, 11 were conference papers and 35 were journal articles.

Approaches such as stochastic programming, Monte Carlo simulations, and robust optimisation are frequently discussed to improve energy system reliability and operational efficiency. Three main categories describe a building's energy flexibility potential from its systems, comprising generation (i.e., using solar PV, micro-wind or fuel cells to reduce demand strain on, or support supply of energy to local grids), storage (i.e., using electrical batteries or thermal storage to shift energy demand away from peak periods), and conversion (i.e., using heat pumps to convert electrical energy to thermal energy as a means of reducing demand for other energy vectors).[48].

Several of the papers consider the use of intermediate scale systems which connect multiple buildings – shared heat sources or distribution [48,49,50], for example – and has been recognised as a promising pathway to promote energy efficiency [51] through more efficient use of resources, alongside enhancing grid resilience [52] by improving building energy flexibility [53]. By leveraging local generation and storage systems significant peak shifting, load modulation can be achieved at the multi-building scale [48,53] also assess how rising EV penetration and capacity-limit settings influence flexibility benefits by embedding load-forecast uncertainty into scenario analyses. A summary of the uncertainty categorisation for building energy systems and controls can be found in Table 4.

Building energy flexibility assessment is hindered by modelling limitations [38], prediction uncertainty [59], control infrastructure [61], and design complexity [55]. Building digitalisation has driven increased use of optimisation-based control, improving upon traditional rule-based controls (RBC) [66], towards Model Predictive Controls (MPC). Robust MPCs have a higher capability to deal with uncertainties because they optimise for the worst-case outcome within a defined uncertainty, set to handle uncertain parameters such as occupant behaviour, weather variability or other building-grid interaction (BGI) signals [67] (each of which are discussed further in Section 3.4). Incorporating feedback processes, has been shown to enhance experimental flexibility [61,68]. Practical deployment of MPC remains constrained by computational efficiency issues [60,58], while simplified models often neglect critical constraints such as power limits and ramp rates, reducing their effectiveness [69]. Scaling and aggregating energy flexibility requires significant coordination of assets [49], with standardisation and interoperability being essential to achieve seamless energy system coordination. The building-to-distribution-network (B2DN) framework shows promise in overcoming fragmentation by reducing heterogeneity at scale through inter-system connectivity [70].

By improving data collection and sensing technologies it is possible to reduce epistemic uncertainty by incorporating measured data from in-use building operations to enable prediction refinements [71,72]. Mentioned earlier, the use of real-world to train an MPC is one way of reducing uncertainty in predictions, but current technologies for acquiring and processing such data are not established enough [73]. As an uncertainty modelling approach, e.g., polyhedral and box methods to handle variability in RES output, EV charging behaviour, and load demand in [74], a two-stage stochastic probability optimization method that incorporates operational uncertainties in [75] and an interval optimization theory with a soft actor-critic deep reinforcement learning algorithm was introduced in [76] to address uncertainties from renewable generation and demand response.

Table 4
A table of findings from the review which categorises the main sources of uncertainty for building energy systems and controls between aleatory and epistemic uncertainty types.

Aleatory Uncertainty Stems, primarily, from the stochastic externalities and occupant preferences that set boundary conditions which propagate through control sequences and impact the control decisions made for the system.	**Epistemic Uncertainty** Arises from simplifications or lack of understanding of what systems are available, the control methods used and reliance on assumptions about system performance and communication reliability for inter-operation with other systems.	**Reference**
Propagation of stochastic uncertainties from externalities influencing energy system performance (e.g., weather, market prices and other boundary conditions).	Assumptions made during modelling and design stages, such as HVAC efficiency, predicted generation, and energy storage systems. i.e., discrepancies between the model and the actual building performance (performance gap).	[17,54–58]
Fluctuations and errors in forecasts of renewable energy generation, measurement noise, and occupant-driven dynamic load conditions causing grid instability and load imbalances at a multi-building scale.	Inaccurate and lack of empirical data for calibrating control models, leading to reliance on simplified assumptions (i.e., perfect system response or bounded uncertainties). Inaccuracies in data measurements (e.g., voltage, temperature) and converter control discrepancies affecting power injection accuracy.	[51,56–61]
Variability in HVAC operating patterns, such as defrosting cycles in air-source heat pumps, and internal algorithms in system controls. This causes random disturbances in system dynamics and demand fluctuations.	Simplifications in models by ignoring penalties like efficiency losses during partial load operations or defrosting cycles. This necessitates dependence on robust control methods to account for worst-case scenarios, which may limit the granularity of captured uncertainties.	[4,45,59,62,63]
Interaction of renewable generation and stochastic occupant-driven building loads affecting energy storage systems.	Reliance on unvalidated models and assumptions about perfect communication systems or uniform HVAC responsiveness.	[32,62,63]
Long-term variability in renewable energy generation and residential loads (e.g., annual changes in system inputs).	Stochastic models assuming fixed distributions or probabilities, which might not adapt well to dynamic system characteristics over time.	[58,59,61]
	Model simplifications in energy storage integration, such as AC versus DC distribution and uncertain design parameters (e.g., thermal storage capacity).	[48,64,65]
	Simplified probabilistic models and scenario-based optimisation approaches that may not fully represent real-world variability.	[45,60,62]

As discussed in Section 3.2, the co-dependency and propagation of uncertainties between occupant behaviour and control sequences at scale complicates effective evaluation of energy flexibility potentials when actuating/delivering a flexibility action. This uncertainty at the control stage is also affected by intermittent renewable energy sources which introduces risks to grid stability, necessitating robust flexibility control strategies [56,59]. High initial costs, as noted in Section 3.1, can introduce epistemic uncertainty via reduced consumer adoption rates, which necessitates greater data collection to make informed decisions about the costs and benefits at scale [55,77].

3.4. Externalities and interactions

This literature discussing the role of externalities and grid interactions comprises 34 papers published between 2011 and 2024, combining quantitative modelling and simulation studies, as well as qualitative review. This duality highlights the focus on the need to qualitatively explore concepts relating to these externalities but also quantify the effects of BGI through efficient data communication and sharing. This section differentiates itself from the others due to the discussion being focussed on non-building factors (i.e., political, economic, technology uptake, social and societal aspects). A summary of the uncertainty categorisation for externalities can be found in Table 5.

The externalities impacting the effective use of BGI can be considered as economic barriers, regulatory and institutional barriers, or system-specific barriers.

Economic barriers are mostly due to the inconsistency and unreliability of market signal data [32]. This uncertainty further complicates investment decisions in renewable systems due to unpredictability of energy prices in day-ahead and balancing markets [34,60,80]. Variations in customer responses to demand response programs [81] make it challenging for aggregators to optimise energy arbitrage and delivery strategies. The potential lack of consumer engagement with price-based BGI signals and minimal understanding of electricity markets exacerbates these challenges, further hindering effective demand response and energy flexibility services. BGI signals, defined as “a dynamic signal that prompts adjustments in a building’s systems or processes to align with operational goals and external factors such as grid service requirements”, can be used to trigger energy flexibility at scale. The complexity of producing communicable BGI signals causes challenges due to the mismatches between desired and delivered outcomes from uncertainty in the BGI signal.

Current regulatory and institutional barriers create misalignment between market pricing structures and the potential of energy flexibility services due to poor incentives causing poor participation from consumers in demand response programs [79]. [58] highlights that despite technical feasibility, the realisation of flexibility at scale is often hindered by regulatory fragmentation, unclear market incentives, and organisational complexity. This is compounded by the lack of Flexibility Capital, to enable consumers to participate in these services – discussed further in Section 4.3.1. Generating and acquiring high-quality input data for building-level systems requires substantial time and financial investment, adding further complexity to improving the regulatory and institutional landscape [31].

System-specific barriers ensue from coordinating energy flexibility across multiple buildings, assets and networks. Real-time coordination over 15 min or shorter periods necessitates seamless interactions between BEMS, distributed energy resources (DERs), and the grid – processes often disrupted by communication delays and forecasting errors [82,80,81]. The absence of infrastructure to support the aggregation of flexibility across multiple buildings (i.e., smart metering and communication devices that are interoperable with BEMS) create additional challenges and inhibits the scalability of energy flexibility solutions [68]. Furthermore, the lack of standardised protocols for data sharing between buildings and grid operators introduces inefficiencies in real-time energy dispatch and control operations [78].

The first part of this research, completed in this section, aimed to identifying dominant factors and their uncertainties. The next section addresses the second part of the aim by discussing uncertainty management and mitigation strategies for the four stakeholder groups – as categorised in Section 1.2- comprising occupant, service providers, system operators and decision makers.

Table 5
A table of findings from the review which categorises the main sources of uncertainty for externalities between aleatory and epistemic uncertainty types.

Aleatory Uncertainty The inherent randomness due to seemingly uncontrollable factors like weather patterns, energy policy, and variations impacting stakeholders at different scales.	**Epistemic Uncertainty Arises from lack of understanding and limited data on behavioural and socio-technical non-building factors for stakeholders at the single and multi-building scales.**	**Reference**
Impacts and behaviours due to current and future regulation and policy changes.	Economic barriers for multiple stakeholders from inconsistent and unreliable data sources	[18,78,79]
Variability in user participation in demand response programs and response to price incentives.	Errors in demand forecasting due to insufficient real-time data on system-level building-grid interactions and market conditions.	[58,65,72,76]
	Incomplete data on current and future system configurations, and interactions across energy carriers (electrical, gas, thermal networks).	[42,72–74]
	Aggregation challenges of flexibility resources across buildings due to data quality and granularity discrepancies.	[65,74,75]
	Delays in communication systems and inaccuracies in network-level data further amplifying prediction errors.	[31,65]

4. Uncertainty management and mitigation for stakeholders

4.1. Uncertainty propagation and factor interactions

The review highlights that uncertainty arises early on when input parameters are first introduced to a model, or when a baseline assessment is needed for real world implementation. For example, inaccuracies in weather forecasts not only introduce aleatory uncertainty but also produce epistemic uncertainties from MPC-controlled systems [83]. The failure to capture the complexity of real-world dynamics and performance contributes to the flexibility gap [42].

Feedback mechanisms in building controls can propagate errors and uncertainty when initial assumptions or data inputs are flawed. This can happen, for example, when an MPC attempts to mitigate uncertainty by using probabilistic scenarios which, unknowingly, have poorly characterised uncertainty values. This leads to compounding of uncertainty as subsequent decisions are made [61,84]. The interactions between factors can be considered as a multi-layer feedback loop, as per Fig. 4. Here, interactions between the layers are crucial in identifying the sources of uncertainty and their propagation to understand how they can be mitigated.

4.2. Aggregation effects

Aggregation effects are central to realising energy flexibility at scale, particularly for grid-level applications where individual buildings contribute collectively to provide energy flexibility services [85]. The levels of diversity achieved at multi-building scales, by levelling differences across building characteristics, occupant behaviours, and energy systems, plays an important role in reducing uncertainty of energy flexibility at multi-building scales [85]. This review emphasises that as building populations increase, so does the level of diversity – which can help mitigate aleatory uncertainty due to the levelling effects on individual buildings’ energy consumption variability – a similar finding to work by [86]. While differences in levels and distribution of thermal mass, insulation, and energy system configurations across building portfolios can enhances resilience, it also introduces epistemic uncertainty due to simplified assumptions made during aggregation

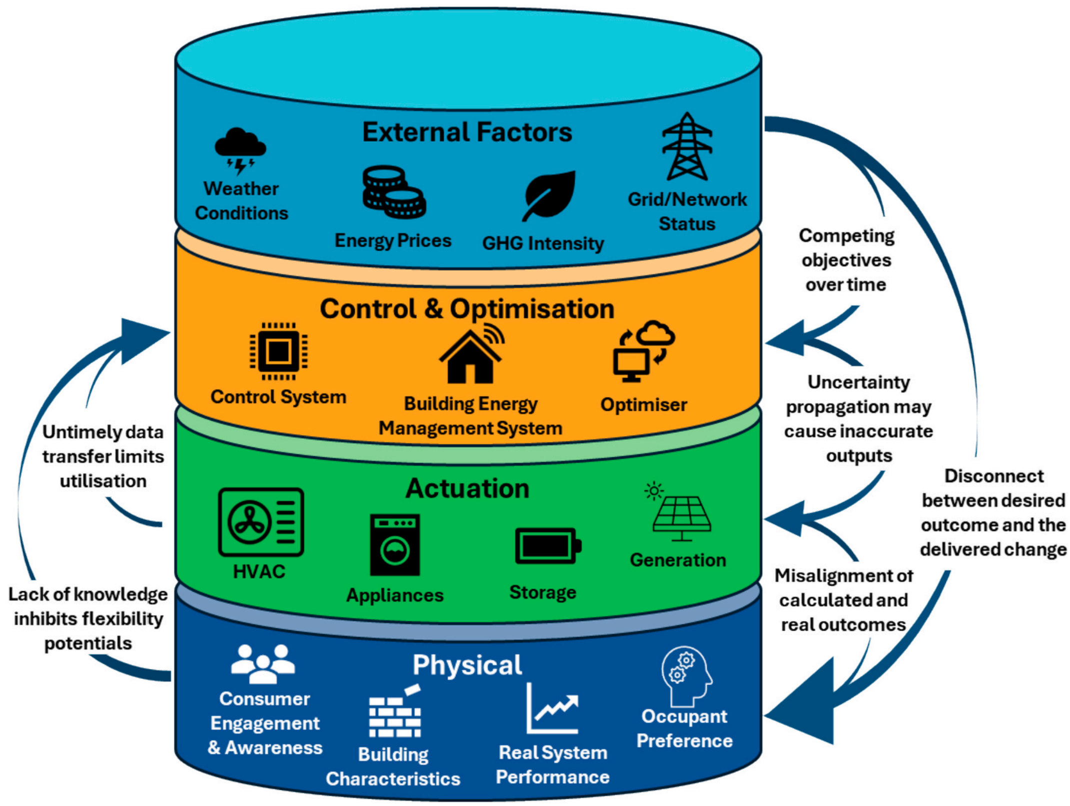

Fig. 4. A physical representation of the interrelationships between a four layered feedback loop, considering the dominant factors of energy flexibility and the propagation of uncertainty between the layers.

modelling [29,30]. This is because using averaged building archetypes can obscure significant differences that influence the overall energy flexibility potential [38]. Temporal differences in single-building energy use caused by varying energy usage patterns also have a similar effect as diversity. This is because varying the time of peak load across a portfolio can create a more predictable and reliable aggregate demand response [34].

As illustrated by [86], population sizes of approximately 100 households could be considered diverse enough to fully represent changes in peak heat demand. These findings were corroborated by other research, as can be seen in Fig. 5 which suggests the uncertainty in average peak demand dramatically decreases between sample sizes of ∼ 10 households up to 100 households. This scale is especially of relevance to aggregators, as they will typically operate at this range of building population. Not enough data were available for a non-domestic comparison, but it may be important to note the increase in demand and less variability that often ensues with non-domestic energy usage [87].

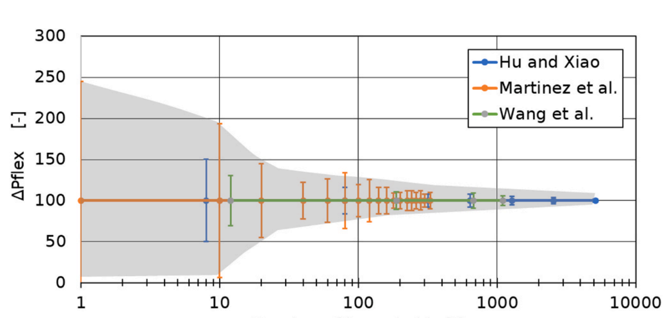

Fig. 5. Variation in average peak load during a flexibility event (dimensionless unit) with increasing number of households (shaded area corresponds to the estimated confidence interval).

When tackling occupant behavioural challenges, it is noted that the benefits in reduction of stochasticity and aleatory uncertainty can only be achieved with larger scales. Working at an aggregate level can be achieved by utilising clustering approaches of populations, for example K-means clustering can be used to group occupant profiles based on similar energy usage patterns [88,89,90]. Clustering can allow for more generalised predictions of behaviour, making it easier to model energy use across large populations of buildings, but at the expense of increased epistemic uncertainty from heterogeneity (reduction in detail variation across the population). Additionally, managing a diverse portfolio of flexible buildings provides a form of redundancy – meaning that flexibility in one part of the portfolio can compensate for limitations in another: reducing the impact of lower-than-expected flexibility at the single building level. To optimise aggregation while managing uncertainty, the following strategies are recommended:

- **Increase diversity across the aggregated portfolio of buildings**: By diversifying the system, occupant and household building typologies, it is possible to mitigate uncertainty in demand profiles at the aggregate level, which are due to uncertainties in dominant factors at the single-building level.
- **Data-driven clustering of archetypes**: Grouping buildings, energy systems or occupants with complementary profiles can enhance diversity while improving predictability in multi-building energy flexibility evaluation. By leveraging machine learning techniques, aggregators can tailor strategies to specific clusters, optimising flexibility outcomes.
- **Infrastructure standardisation**: Developing interoperable systems and communication protocols, such as using open standards [91,92], across buildings and systems can help enable seamless aggregation and reduces variability stemming from inconsistent performance or data exchange across a single building or a portfolio.

- **Incorporation and feedback of real-time data**: Aggregating real-time (15 min or shorter) data from buildings enables dynamic adjustments that optimise the diverse responses of individual components, improving overall reliability for both single- and multi-building scales.

The qualitative assessment of dominant factors and uncertainty makes it difficult to assess the quantifiable impact of different factors on energy flexibility. However, the dominance of factors and impact of uncertainty differs across the scale and resolution of the cluster. Therefore, it is important that metrics are chosen for a given goal (i.e., reduce demand or improve renewable energy utilisation) and uncertainties from different sources can be targeted more effectively for different populations of buildings [93,94]. The impact of these trade-offs between scale, level-of-detail and uncertainty is suggested as an area of further research.

4.3. Framework for identifying and mitigating energy flexibility uncertainties

This section describes the proposed framework in which uncertainties arising from the dominant factors (and other variables) of energy flexibility can be identified and mitigated. Uncertainty remains a critical barrier to effective exploitation of energy flexibility in buildings, therefore a framework which centers around the categorisation of the uncertainty classes as defined in Section 1.2 is proposed. This framework aims to assist stakeholders in systematically identifying sources of uncertainty and applying appropriate mitigation strategies to improve the exploitation of energy flexibility resources.

4.3.1. Step 1: Uncertainty classification

Firstly, one must determine the source of the uncertainty and determine whether it is Aleatory or epistemic based on the definitions introduced in Section 1.2:

- **Aleatory uncertainty** which stems from inherent variability and randomness in a system or process.
- **Epistemic uncertainty** arises from a lack of knowledge or understanding about a system or process.

4.3.2. Step 2: Mapping uncertainty to dominant factors

Under the definition of dominant factors of energy flexibility, Table 7 can be used to link together the dominant factor classification, the type of uncertainty, several sources of uncertainty and potential mitigation strategies.

4.3.3. Step 3: Tiered mitigation strategies

Once the uncertainty sources and relevant dominant factors have been identified, it is possible to apply a tiered mitigation strategy which combines multiple approaches to manage and reduce the uncertainties.

4.3.3.1. Reduction of epistemic uncertainty via improved data collection and use. This involves, for example, making greater use of sensors for real time (<15 min) data acquisition; developing more detailed building stock datasets (such as a building passport which helps track changes to a building over time [95,96]); and better utilisation of data to calibrate models and quantify more realistic energy flexibility potentials.

4.3.3.2. Management of aleatory uncertainty through improving adaptive capability. By utilising probabilistic controls and stochastic programming, aleatory uncertainty can be managed more straightforwardly. Similarly, using worst-case scenario planning can help mitigate the effects of stochastic changes as this provides a buffer for scheduling or dispatch strategies.

4.3.3.3. Increase resilience of aggregated energy flexibility via aggregation. Portfolios of buildings can have diverse buildings, energy system and occupant types across them. By increasing the size of these clusters' heterogeneity can become a strength in balancing outliers or underperformance across the portfolio. Additionally, clustering can be used to help manage diversity and improve the tradeoffs between aleatory and epistemic sources of uncertainty.

4.3.4. Step 4: Mitigation strategy Alignment with stakeholders

At this stage, the mitigation actions can be linked to the relevant stakeholder groups, such as those defined in Section 1.3 – as per Table 6 below.

4.3.5. Practical use of the framework

To support the broader use of this framework a practical, hypothetical, application is outlined below:

Context: An aggregator is planning to deploy a flexibility program across 500 dwellings using smart thermostats and electric heat pumps.

Step 1 – Classify Uncertainty sources:

Aleatory: Variability in occupant comfort preferences and weather conditions; ***Epistemic:*** Limited data on household thermal inertia, accurate thermal performance and participation behaviour.

Step 2 – Map to Dominant Factors:

Occupant behaviour: Randomness in usage patterns (aleatory); ***Building characteristics:*** Thermal performance unknowns (epistemic); ***Energy systems & controls:*** HVAC performance heterogeneity (both); ***Externalities:*** Correct design of BGI signals and efficient data and communication systems.

Step 3 – Apply Mitigation Strategies:

Data-driven reduction: Use of pre-install surveys and in-situ sensors to gather thermal performance data; ***Adaptive monitoring:*** Implement robust MPC accounting for weather and load forecast uncertainty; ***Aggregation:*** Use of clustering to group buildings by usage patterns and flexibility potential and manage population diversity.

Step 4 – Align with Stakeholders:

Occupants: In-home displays and time-based rewards to improve engagement – such as Octopus Energy's "saving sessions" which are run when wholesale energy costs are high [97]; ***Aggregators:*** Predictive analytics dashboards for real-time load shifting; ***Operators:*** Bidding to markets with flexible capacity as firm vs non-firm availability, reducing critical bottlenecks such as market access and inconsistent regulatory frameworks [98].

4.4. Further work & limitations

This review has provided a qualitative assessment of the most dominant factors and uncertainties which impact energy flexibility. Further research should focus on quantifying the impacts of these uncertainties through comparative studies – such as sensitivity analysis – where the ensuing impacts could be compared quantitatively to each

Table 6
A table illustrating how stakeholders can be aligned to the framework by matching their concerns with mitigation strategies to reduce or manage uncertainty.

Stakeholder Group	Primary Concern	Targeted Actions from Framework
Occupants	Participation and comfort	Awareness tools, automation, financial support
Aggregators	Prediction and portfolio control	Clustering, robust forecasting, feedback systems
System Operators	Grid stability and balancing	Multi-scale predictive planning, firm capacity commitment
Decision Makers	Policy and market design and support	Incentive structures, data/communication interoperability standards

Table 7
A Summary table mapping how different dominant factors of energy flexibility produce uncertainties of different categories and suggested mitigation strategies for them.

Dominant Factor	Uncertainty Type	Uncertainty Source	Mitigation Strategy Example
Occupant Behaviour	Aleatory	Stochastic occupant behaviours	Aggregation to improve firmness of demand (or supply) via diversity of sources "Smart" controls which can learn and track changes in behaviours over time
	Epistemic	Limited or inaccurate behavioural data	Clustering to improve accuracy of predictions for those with similar usage patterns or responses
Building Characteristics	Epistemic	Inaccurate building characteristics	Archetype refinement can help minimise heterogeneity from broad clustering techniques
		Unknown building characteristics	Improve baseline understanding of characteristics using retrofit databases or other data collection techniques
Energy Systems & Associated Controls	Epistemic/ Aleatory	Control logic	Robust MPC can improve the management of aleatory uncertainties over a given time horizon
		Appliance availability	Improved sensing and communication protocols can enable better understanding of system status and availability to provide energy flexibility
	Aleatory	Renewable output	Improved understanding of the generating capacity for buildings' self-generation assets
	Epistemic	Model errors	Using data-driven approaches such as digital twins or models based on real data can improve the prediction of energy flexibility
Externalities	Aleatory/ Epistemic	BGI signal volatility (price, grid, emissions etc.)	Designing robust controls and clear BGI signals can help improve the predictability or response for real systems for energy flexibility provision
	Aleatory	Weather conditions	Improved estimation and tracking of weather systems can help improve predictions over hours to days.
	Epistemic	Policy shifts or regulatory uncertainty	Scenario planning can help with long-term strategy around the use of energy flexibility to improve business models

other using a variety of flexibility metrics.

A limitation of the SSSS review process was the ensuing negative bias against more recently published articles (i.e., key papers in 2024/25 may not have received five citations yet) – this was somewhat mitigated by a secondary search focussed on more recent literature. Additionally, limiting the number of articles selected from each keyword search to 10 meant that some keyword combinations were not as representative of the research pool than others. This was somewhat mitigated by papers being ranked by citation number but still does not expose the breadth or depth of the topic fields.

5. Conclusions

Energy flexibility in the built environment will play a critical role in facilitating sustainable energy systems and achieving net-zero goals. This systematic literature review explores the dominant factors influencing energy flexibility and identifies the sources of uncertainty in its exploitation, contextualising established research to shape further research, business, and policy directions.

The study categorises uncertainties into aleatory (randomness and inherent variability) and epistemic (knowledge gaps and simplifications) sources. Both types of uncertainty hinder the widespread development and uptake of building energy flexibility, either in the evaluation of flexibility potential or in the operation of a portfolio. The study identifies the sources and propagation of uncertainty across different dominant factors comprising occupant behaviour, building characteristics, building energy systems and controls, and externalities. Aleatory uncertainty ensues from the stochasticity of weather, energy markets, and human behaviour, and can be managed through probabilistic methods and adaptive controls. Conversely, epistemic uncertainties, arising from incomplete data or understanding of building characteristics and system interactions, require targeted data collection and advanced modelling to enhance prediction accuracy.

This review highlights how uncertainty sources vary by scale; in the aggregate, aleatory uncertainty (e.g., weather or occupant behaviours) can be mitigated by balancing variability and improving resilience through diversity. This can, however, introduce epistemic uncertainty from reduced data or oversimplified aggregate models, such as archetypes masking differences which necessitates refined clustering strategies. The study also mentions uncertainty propagation between interconnected systems. Energy management controls can propagate errors from inputs requiring stochastic optimisation and data input for robust operation. Externalities like market dynamics, poorly designed policies, and inconsistent data standards further complicate scalability and reliability. Several hypotheses were developed which could be the focus of future research from this literature review:

1. The importance of different dominant factors depends on the scale and level of aggregation; occupant behaviour and system dynamics at the single building level, whilst building characteristics and externalities dominate at larger scales due to the challenges of data collection.
2. The impacts of aleatory uncertainty sources are significantly reduced through aggregation, whereas epistemic uncertainty sources become dominant at larger scales.
3. Quick data collection for occupancy will be more important for aggregators, whilst firmer contracted flexibility and weather prediction will be more important for system operators.

This paper contributes to the existing field of knowledge by identifying and categorising the dominant factors of building energy flexibility as identified by state-of-the-art in academic literature. The present research extends beyond the current state-of-the-art by focusing on uncertainty mitigation and the potential of aggregation effects, but suggests that future research focus on addressing the quantifiable aspects of "how dominant are the dominant factors of energy flexibility?"

Further, this work lays an improved foundation for scalable, resilient energy flexibility solutions.

CRediT authorship contribution statement

George Dawes: Visualization, Methodology, Data curation, Writing – original draft, Project administration, Funding acquisition, Conceptualization, Writing – review & editing, Formal analysis. **Tuğçin Kirant-Mitić:** Writing – review & editing, Conceptualization, Writing – original draft, Methodology, Formal analysis, Project administration, Funding acquisition. **Zixin Jiang:** Writing – review & editing, Software, Writing – original draft, Formal analysis, Visualization, Methodology, Conceptualization, Data curation. **Jérôme Le Dréau:** Writing – review & editing, Software, Formal analysis, Visualization, Data curation, Writing – original draft, Methodology, Conceptualization. **Hanmin Cai:** Methodology, Writing – review & editing, Conceptualization, Writing – original draft, Formal analysis. **Jiyuan Cui:** Writing – review & editing, Formal analysis. **Jordan Townsend:** Writing – original draft, Formal analysis, Writing – review & editing. **Adamantios Bampoulas:** Formal analysis, Methodology. **Rongling Li:** Conceptualization, Writing – review & editing. **Rui Amaral Lopes:** Conceptualization, Methodology, Writing – review & editing. **Bing Dong:** Writing – review & editing, Software, Data curation, Methodology.

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.

Acknowledgement

The authors would like to gratefully acknowledge the IEA EBC Annex 82 for providing excellent interdisciplinary collaboration, discourse and the framework to complete this research. The UK contributions to this work were made possible by support from the EPSRC & SFI Centre for Doctoral Training in Energy Resilience and the Built Environment (ERBE CDT) (grant EP/S021671/1). The German contribution to this research was funded by the Living Lab NRW project (contract number EFO 0027). We acknowledge the European Commission for the ARV (grant number 101036723) and SEEDS (grant number 101138211) projects; the Danish Energy Agency for supporting the Danish delegates participating IEA EBC Annex 82 through EUDP (grant No. 64020-2131); Innovation Fund Denmark in relation to SEM4Cities (IFD 0143-0004). The Portuguese contributions were supported by the Portuguese “Fundação para a Ciência e a Tecnologia” (FCT) in the context of the Center of Technology and Systems CTS/UNINOVA/FCT/NOVA, reference UIDB/00066/2020. The Irish contributions were co-funded by the Sustainable Energy Authority of Ireland and the NeXSyS project under the auspices of Science Foundation Ireland (SFI) Grant No.: 21/SPP/3756. The Swiss contributions were co-funded by the European Union’s Horizon Europe (grant No. 101136211) and the Swiss Secretariat for Education, Research, and Innovation (grant No. 23.00601). The US contributions were supported by the U.S. National Science Foundation Grant (No. 1949372). For the purpose of open access, the authors have applied a Creative Commons Attribution (CC BY) 4.0 International licence to any Author Accepted Manuscript version arising.

Data availability

Data will be made available on request.

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