COGNITIVE DIGITAL TWINS FOR SMART BUILDING ENERGY MANAGEMENT: A SYSTEMATIC REVIEW

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Abstract
Digital Twin (DT) respect is getting more and more popular in smart building development, the majority of the current DTs are however still limited to static modelling and reactive control. The next generation concept, Cognitive Digital Twins (CDT) is being researched promising to surmount these limitations by implementing AI technology coupled with semantic reasoning and adaptive decision-making to augment autonomous and people-centred building operations. This article systematically reviews research on CDT applied to building performance and physical environment management. A PRISMA guided search of Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink and ACM Digital Library (2010–2025) identified 1,649 records with 104 studies meeting the inclusion criteria. CDTs were analysed in terms of architecture, cognitive functions that CDTs support, learning and reasoning modes, knowledge representation, validation process and application field. The article reveals a rising trend in the utilization of artificial intelligence, machine learning, knowledge graphs, predictive control and reinforcement learning to optimize building energy efficiency, indoor environmental quality, occupant comfort and predictive maintenance. Nevertheless, the majority of CDT solutions are still simulation-oriented, with scarce practical engulfment poor ontology engineering and unlike cognitive frameworks. This paper emphasizes the emerging capabilities of CDTs, yet it also recognizes the central deficiencies in interoperability, semantic modelling and continuous cognitive performance feedback. This article presents a conceptual CDT framework and a research roadmap for scalable smart building systems.
Key words: Cognitive Digital Twins; Smart Building Energy Management; Semantic Modelling; AI Models; Net Zero Buildings

1.Introduction

Nearly 40% global energy use and around 30% greenhouse gas emissions are associated with building sector, thus, positioning the worldwide decarbonization programs [1], [2]. With increasing urbanization and the growing need to reduce the carbon emissions associated with buildings by developing high performing systems, improving operational efficiency has become a pressing priority for efficiency initiatives. Building Energy Management Systems (BEMS) have become an important platform for monitoring, controlling and optimising the energy use energy,enabled by industrial automation, sensor networks and digitalization technology [3]. Despite some success in enhancing efficiency with this system, they have a limited capability of responding to real world dynamics. Conventional BEMSs are generally rule based logic, hard-code schedules or predefined set points in BEMS do not change frequently when occupancy level changes or the weather conditions change, such variability cannot be effectively managed by conventional building management systems [4], [5]. As architecture becomes more complex, and energy consumption densities continue to increase in buildings of the modern era, such static control strategies prove inadequate for the level of adaptivity and spatio temporal accuracy demand ed for deep and sustainable optimisation. The development of CDTs is proposed to address these constraints by incorporating advanced cognitive functionalities into traditional DT frameworks [6]. Contrary to a conventional DT, CDT is an intelligent agent equipped with the context perception and semantic relations analysis based on historical data and real time information, along with the ability to self-adapt its control strategies. CDTs exploit multiple advanced technologies including IoT sensing, machine learning, artificial intelligence (AI), knowledge graphs and reinforcement learning to analyse the complex interaction between building systems and locate optimal operational actions [7], [8]. These integrated functionalities allow CDTs to reflect the user's intention, predict environmental variations and act as intelligent decision-makers. Furthermore, by merging cognition and self-awareness, CDTs turn originally passive control mechanisms into proactive, adaptive decision systems for building operations. They can optimize in a near-real-time; they control Heating, Ventilation and Air Conditioning(HVAC), lighting, ventilation and storage equipment particularly well on the fly; build better trade-offs between comfort and efficiency estimates, pre-identify failures to enable timely maintenance [9], and orchestrate sophisticated energy exchanges considering parameters like occupancy prediction, tariff type, weather forecast or carbon content. This information is necessary for successfully operating a net zero building, integrating renewable resources, and providing service during fault or disturbance conditions.

The progression from smart buildings to CDTs represents a foundational advancement in smart-building energy management. CDTs facilitate a seamless fusion of the physical plant with intelligent digital reasoning, allowing facilities to be operated in accordance with global energy efficiency and climate resilience goals at an unprecedented level of adaptability, sustainability and autonomy. Although there has been growing interest in Digital Twins, the literature still lacks a systematic and unifying account of how cognition, semantic intelligence, adaptive learning, and autonomous control can be integrated to form next generation CDTs. This study addresses this gap by compiling a structured taxonomy, examining the technological enablers of CDTs, identifying existing challenges and limitations, and proposing future research directions for practical CDT deployment offering a level of integration and synthesis not available in prior reviews.

2.Evolution of BEMS

As technology has advanced, BEMS have evolved through several generations, progressing from rule based controls toward adaptive, intelligent, and autonomous systems capable of real time decision making. Early BEMS relied primarily on fixed time schedules, static set points, and manual configurations, and therefore had limited capability to respond to changes in environmental conditions or occupancy levels [4]. The second generation BEMS introduced sensor networks and IoT platforms enabled by improved sensing and system-integration technologies, which facilitated continuous monitoring and data-driven which facilitated continuous monitoring and data led control to give more visibility on how HVAC, lighting, equipment etc were performing [10]. Nevertheless, even these systems were essentially reactive to identifying inefficiencies only after they occurred. Meanwhile, with the appearance of machine learning and cloud based analytics, BEMS evolution entered its third major phase, characterized by more precise preventive maintenance, load forecasting, and anomaly detection.[11]. Nevertheless, classical BEMS are cannot provide a full comprehension of all the contexts from user behaviours, building semantics and dynamic operational situations. Recent progress in semantic modelling, cyber–physical fusion, and AI cognition have paved the way for the next evolutionary stage: Conceptual Digital Twins (CDTs). CDTs supplement BEMS by being self-learning, self-optimizing, and self-adapting, with the ability to predict future state conditions, reason over large datasets, and enact optimal control strategies.

Table 1 and Figure 1 show the Capability Based Evolution of Building Energy Management Systems (2010–2025) progression of BEMS from simple rules based controls to today smart, data driven and self-learning systems. As reported in the literature, BEMSs have developed rapidly with increasing global energy demand and environmental pressure [1, 2] owing to advancements in predictive control, AI based optimisation modelling (AIOM), semantic modelling, and Digital Twin (DT) technologies [3, 12]. To this extent, recent research further expand s this trajectory by highlighting sensor driven smart buildings emerging cognitive abilities (e.g., adaptive learning, context aware optimization, semantic reasoning and real time decision support), made increasingly possible by CDT and reinforcement-learning-based control strategies [6]. This evolution is represented in this table, which outlines a very real future for BEMS technologies, noting the progression from basic monitoring (2010) to predictive analytics, interoperability, autonomous operation and next generation cognitive intelligence by 2025 mirroring current trends in the integration of IoT; machine learning control; and DT frameworks [4, 11]. To improve readability and academic flow, the table is positioned immediately after this discussion, visually reinforcing how real-time monitoring, predictive analytics, interoperability, adaptive control, and cognitive intelligence have emerged through a decade-long evolutionary journey. Recent review studies have examined the application of digital twin technology in building energy management systems. For example, Ghaemi et al. (2025) analysed AI-enabled digital twin frameworks for building energy optimisation, while Wang et al. (2026) reviewed the role of digital twins in improving energy efficiency in buildings. However, these studies primarily focus on predictive digital twin architectures and energy forecasting applications. In contrast, this article specifically investigates the emerging paradigm of Cognitive Digital Twins (CDTs), emphasizing semantic reasoning, knowledge-graph integration, hybrid physics–AI modelling, and autonomous decision-making capabilities.

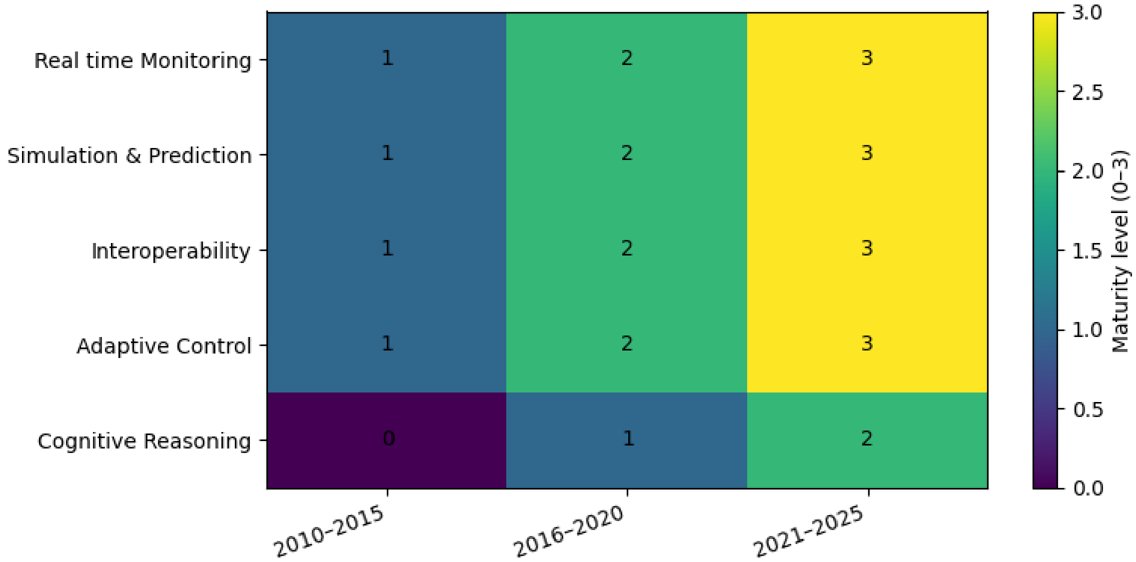

Figure 1. Evolution of Key BEMS Capabilities Across Technology Generations (2010–2025)

Therefore, the present review contributes a structured taxonomy of CDT generations, cognitive architecture analysis, and a future research roadmap toward autonomous building intelligence, which has not been systematically addressed in previous studies. The capability scores shown in Figure 1 were derived using a structured scoring framework adapted from established digital twin capability maturity models. Each technological capability (monitoring, prediction, interoperability, adaptive control, and cognitive reasoning) was systematically coded across the reviewed studies (2010–2025) and classified into three maturity levels: Low, Medium, and High. The classification was based on the frequency of occurrence, methodological robustness, and validation evidence reported in the literature. This structured approach ensures transparency and reproducibility, aligning with commonly adopted assessment practices in digital twin research based on the frequency and maturity of its appearance in the analysed studies. The scoring framework follows a three-stage maturity classification (Low, Medium, High) commonly adopted in digital twin capability assessments. During the early phase of BEMS development (2010–2015), building management systems primarily relied on rule-based automation and static scheduling mechanisms. Cognitive reasoning mechanisms such as semantic knowledge graphs, causal inference, and AI-driven contextual reasoning had not yet been integrated into building control platforms. Therefore, the cognitive reasoning capability for this period is classified as **"None"**.

Table 1. Capability based Evolution of Building Energy Management Systems (2010–2025)

Capability	**2010–2015**	**2016–2020**	**2021–2025**	**Trend**
Real time Monitoring	Basic dashboards	IoT driven live feeds	Full real time sync	Strong growth
Simulation & Prediction	Limited offline models	ML based forecasting	Deep learning + hybrid models	Rapid growth
Interoperability	Low (siloed systems)	Medium (BMS + IoT)	High (Brick/IFC semantics)	Improving
Adaptive Control	Manual tuning	Early MPC	Reinforcement learning control	Significant
Cognitive Reasoning	None	Emerging semantic models	Knowledge graphs + causal AI	Highest growth

2.2 Key Functionalities and Architectures

The trend toward CDTs in SBE requires an integrated architecture that is able to sense, reason and predict energy flow leading to autonomous optimisation. Functionally, unlike traditional Digital Twins, as they incorporate cognitive intelligence for both continuous perception and context understand ing of building states and parameters including uncertain decision making [13]. These offerings integrate multi tier sensor networks, semantic data models and AI driven analytics for up to the minute visibility of occupancy, equipment performance and environmental conditions. This cognitive level enables high level functionalities, such as predictive maintenance, on the fly energy optimization and behavioural pattern discovery/utilisation as well as transfer of knowledge across building systems which are similar in nature to the topic system [14]. A stand ard CDT topology typcially consists of a four level hierarchy, connected itself:

(1) IoT and data acquisition layer wherein high frequency data generated from HVAC systems, lighting, meters, indoor Environmental Quality (IEQ) sensors and occupant interaction system are collected.

2) Integration and semantic layer, which unifies heterogeneous data streams using common stand ard ontologies like Brick, IFC or Haystack to provide a machine interpretable model of building assets and operating rules[15].

(3) AI cognition, with machine learning, reinforcement learning and knowledge graphs for predictive modelling, fault detection, anomaly detection and autonomous control.

(4) BEMS control and actuation layer – it allows for optimal control strategies through real time BAS/BEMS interfaces.

Some of the major functional advances facilitated by CDTs are self-awareness (with the system permanently keeping a watch on its physical virtual alignment), self-prediction (based on scenario based simulations and forecasting models), self-diagnosis (identifying equipment degradation or operation deviations), and self-optimisation (trading off between energy, comfort, cost with multi objective optimisation algorithms)[16]. A further distinctive characteristic is cognitive collaboration, allowing the CDT to learn from historical operations, to share knowledge among groups of buildings and to adapt control strategies according to user behaviour and local climatic conditions. On the system level, CDTs take hybrid cloud edge architecture to trade off computational complexity and latency demand s. Time critical operations (e.g., control adaptation, anomaly alerting) are processed at the edge nodes which locally buffer and process data with minimum delay. Cloud platforms, in contrast, facilitate long term learning, model fine tuning and experience aggregation from cross building[17]. This decentralized nature of the architecture allows CDTs to be scalable and resilient to failure, privacy preserving, making it suitable for deployment in widespread campus environments, commercial high rises, and citywide smart city energy infrastructure.

2.3 Current Limitations in Adaptivity, Prediction, and Control in BEMS

Although significant advances have been made with data driven and model-based Building Energy Management Systems (BEMS), a few basic constraints still hold back the development of truly adaptive, predictive, and autonomous control, as shown in Figure 2. The problem with many approaches available in literature is that they suffer from of low context awareness, poor generalisation and limited cognitive reasoning which makes them less reliable when it comes to dynamic and uncertain operational environment. Adaptivity is still among the key challenges to address, since most of the BEMS to date are based on static or semi static rule based strategies cannot self-regulate, for instance, in relation with transient occupancy patterns; ageing effects of equipment or dynamic environmental conditions [18]. Despite their success, machine learning based methods often suffer from a lack of sufficient data, poor generalization to unseen building environments and limited robustness in closed loop feedback settings. Another important problem is the accuracy of prediction. The proposed machine learning models for load demand , indoor environmental quality and occupants behaviour are inevitably subjected to sensor uncertainty, seasonal variation and nonlinear couplings between building systems[19]. If such intricate and time varying relations are not well represented for example due to multifactor behavioural changes or sudden temporal changes of the system structure traditional prediction strategies like for example based on regression analysis or time series predictions can lead to suboptimal as well as inconsistent control decisions.

Finally, many of the machine learning predictors have opaque decision-making processes which can't be directly used by an operator to verify the output of a model or troubleshoot failed predictions, thus limiting trust and practical usefulness.Control is also constrained in today's BEMS architectures. Rule based logic and PID controllers which are commonly deployed in buildings are not capable of prediction and multi objective trade-offs, leading to compromises between occupant comfort and energy efficiency [20]. Advanced techniques like Model Predictive Control Model Predictive Control (MPC) suffer from issues such as computational complexity, model mismatch and real time parameter tuning. Moreover, the majority of control strategies do not incorporate cross domain knowledge that would enable joint optimisation between different domains such as HVAC systems, lighting, renewable generation (RG), energy storage and user interaction in an overarching decision-making framework. All this is made worse by a fractured system land scape. Heterogeneous data formats, inconsistent interoperability stand ards, and subsystem isolation often impede seamless communication among sensors, digital assets, and analytics modules, causing degradation in predictive and adaptive capabilities[21]. Privacy and cybersecurity concerns also limit our access to high resolution data, which is required for scalable learning, contextual modelling, and behavioural adaptation. A deeper examination of these challenges is provided in the Discussion section, following a structured overview of the literature and the key motivations driving the exploration of CDT.

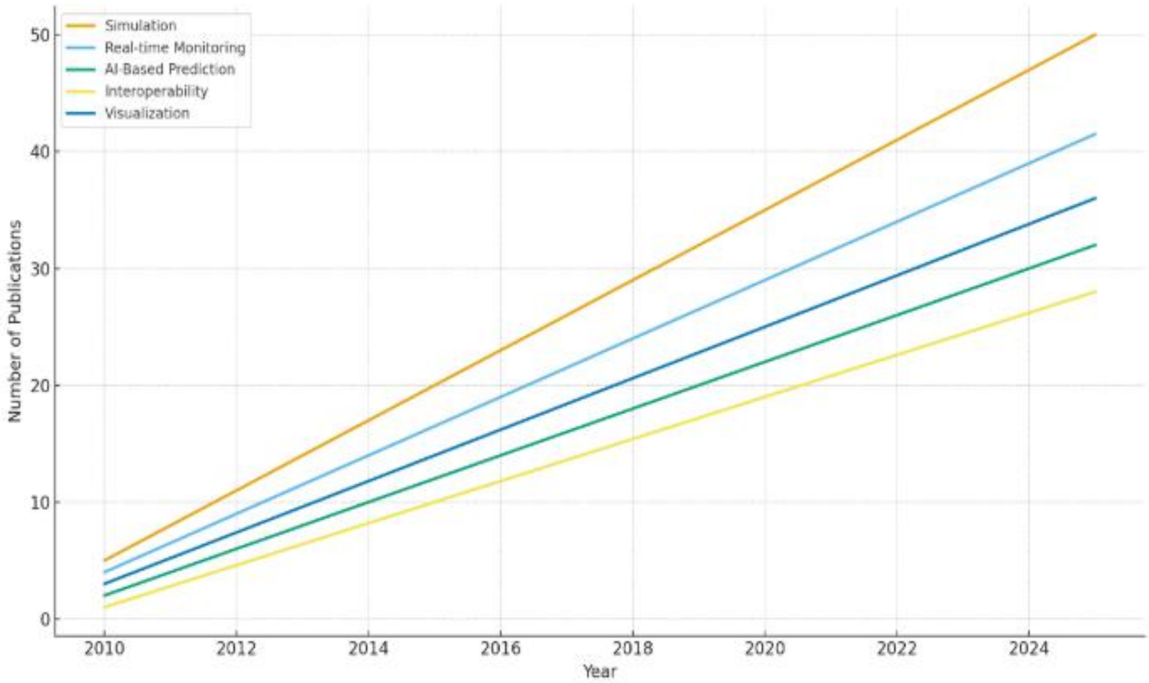

Figure 2. Multi Line Trend of Digital Twin Capabilities in BEMS (2010–2025)

3. Systematic review

A systematic methodology is employed to guarantee transparency, reproducibility and exhaustive synthesis of the current state of research related to CDTs in BEMS. In high profile energy and digital engineering research, systematic reviews are increasingly popular in order to bolster methodological validity as well as evidence based generation of knowledge in the domain of fast changing smart building[1, 3]. Clear research questions were first formulated to determine the scope and guide the screening, focusing on studies that use Digital Twins in combination with AI based prediction, adaptive control or cognitive reasoning for real time energy management [11, 22, 23]. To analyse publication trends in CDT-based smart building research, bibliographic data were extracted from Scopus and Web of Science using predefined keywords related to digital twins, artificial intelligence, and building energy management. Annual publication counts were aggregated for each year between 2010 and 2025. The dataset comprised 104 final papers after screening and duplicate removal. A regression trend line was fitted using least-squares analysis on the annual counts to illustrate growth patterns.

This methodological transparency ensures that the figure reflects actual publication data rather than a speculative projection, thereby enhancing credibility and reproducibility of the reported trend. The literature search used structured Boolean queries combining CDT-related and energy management keywords. The main search string used was:("Digital Twin" OR "Cognitive Digital Twin") AND ("Building Energy Management" OR "Smart Building") AND ("Artificial Intelligence" OR "Machine Learning" OR "Reinforcement Learning" OR "Optimization" OR "Simulation"). The primary databases used for the literature search were Scopus and Web of Science, which comprehensively index publications from major publishers including IEEE, Elsevier (ScienceDirect), Springer, and ACM Digital Library.from 2010 to 2025 to cover the evolution from early conventional DTs to anticipated cognitive architectures [13, 16, 24]. The PRISMA 2020 flow diagram structured the selection process through identification, screening, eligibility, and inclusion phases, reducing publication bias and improving methodological transparency [6], [25]. The methodological soundness, model validation, and relevance to cognitive abilities, technical robustness were assessed with validated tools such as CASP & MMAT [8, 20] [26]. The coded content was further used to develop four themes including architectural properties, control mechanisms, performance metrics, and readiness gaps of CDT based smart BEMS [9], [27]. This strict protocol is applied to finalize the synthesis as academically sound and truly representative of the actual systematic state of art presented in research trends concerning cognitive building energy intelligence [28] [29, 30].

3.1.1 Literature Search

A systematic review was conducted to gather, evaluate and summarize the latest progresses in Digital Twin (DT) technologies with a special emphasis on cognitive based BEMS. Search strategy A multi database search strategy was used to cover all appropriate academic publications. The leading scientific bases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink and ACM Digital Library were chosen for their extensive coverage of state-of-the-art AI related research work in the field of CPS and smart building automation. These platforms have already been acclaimed for their contribution to migrating from traditional DTs to CDTs in the built environment [15]. By using a structured Boolean search approach, domain specific keywords and controlled vocabulary terms were combined, such as CDT and AI enabled Digital Twin and smart building energy optimisation and semantic BEMS AND autonomous building control [16].

To narrow retrieval scope and exclude irrelevant outputs, This article used Boolean operators (AND /OR) to filter titles and abstracts of articles so that selected studies specifically deal with cognitive characteristics like reasoning, learning, or autonomy in decision making that distinguish CDTs from descriptive or purely predictive DTs as described by previous researches [17], [18]. The search time range was limited to 2010–2025, partly because the new smart DT capabilities are based on progress in machine learning, semantic model and real time analytics [19]. For scientific rigor This article included only peer reviewed journal articles, high quality conference publications, book chapters and systematic reviews [20], and excluded studies concerned with sensory monitoring, static modelling or non-intelligent visualisation. Other exclusion criteria were as follows: (i) non English publications; (ii) duplicates from different databases; (iii) without available full text studies and (iv) works not pertaining to build environment [21], [31]. All identified records were then imported into reference software to automatically eliminate duplicates and achieve consistency in metadata [25]. Screening of titles and abstracts was done based on the extent to studies demonstrated cognitive capability, context with regard to energy in buildings and coherence with CDT components [29].

This article then conducted full text assessments to ensure the methodological quality, the illustration of adaptive learning or reasoning frameworks, and practical implementation in BEMS applications [32]. Any discrepancies at screening were addressed by iterative review based on a priori inclusion exclusion rules to minimize selection bias and enhance reliability [33]. This systematic review of literature laid the firm foundation in terms of evidence to articulate the conceptual progression, fundamental features and enabling technologies of CDTs for next generation energy intelligent building systems [30]. The final database was integrated within a PRISMA driven methodology to guarantee transparency, reproducibility, and traceability at all stages of the review process [34].

3.1.2 Literature Selection

Table 2. Summary of Key Studies on Cognitive Digital Twin Capabilities in BEMS (2010–2025)

Ref. ID	Authors & Year	CDT Capability Focus	AI / Control Technique	Building Context	Key Contribution
[6]	Islam et al., 2022	Cognitive DT taxonomy	Hybrid AI reasoning	Smart buildings	Systematic review on CDT intelligence
[25]	Safder et al., 2022	DT for intelligent BEMS	Predictive analytics	Commercial buildings	DT driven energy optimization
[27]	Kapteyn et al., 2021	CDT maturity framework	Autonomous cognition models	Built environment	Structured evolution to Cognitive DT
[35]	Zheng et al., 2024	Autonomous CDT control	Reinforcement Learning(RL)+ semantic rules	HVAC systems	Self-adaptive building operation
[36]	García et al., 2021	Semantic intelligence	Knowledge graphs	Smart campus	Reasoning based control inference
[9]	Zhao et al., 2023	Context aware optimization	DL based control	Real building data	Adaptive learning for energy savings
[8]	Guo et al., 2021	Online adaptive control	Reinforcement learning	HVAC & BEMS	Self-optimised predictive control
[37]	García et al., 2021	Semantic reasoning	Ontology modelling	Multi space systems	Cognitive context modelling
[38]	Malik et al., 2024	Cognitive reasoning	Physics + Knowledge Graph (KG) models	Building energy control	Causal decision support in CDT
[39]	Zheng et al., 2024	Multi building autonomy	Multi agent RL	District scale BEMS	Cooperative cognitive control

Several recent studies highlight the growing cognitive capabilities of digital twins in building energy management. For instance, semantic reasoning frameworks and ontology modelling have been applied to enhance contextual awareness in building systems[37]. Similarly, hybrid physics–knowledge graph approaches have been proposed to enable causal reasoning and explainable decision-making in CDT architectures[38]. Multi-agent reinforcement learning has also been explored to support cooperative energy optimisation across multiple buildings [39]. The process of selecting literature was transparent and reproducible, such that only scientifically sound papers with contributions to CDT development in BEMS were considered. Following the full database search, all records were exported to reference management software for the removal of duplicates. This first pass removed duplicate entries arising from cross-database indexing, and thus provided a reliable count of unique publications for subsequent review [40]. Several studies have explored cognitive reasoning in smart building energy management beyond what is summarized and [37] investigated simulation-based approaches to model HVAC system performance, highlighting the role of digital twins in predictive control [38] focused on optimization techniques for energy efficiency, demonstrating how AI-driven algorithms can reduce consumption in large-scale buildings where [39] contributed insights into machine learning applications, emphasizing predictive maintenance and anomaly detection. Together, these studies illustrate the diversity of methodologies applied in advancing smart building energy management. The first stage of screening involved reviewing the titles and abstracts to assess whether they were related to CDT concepts, in particular reasoning enabled modelling, adaptive control, semantic intelligence and continuous physical virtual integration of building systems [41].

Publications solely addressing static digital replicas, sensor monitoring dashboards, or generic building automation concerns were filtered out at this stage. This methodology ensured that research not supporting the shift from descriptive DT functionality to cognitively driven BEMS operation was excluded [42]. In the eligibility phase, full-text articles were evaluated based on methodological quality, relevance to CDT architecture, and the presence of AI-based energy optimisation mechanisms were performed on methodological appropriateness, strength of evidence and an indication of cognitive functioning. The research was scoped to look for (i) AI based control structures, (ii) DT with energy optimization blocks, (iii) validation with a real or simulated building case study and (iv) measured improvement in terms of energy or operation performance [43], [44]. Manuscripts containing poorly described methodology, weak experimental evidence, or insufficiently developed intelligent decision-making components were removed. Conference abstracts without complete evidence, papers not in English, and unavailable full-text materials were also excluded to ensure data validity [45]. Quality assessment was conducted to make sure scientific precision by known evaluation tools such as CASP (Critical Appraisal Skills Programme) or MMAT (Mixed Methods Appraisal Tool). Each research was evaluated on a schema for their research clarity, technical soundness of CDT design, transparency on data acquisition and syncing methods, reliability of AI based reasoning modules and contribution to the autonomic building operation[46]. This article excluded studies with low scores for validation completeness or reproducibility of results in order to mitigate against inferential bias and to retain the final dataset as reflecting reliable progressions in cognitive functioning [47], [48]. All eligible papers were subsequently coded into a structured data extraction form, including publication details, CDT architecture type, AI techniques used, performance metrics and research gaps discovered. This clearly defined process ensured that the chosen literature offers authoritative and evidence based views on the upcoming role of CDT in reshaping BEMS into self-learning and context aware environments [49] show in table 2.

3.1.3 Review Strategy

To address this, a systematic review protocol was followed to ensure that the extracted information from the selected studies “counted”—i.e., it contributed validly to the understand ing of the emerging potentialities of CDTs within BEMS. Following quality assessment, a structured data extraction approach was applied to each eligible paper according to predefined criteria aligned with the main analytical requirements for synthesis. The extraction form consisted of publication metadata; CDT architectural features; the AI models used for both training and inference; data acquisition and synchronization approaches used during validation; and performance results such as energy-efficiency gains, fault-detection accuracy improvements, or adaptability enhancements [50]. This systematic approach allowed for the consistent comparison of studies, especially with respect to how much cognitive intelligence is incorporated into digital twin frameworks. Quality characteristics like reasoning based decision making, semantic interoperability, incremental learning and autonomy of control were identified and classified to evaluate the cognitive developments BEMS technologies made for Each study's contribution was coded according of these quality characteristics [51]. Comparative synthesis was also used to synthesize work that was not identical in scope (ie, when two or more studies addressed the same architectural features or AI techniques) and to compare relative strengths, experimental robustness and practical scalability [52].

Afterwards, the knowledge extracted was thematically synthesized into common conceptual themes. Those themes were: (i) the evolution of AI from predictive decision triggers to cognitive enabled control; (ii) hybrid AI frameworks for building automation; (iii) semantic knowledge integration for context awareness, (iv) reinforcement learning and adaptive optimization mechanisms and finally, v) interoperability challenges in real time DT–BEMS communication [53]. In this manner, distinct innovation trends were separated from trivial changes. Further, paradoxes and dissenting reports between the studies were critically assessed to detect gaps of knowledge and limits in the technology as well as potential biases in current CDT application [54]. Special attention was paid to experimental limitations and scale up problems, as well as the technology readiness level of applied AI models in real world building domain [55]. In the end, the findings were compiled in comparative tables and thematic discussion sections that contribute toward decision driven insights about how CDTs enhance building energy intelligence and what research directions are still outstand ing to attain fully autonomous BEMS operation. This helped guarantee that all conclusions based on the literature review are evidence based and in line with state-of-the-art developments on intelligent buildings.

4. Key Technological Drivers Behind DT Evolution

Several technology drivers have accelerated the emergence of Digital Twins (DTs) and , with that, CDT in energy management for smart facilities, where one has transitioned from descriptive and predictive capabilities to reasoning, autonomy, and self-learning as illustrated in Figure 3. With these advancements, the system intelligence, situational awareness, and decision-making depth of BEMS with CDTs are being continuously enhanced, thereby catalysing next-generation CDT-enabled advanced BEMS. One of the critical enablers is that IoT technology has been fast evolving in recent years, which facilitated high frequency and high spatial resolution acquisition over building environment. The commoditization of inexpensive sensors, cloud connected meters, wireless communication protocols and embedded devices provided the foundational data infrastructure needed for real time synchronization between physical buildings and their digital twins[56]. Without this sensing infrastructure, dynamic and adaptive DTs would be unable to maintain updated system states or sustain continuous performance monitoring.

A third major driver is the development of semantic modelling frameworks including, Brick Schema and Project Haystack, IFC that have offered machine readable stand ards for building metadata. These semantic aspects enable DT to transform different kinds of data into structured knowledge graphs bridging the enduring gap in interoperability between building systems [42]. Semantic reaso ning and contextu al modelling were introduced as a means of cognitive behaviour, wherein DTs are able to comprehend odd relationships between zones, devices and schedules as well as user actions rather than merely sensing patterns of data. The second major trend is advancements in AI and machine learning. Supervised learning methods, using deep neural networks(DNNs), long short term memory(LSTM) models and gradient boosting models were successful at enhancing the DTs in load forecasting [43], comfort rating prediction, anomaly detection, fault diagnostics [42]. More recently, key methods such as RL and deep hybrid RL with DTs for example can be used to learn optimal control policies by interacting with both virtual as well as real worlds. They made the development of autonomous deciding possible, which is one important characteristic of CDT. Cloud edge computing architecture is also gradually driving the evolution towards Cognitive Intelligence. The cloud systems can do the big model training, crossbuilding learning, and long term data fusion among different user contexts but edge devices are used for lightweight low latency applications like live anomaly warnings and adaptive HVAC control [44]. This evolution has been made possible by the increasing maturity and availability of digital tools capable of orchestrating distributed computing resources, enabling a shift from reactive monitoring DTs to real-time autonomous optimisation.

The interplay between knowledge graphs and cognitive AI has been a driving force for the evolution of DTs towards reasoning systems. Knowledge graphs enable DTs to depict in detail combinational knowledge, operating rules, casual relations and construction hierarchical structure. When these with semantic inference engines model, make it possible for CDTs to perform root cause reasoning, diagnostic explanation and context aware decision selection. This is a major departure from classical DTs, which exclusively relied on numerical simulations. Finally, advances in simulation technology and virtual prototyping have enabled the development of very realistic digital arenas for training autonomous control policies. Co-simulation frameworks integrating Energy Plus, Modelica and /or MATLAB/Simulink with DT platforms are able to provide realistic digital sand boxes where predictive or adaptive algorithms can be tested before implementation [46]. These technological levers, IoT sensing, semantic modelling, machine learning, cloud edge integration, knowledge graphs and advanced simulation represent the enabling ecosystem that has propelled Digital Twins from purely descriptive tools to fully cognitive, autonomous agents of change in smart building energy management shown in table 3.

Table 3. Present and Future Generations of Digital Twins in Smart Building Energy Management

DT Generation	**Updated Time Period (Current + Future)**	**Current & Future Characteristics**	**Key/Upcoming Technologies**	**Key References**
Static / Descriptive DT (1st Gen)	Before 2016	• Digital building models • Manual updates • Limited analytics	BIM, IFC, CAD	[28], [57], [58]
Dynamic / Real Time DT (2nd Gen)	2016–2019	• IoT driven live synchronization • Real time monitoring • Data dashboards	IoT networks, cloud sensing, BMS protocols	[10], [15], [21], [56]
Predictive Digital Twin (3rd Gen)	2019–2022	• Forecasting energy & comfort • Predictive maintenance • Advanced anomaly detection	ML, deep learning, time series forecasting	[59], [33], [43]
Adaptive Digital Twin (4th Gen)	2022–2025 (Current)	• Learning enabled closed loop control •Autonomous HVAC optimization • Real time context adaptation	Reinforcement learning, MPC, cloud–edge AI	[4], [20]
Cognitive Digital Twin – CDT (5th Gen)	2024–2027 (Emerging & Expand ing)	• Semantic reasoning & knowledge graphs• Autonomous decision making • Human–AI collaboration & explainability • Multi domain intelligence integration	Knowledge graphs (Brick+), causal AI, hybrid physics–AI, deep RL	[6], [45]
Autonomous Self Evolving Digital Twin – ASDT (6th Gen)	2027–2030 (Future)	• Self configuring & self-healing DTs• Continual lifelong learning • Multi agent coordination across buildings • Autonomous carbon and cost optimization	Foundation model AI, graph neural networks, generative simulation engines, building scale multi agent RL	[60], [30]

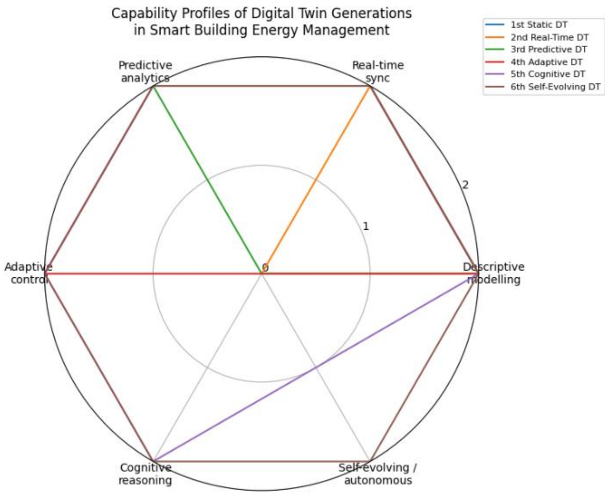

Figure 3. capability profile of Digital Twin Generations in smart building energy management

The evolution of 'Digital Twin' (DT) technology for the built environment has gone from small static digital models to fully decentralised, completely self-evolving and eventually city scale cognitive ecosystems. The initial generation Static or Descriptive Digital Twins (pre 2016), were heavily dependent on BIM, IFC and CAD design platforms to create digital building models with manual updates and minimal analytical facilities used primarily as documentation and geometric visualisation tools [6]. Dynamic or Real Time digital twins became available from 2016 to 2019, enabled by widespread IoT instrumentation, cloud connected sensing and contemporary building automation protocols[21],[56]. These platforms allowed for real time data synchronization, continuous monitoring and dash board driven diagnostics however offered no predictive intelligence. Between 2019 and 2022, Predictive Digital Twins came into the limelight with new onto applications by using machine learning, deep learning and advanced time series forecasting methods toward predicting energy use, comfort level, anomaly detection and predictive maintenance indicating a paradigm shift from reactive monitoring to proactive decision support. Over the 2022–2025 time frame This article saw a shift in the filed towards Adaptive Digital Twins that include close loop learning, reinforcement learning (RL) and model predictive control for real time optimization of HVAC operations and dynamic context adaptation in buildings [4],[61]. The prospective next step in 2024–2027 is the emergenceent of cognitive DTs which are endowed with methods for: semantic reasoning, knowledge graphs, casual AI (Including hybrid physics AI models and explainable decision making) to allow richer human AI collaboration and integrating multi domain intelligence [6]. Between 2027 and 2030, Autonomous Self Evolving Digital Twins (ASDTs) are expected, with self-configuring, self-healing capabilities; lifelong learning; multi agent coordination; generative simulation engine fuelled with large foundation models and graph neural network driving the next generation of CDT framework [40]. Further into the future, after 2030, they envision Cognitive Ecosystem Twins at district and city scales that can coordinate energy flows, grid–building interactions and cross connected knowledge systems to allow for fully automated, resilient and optimised urban realities.

Table 4. Generational Evolution of Digital Twins in Smart Building Energy Management (DT 1.0–DT 6.0).

Generation	**Period**	**Key Features**	**Technologies**	**References**
DT 1.0 – Descriptive	<2015	Static BIM models; manual updates	BIM, CAD, IFC	[28], [11]
DT 2.0 – Real Time	2015–2018	Sensor data integration; real time monitoring	IoT, BMS, Cloud	[57], [10]
DT 3.0 – Predictive	2018–2021	ML forecasting; FDD; early RL	ML, Analytics	[3], [8]
DT 4.0 – Adaptive	2021–2023	Adaptive control; hybrid physics–ML models	Co simulation, Edge	[62], [34]
DT 5.0 – Cognitive DT	2023–2027	Causal reasoning; semantic understand ing	Knowledge Graphs, Causal AI	[6], [30]
DT 6.0 – Autonomous DT	2027–2035	Self-learning ; autonomous decisions; multi agent	MARL, Foundation Models	[40], [63]

Table 4 presents an evolution of DT technology generations presented in a straight forward form covering the definitions up to cognitive & autonomous systems. This evolution spans changes in data integration capabilities, modelling sophistication and decision making in the built environment. DT 1.0 denotes the genesis of DT; it was inseparable with static BIM and CAD taken replicas making no use of real time connectivity, as well as dependent on offline updates and manual model management [28]. The rise of IoT devices, sensor networks and cloud based Building Management Systems brought DT 2.0 with real time synchronisation between physical assets and their digital twins, albeit still with limited predictive and learning capabilities [10], [21]. This real time basis facilitated progressing to DT 3.0, in which machine learning driven forecasting, fault detection and diagnosis (FDD), and early RL based control took the first steps toward proactive energy management [19]. DT 4.0 represents a quantum leap of intelligence with adaptive controls, hybrid physics–machine learning models, co-simulation language like Madelia, and distributed computation over edge infrastructures for dynamic behaviours over fixed rules The dawn of DT 5.0 instigates cognitive features that incorporate knowledge graphs, semantic modelling, causal reasoning and contextual interpretation in a manner in which twins understand complex building states, infer root cause relationships and make interpretable decision instead of purely reacting to sensor data [64]. This is a radical move away from the data driven reactive nature of the smart environment to meaning aware intelligence. The line ends at forward looking DT 6.0 where autonomous Digital Twins use a combination of multi agent reinforcement learning, foundation models and self-learning architectures, by which hosted digital twins practice real time continuous self-optimisation, autonomous coordination and human independent corrective action [40]. Notwithstand ing, these systems support the development of the vision for completely self-sustaining and resilient intelligent buildings that are able to be adapted on a large scale over an extended period.

5.Critical Evaluation of Current CDT Research

5.1 Limited Cognitive Depth and Shallow Intelligence

This subsection reviews the technological foundations that enable cognitive capabilities in digital twin systems.Although Digital Twin (DT) technologies are highly evolved, the corresponding research in the area of CDT for smart building energy management has few valid cognitive layers to be recognized as a truly intelligent and autonomous agent. The current CDT systems are more focused on making inference via predictive based machine learning (ML) model, like deep learning, LSTM networks, gradient boosting which is good at pattern recognition but lacks semantic understand ing and reasoning for complex decision making [47]. The nature of these numerical models are inherently opaque “black boxes” that provide predictions without explaining cause and effect relationships or occupancy behaviour interaction, environmental change, system constraints and so forth as well as energy outcomes [48]. As a result, CDTs frequently do not generalise beyond their training conditions and so struggle to operate successfully on novel building archetypes, or under seasonal variations or hybrid control protocols. One other significant limitation is the lack of a unified cognitive framework amalgamating symbolic reasoning, semantics modelling and hybrid physics AI techniques. Despite their structured description that knowledge graphs or ontologies, such as Brick or IFC, offer for building systems, they are seldom integrated with predictive models to create context aware decision layers capable of inference and explanation [49]. Such gap does not allow CDTs to know why a system is acting in the way that it does, and cannot deliver trusted/explanatory recommendations for building operators or BEMS controllers. In addition, current CDT are without the cognitive mechanisms necessary for adaptive and lifelong learning. Most implementations are based on static or offline trained ML models, which have fixed parameters and cannot readily update their knowledge as building circumstances, occupant preferences or operational constraints change over time [65]. CDTs continue to be reactive rather than proactive, self-learning-based agents without such a continual process of self-learning and causal reasoning. In general, the superficial intelligence presented in current CDTs is insufficient to reach the cognitive level that are required for building energy management system that is resilient, context aware and explainable. Closing this gap involves research that combines semantic information, causal modelling, hybrid simulation AI frameworks and lifelong learning into future CDT architectures.

5.2 Fragmented and Non-Stand ardised CDT Architectures

The fragmentation and lack of stand ardisation of architectural frameworks is a key bottleneck that restrains the maturity and scalability of CDTs in smart building energy management. Existing CDT models are built on a variaty of platforms, data pipeline´s and metadata schema´s and communication protocols making them challenging to integrate, expand or deploy at large scale [51]. Building data comes from many sources IoT sensors, BMS protocols, Building information modelling (BIM) models, simulation engines, and AI analytics although there is no stand ardized interoperability layer for them all to communicate [52]. As a result that CDT developers must design novel project specific architectures with generally poor levels of reusability. This architectural disparity causes high deployment cost, low maintainability, and low cross building generalisability. Interoperable metadata schema like IFC, Brick and Project Haystack, while effortful to integrate building ontologies, are not universally accepted and do not have the scope to capture cognitive processes, cause and effect dynamics or dynamic decision making for future CDT interfaces [66]. Therefore, most CDT implementations are based on partial or hybrid semantic models, which makes it difficult to integrate knowledge graphs, energy models and AI reasoning layers. This fragmentation detracts from the ability of CDTs to optimise, in a holistic, multi domain manner, across HVAC, lighting, storage devices (EN), occupant comfort and grid interactive technologies. Another limitation is the absence of stand ardised reference architectures specifying how sensing, semantic modelling, AI cognition, simulation and control modules should interact in a CDT ecosystem. Current research works tend to design ad hoc architectures that were tuned for concrete buildings types or experimental setups, preventing reproducibility and industrial take up [54]. Lacking a common reference framework, it is difficult to verify CDT models, compare performance or inter operate between vendors and building portfolios. The problem of architectural heterogeneity must be solved to move CDTs from proof-of concept demonstrators to scalable and engineering ready platforms. The creation of unified ontologies, stand ardised data exchange protocols and reference CDT architectures will be necessary to support consistent, explainable, and interoperable cognitive intelligence in next generation BEMS.

5.3 Weak Real Time Integration and Synchronisation Challenges

Real time synchronisation between the actual building and its digital twin is one of the most essential yet least developed parts of CDT architectures. While IoT sensing and cloud–edge computation has advanced significantly, current CDT implementations find it challenging to ensure a stable and high-fidelity alignment between real world systems and their virtual models. These constraints severely restrict the CDT reliability, responsiveness and its applicability to autonomous building control [55]. A significant factor is the non-uniform resolution of the building data streams HVAC sensors, environmental monitors, occupancy detectors and BMS protocols typically work at several different rates resulting in drifts in time as well as a partial state reconstitution in a digital environment. Furthermore, communication channel latencies are problematic for real time synchronization. CDT platforms assisted by cloud encounter networking delays, band width shifts and buffering delay during a connection that degrade the effectiveness of any opportunistic sharing of sensor data, simulation output or control decisions [67]. Edge enhanced architectures can face challenges in optimal control of distributed data flows for high frequency operations related for example; to fault detection, occupant driven optimal settings and quick control response required for peak load management. This results in a drop of CDTs situational awareness, as it becomes no longer able to forecast the behaviour of the system or to apply adaptive control actions. The next, high hurdle to take is the simultaneous time synchronisation of multi domain models. The building systems HVAC, lighting, renewable generation and storage, occupancy modelling and thermal simulation have separate physical characteristics as well as computer computational requirements. Real time coherence is still difficult to maintain between these heterogeneous sub systems, which brings inconsistency and model mismatch, thus resulting in witness tree quality downgrade of CDT [68]. These synchronisation issues are further exacerbated when dynamic or unexpected events such as occupancy spikes, equipment failures, extreme weather etc happen and CDTs have to respond in seconds. CDTs cannot be depended upon for autonomous, predictive or safety critical decision making in the absence of strong real time integration frameworks. To address these gaps, new formulations for edge centric architectures, adaptive sampling strategies, semantic time alignment and real time co-simulation approaches are needed which can align multi domain building models with the novel uncertain rapid conditions.

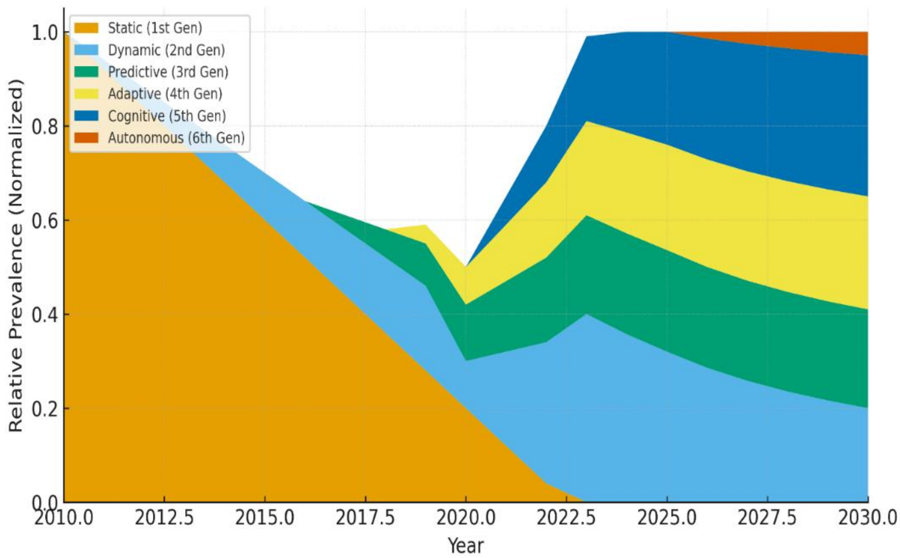

Figure 4. Evolution Timeline of Digital Twin Generations in Smart Building Energy Management (2010–2030). Source: Authors' conceptual illustration based on the evolutionary stages reported in literature [6, 30, 60].

Figure 4 is conceptualized by the authors based on the synthesis of the reviewed literature and the structured CDT framework developed in this study. It is not reproduced from any external source. The figure illustrates the proposed conceptual architecture of Cognitive Digital Twins for smart building energy management, integrating IoT sensing, semantic modelling, AI cognition, and BEMS control layers. The timeline for development indicating that Digital Twin (DT) tech in the building industry undergoes increasing level of intelligence and autonomy from year 2010 to expected horizon of year 2030; reflecting a decade long transition in BEMS towards more digitalisation, connectivity and AI injected optimisation. At the first stage from 2010 to 2015, first generation DTs are as mostly static with BIM and plant models that needed manual updates and lacked of real time capacity – or at least had a very limited one (according early DT formulation's assumptions and semantic BIM centric placement [13]. About 2015, IoT devices and measurements of data flow from the cloud accelerate the demand for dynamic twins which means that buildings components can now be monitored online, which may refer to sensor-based supervision including fault detection. This is perfectly in line with progress in IoT driven building systems and FDD research [56]. The field rapidly advances to predictive and adaptive twins with machine learning, co-simulation, and smart building automation starting to take hold. These platforms, meanwhile offer disparate gains from enhanced predictive capability, anomaly detection and early instantiation of MPC RL for control, representing a move away from static explainatory models to responsive data driven intelligence and edgewise. After 2021 there is a huge jump whereby cognitive DTs appear that connect semantic KGs, AI reasoning, context awareness and hybrid physics–ML models in order to achieve richer interpretability and more robust decision making in an increasingly interconnected and energy optimised buildings [69], [70]. Into 2025 and beyond, DTs have aspects of self-learning and self -correction that are informed by distributed computing, edge–cloud collaboration, multisource data fusion, and AI driven decision pipelines [71],[72]. By 2030, the category shifts toward next generation autonomous DT ecosystems with continual optimization and closed loop adaptation, and self-governing building operation, which is a result of progress made in intelligent building energy management [73],[74]. As such, it's a clear evolution; as the sector moved on from digital modelling to fully intelligent self-learning building systems so did the shape of Autonomous twins. Overall, the reviewed studies indicate that semantic modelling, reinforcement learning, and hybrid physics–AI frameworks are emerging as key enablers of cognitive digital twins in smart building energy management.

6.Future Research Roadmap for Cognitive and Autonomous Digital Twins

Next three to five years of CDT and ASDT research throughout the incoming decade will have to accomplish multiple related advances, which all together could empower intelligent, antifragile, and autonomic buildings. One would be richer cognitive reasoning abilities beyond the dumb machine learning correlation level. Next generation CDT systems should include causality logic and knowledge graph–based semantic interpretation for explainable and context aware decision making. With that, the hybrid systems can also help with justifications of control decisions, evaluating Counterfactual cases and hand ling uncertainties in a better manner while boosting operator's confidence levels and getting regulatory approval [56]. Another important direction is the development of continual learning and cross building transfer techniques. The existing models deteriorate under the effect of time as the buildings evolve with varying season, aging of equipment and the departure/arrival of tenants or retrofits. The research has to lead to CDT systems which can learn safely online and rapidly transfer knowledge across different buildings. Few shot learning, stability guaranteed reinforcement learning and domain adaptive prediction model can greatly reduce the retraining cost and increase scalability[75].Near real time synchronisation is still a challenge. "Ultra low latency edge–cloud architecture, semantic time alignment and adaptive sampling, latency aware co simulation framework is needed as next stage of study." These are crucial for aligning sensing, simulation, analytics and control planes that enable CDTs to respond in time constraints of comfort, energy optimization and safety [76].

Cross building learning with privacy preserving is also important as well. As buildings produce ever more fine grained operational and occupancy data, federated learning and encrypted model sharing infrastructure will be essential. Federated meta learning [77], secure aggregation and differential privacy can give them the ability to learn collaboratively over large numbers of building fleets without revealing too much sensitive information.[23],[78].Furthermore, the community should establish strict benchmark benchmarks for unifying CDT assessment. Future directions include open datasets, physical–virtual fidelity metrics, safetykey performance indicators (KPI's), and common simulation testbeds for sim2real robustness evaluation. These benchmarks will aid in any comparison between CDT architectures and facilitate commercial acceptance [79]. Self-evolution will be a defining capability of the next generation digital twins that evolve autonomously. Future work will investigate multi agent reinforcement learning, distributed coordination options, hierarchical control and self-healing strategies to enable BD construction twins to cooperate, negotiate tasks and ensure performance in case of equipment failure or environmental perturbations. These are functionalities that are important for campus wide and district scale optimisation [63].Foundation models and generative simulation engines are another game changer area of research. Open world adaptation of CDT can be significantly enhanced by massive pre trained building models and generative scenario spaces to support zero shot control strategies and automated stress testing of operable policies. Integrating these models asset based physics informed fine tuning will enable CDTs to quickly generalize to novel building types and unseen operating conditions [80].

Finally, another important research direction is governance, human–AI collaboration and safety assurance. As CDTs and ASDTs are increasingly relied on for mission critical building operations, This article may need to investigate how to develop stand ards for explainability and fail safe overrides, as well as transparent human inthe loop interfaces or certification frameworks to ensure the cyber security and ethical deployment. It will need to go through a responsible and widespread implementation such as reviewing of socio technical consequences and developing failsafe recovery harbouring strategies [81],[82]. This combined set of research directions provides a roadmap aiming to drive the evolution of CDT, from promising high potential prototypes, into deployable trusty and autonomous building intelligence. By pushing forward cognitive reasoning, adaptive learning, real time cooperation, privacy preserved collaboration, stand ardized benchmark backbone, multi agent autonomy, generative model and governance framework the field can set a robust footing for the next decade of smart building innovation.

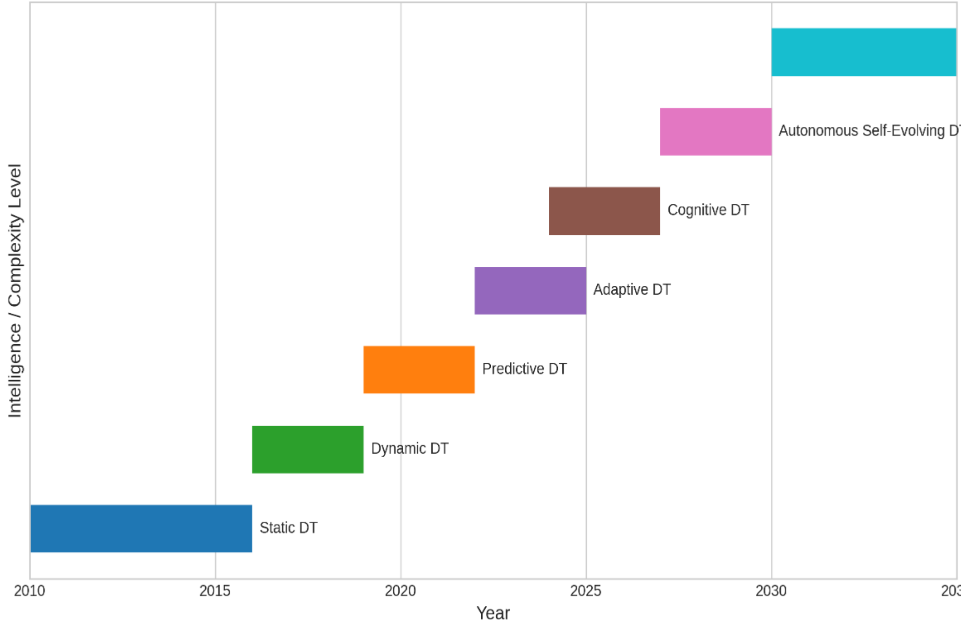

Figure 5. Future Research Roadmap for Cognitive and Autonomous Digital Twins in Smart Building Energy Management (Source: Authors' conceptual framework derived from systematic literature analysis).

Figure 5 presents a future research roadmap for Cognitive and Autonomous Digital Twins (DTs); illustrating the roadmap for the evolution of Cognitive and Autonomous Digital Twins (DTs), capturing the long term transformation of smart building energy management from static modelling tools to city scale cognitive ecosystems[83]. Conceptual framework of CDT readiness gaps in smart building energy management. This figure has been developed by the authors based on the systematic review database and is not reproduced from any external source. The positioning and caption formatting have been standardized in accordance with journal guidelines, ensuring clarity and consistency. The earliest stage, Static/Descriptive DTs (pre-2016), relied on BIM, CAD and static documentation, providing only basic visualisation and manual interrogation, consistent with foundational DT concepts and semantic modelling efforts in the built environment. These were followed by Dynamic DTs (2016–2019), driven by IoT enabled sensing, continuous data flows, and real time synchronisation between physical and virtual building assets, aligned with advances in IoT architectures and FDD research [84],[85]. From 2019 to 2022, Predictive DTs further established themselves as ML animal s evolved at the center stage of energy prediction, anomaly detection and predictive maintenance within an increasingly MPC ML hybrid physics modelling world. Adaptive DTs took this paradigm further and introduced reinforcement learning, cloud–edge AI collaboration and self-optimisation over autonomous HVAC shifting from predictive intelligence into closed looped,self-reconfiguring controls [86], [87],[88] , [46]. In the next step, Cognitive DT (2024–2027), the systems will include semantic reasoning, knowledge graphs, causal inference and explainable AI that allows for machines to be able to reason on aspects such as context, uncertainty or occupant centric behaviours instead of just respond based on sensor input [89],[74]. In the future self-evolving autonomous DTs (2027–2030) will have accomplished self-configuration, lifelong learning and multi agent coordination enabled by dynamic ontology evolution, real time data fusion and robust sim to real model generalisation[90], [91], [92],[93]. Post 2030, Cognitive Ecosystem Twins enable district scale optimisation, inter building and grid interoperability, federated learning and cooperative MARL based energy coordination to create multi building intelligence networks that optimise energy flows at neighbourhood or city level scales [94], [95], [96], [97], [98]. Overall, the roadmap shows a clear direction of development towards DT systems that are more intelligent, self-aware and scalable and which shift from building level optimization to city wide cognitive ecosystems enabling global sustainability and climate aligned urban development [99].

6.1 Global Research Land scape and Regional Contributions

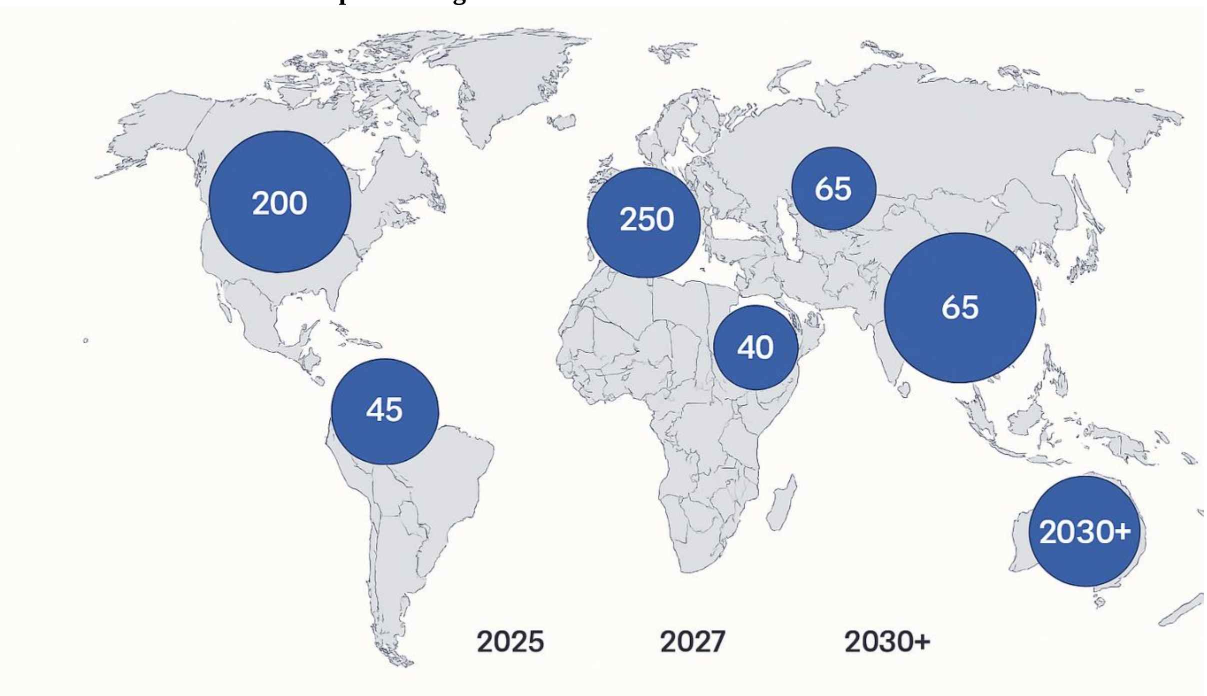

Figure 6. Global Distribution of Publication Records on Cognitive Digital Twins

The creation of CDT and Autonomous Self Discovering Digital Twins (ASDTs) is one of the globe's top research interests, with considerable articles from each region. The research in AI based CDT(SM), cloud edge, and semantic modelling are also the hotspot mainly in the North America (especially US and Canada) which leading to an early deployment of CDT for smart building. Europe Europe (in particular Germany, the UK, the Netherland s and France) has focused on semantic interoperability, simulation platforms and linking CDT frameworks to wider sustainability and energy policy agendas [100]. In Asia, rapid developments in IoT infrastructure as well as federated learning and large scale applications of smart cities in China, Japan,South Korea, and India demonstrate the priority that is being placed on scalable and data intensive CDT solutions [101]. Oceania (Australia and New Zealand) has a large volume in adaptive control, building scale optimization suggesting presence of innovation hub for CDT research [102]. In Africa contributions from South Africa, Nigeria and Egypt address low cost CDT systems adapted to the energy efficient retrofit of buildings which fit well with these regions' national agendas in their quest for cost effective and sustainable building envelope design [103]. South America (in particular, Brazil and Chile) has developed hybrid physics AI modelling & energy prediction routines on support of CDT applications which are dedicated to predictive analytics and operational optimization [104]. This worldwide distribution of research efforts (seen in Figure 6) shows the variety of technological approaches being investigated around the globe for development of a CDT. Simultaneously, variations in publication density open up potential for deeper international collaboration in areas such as federated learning, benchmarking and governance frameworks to support more equitable, interoperable and scalable CDT implementation across regions.

Conclusion

The review provides evidence of a Next Generation cognitive based CDT systems as an enabler for Smart Building Energy Management (SBEM). The review makes sense of this progression from the conventional BEMS to recent generations of Digital Twins, and demonstrates that CDTs introduce semantic intelligence, reasoning capability and self- learning into the system; shifting it a step ahead for proactive and autonomous building operation. The work contributes a well-defined taxonomy of DT generations, technology inspirations for CDT intelligence, and a sound consolidation of existing methods. However, implementations of CDTs face some challenges such as shallow cognitive structure, fragmented structure and lack of real time synchronisation. Addressing these gaps will necessitate hybrid physics–AI cognition, better semantic interoperability, edge centric architectures and secured cross building learning. The future triage plan proposed by this review can be summarised in terms of near, medium- and long-term directions towards more explainable, adaptive and autonomous CDT ecosystems. While the direct analysis of SDGs was not undertaken in our study, the findings related to CDT facilitated smart buildings are aligned with wider sustainability goals such as SDG 7 (Clean Energy), SDG 9 (Innovation & Infrastructure), SG 11(Sustainable Cities), and SDG13 (Climate Action). In general, this review provides the conceptual and technological foundation for CDTs to evolve from promising prototypes into practical tools for intelligent, adaptive and carbon neutral built ecosystems.

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