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Review

Digital Twin Architectures for Energy-Efficient Buildings and Renewable Energy Communities: A Systematic Scoping Review on Monitoring, Demand Response, and Net-Zero Readiness

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Abstract

Buildings are the primary energy consumption layer of Renewable Energy Communities (RECs) and a key target for net-zero policy under the EPBD recast. This scoping review applies the PRISMA-ScR framework to map Digital Twin (DT) architectures for building-scale and community-scale energy management in REC configurations. A Scopus search yielded a final analytical corpus of 102 studies, coded through an eight-dimensional thematic matrix covering lifecycle phases, digitalization objectives, enabling technologies, DT capability dimensions, and data realism. DT is the dominant enabling technology (55.9%), followed by IoT (23.5%) and machine learning (22.5%). Research is concentrated in the Planning and Design phase (77.5%) and markedly underrepresented in Implementation and Commissioning (16.7%). Notably, only 10.8% of studies integrate real-time operational data, exposing a significant gap between simulation-based research and the deployment conditions required under current EPBD mandates. The evidence base supports building energy monitoring, demand forecasting, and flexible grid operation but remains limited for retrofit verification, standardized net-zero KPIs, and operational workflows in existing stock. Critical DT capability gaps persist in Data Services (7.8%) and User Experience (18.6%). Overall, DT architectures show genuine potential for grid-interactive, net-zero building management, yet the field presents unresolved structural challenges for large-scale real-world deployment.

Keywords: digital twin; energy-efficient buildings; building energy management; renewable energy community; net-zero emissions; demand response; retrofit; IoT; machine learning; smart homes

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1. Introduction

1.1. Renewable Energy Communities in the European Energy Transition

The European energy transition represents one of the most structurally ambitious policy undertakings in the history of the European Union [1]. Anchored in the European Green Deal (COM/2019/640) and substantially accelerated by the REPowerEU Plan (COM/2022/231) in the wake of the 2021–2022 global energy crisis [2], the transition pathway is codified through the Renewable Energy Directive II (RED II, Directive 2018/2001), which establishes a binding target of 45% renewable energy in EU consumption by 2030 [3]. The Fit for 55 package (2021) operationalizes this objective through sectoral decarbonization policies, while the broader EU decarbonization strategy envisions a structural transformation of energy systems [4]: from centralized and fossil-dependent toward distributed, citizen-centered, and renewable configurations [5]. A critical and often underappreciated dimension of this transition concerns

the built environment: buildings account for approximately 40% of total final energy consumption in the EU and are responsible for 36% of greenhouse gas emissions [6]. The recast Energy Performance of Buildings Directive (EPBD, Directive 2024/1275) constitutes the most significant regulatory update to EU building policy in a decade, mandating near-zero energy standards for new constructions [7]; accelerated renovation of worst-performing buildings; and, crucially, the development of interoperable national databases of building energy performance (EPC/APE) [8], machine-readable data architectures, and smart-readiness indicators (SRIs) for connected building systems [9]. The EPBD recast thus creates a direct regulatory mandate for the digital intelligence layer that Digital Twin architectures are uniquely positioned to provide.

Within this context, Renewable Energy Communities (RECs) have emerged as a pivotal governance and infrastructure model [10]. Defined in Article 22 of RED II, RECs enable citizens, SMEs, and local public authorities to voluntarily work together in the collective production, consumption, sharing, and storage of renewable energy, operating as legal entities with primary social, environmental, and community objectives rather than financial profit maximization [11,12]. RECs embody a dual transformation: they simultaneously decentralize energy infrastructure and democratize energy governance, enabling communities to transition from passive consumers to active prosumers and collective energy managers [13].

The socio-economic relevance of RECs extends substantially beyond technical energy management. Scholarly research has documented their role in reducing energy poverty [14,15], fostering local economic development, increasing citizen engagement with the energy transition, and generating social capital through cooperative governance mechanisms [16,17]. Business model analysis reveals that RECs operate across a spectrum from community-owned cooperative structures to complex multi-stakeholder configurations and that their economic viability is critically dependent on the quality of their digital governance architecture [18,19]. In Italy, the transposition through Decreto Legislativo 199/2021 and the incentive framework established by the MASE Ministerial Decree (January 2024) at 110 EUR/MWh for shared energy have catalyzed rapid proliferation, with over 300 REC configurations currently registered [20].

However, the operational complexity of RECs represents a substantive governance challenge [21]. An REC involves the dynamic coordination of heterogeneous assets (residential photovoltaics, wind generation, battery storage, and flexible loads); multi-stakeholder decision-making (prosumers, distributors, public administrations, and aggregators); regulatory compliance requirements; and the simultaneous optimization of economic, energetic, and environmental objectives [22,23]. Current digital tools for REC management remain largely fragmented. Smart metering infrastructures mainly support high-resolution data acquisition, communication, and monitoring, while predictive capabilities typically depend on separate analytics and forecasting layers. Likewise, commercial energy management platforms often provide optimization functions for distributed energy resources, but REC operation also requires integrated support for stakeholder coordination, data management, legal and regulatory issues, communication, and governance, which are still seldom unified within a single digital architecture [24,25].

1.2. The Twin Transition: Convergence of Digital Twins and Green Economy

The European Commission has formally articulated the concept of the "Twin Transition," affirming that the digital and green transformations are not parallel processes but structurally interdependent [26]. In the energy domain, this interdependence is particularly acute: the transition to distributed renewable energy systems requires not only new hardware infrastructure but a correspondingly sophisticated digital intelligence layer capable of governing the increased complexity, variability, and multi-stakeholder character of decentralized systems [27].

The twin transition framework implies that digital technologies are constitutive enablers of new energy paradigms: IoT sensor networks provide real-time awareness of distributed asset states [28]; AI and machine learning algorithms enable predictive capabilities for variable renewable generation and demand response [29]; blockchain technologies offer transparent governance mechanisms for prosumer transactions [30]; and Digital Twin platforms provide the integrative computational environment where physical and virtual components co-evolve [31]. From a governance perspective, the twin transition creates new demands on institutional capacity: local authorities, utilities, and community organizations must develop competencies to design, operate, and regulate digitally governed energy systems [29,32,33].

The Digital Twin (DT) paradigm, originating in Michael Grieves' Product Lifecycle Management studies (2003) and formalized by the Digital Twin Consortium (2020), aligns naturally with the operational complexity of both building energy management and REC governance [32]. The Digital Twin Consortium defines a DT as "a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity" [33]. Applied to the built environment within an REC configuration, a DT integrates [34,35].

1. A physics-based simulation model of individual buildings or building clusters (thermal envelope, HVAC systems, occupancy, generation, storage, and grid interaction);
2. A data acquisition layer from distributed IoT sensors, smart meters, and building management systems (BMSs);
3. An AI/ML engine enabling predictive and optimization capabilities, from occupancy-based HVAC control and fault detection to demand response orchestration and net-zero KPI tracking (kWh/m^2, kgCO_2/m^2, self-sufficiency ratio, and comfort indices).

This building-first DT architecture is not merely a technical enhancement; it is a governance tool that translates complex energy data into actionable information for prosumers, building managers, and public administrators, enabling verifiable progress toward net-zero targets at the asset and community levels [36].

Documented DT applications in the scientific literature span virtual power plant (VPP) management, microgrid control, predictive maintenance for renewable assets, demand response optimization, and scenario simulation for grid integration planning [37]. The DT Consortium operationalizes DT capabilities across six dimensions: Data Services (DS), Integration (IR), Intelligence and Analytics (IA), User Experience (UX), Management (MN), and Trustworthiness (TW) [32]. Despite growing interest, DT implementations for energy systems predominantly remain at conceptual or simulation levels, with limited documentation of fully operational, large-scale deployments [32–38].

1.3. Research Gap and Study Objectives

Despite growing research on DT applications in energy systems, two critical and interrelated gaps persist. First, no scoping review has comprehensively mapped DT architectures specifically designed for Renewable Energy Communities as defined under the EU normative framework (Directive 2018/2001), operating across the full building-to-community scale. Existing reviews address DT in building management, industrial IoT, or generic smart grid contexts [39,40] but do not interrogate the intersection of DT architectures with the governance, multi-stakeholder, and lifecycle complexities characteristic of RECs. Second and more strategically, no review has systematically examined how DT architectures can serve as the connective tissue between building-scale energy performance management, with its building physics models [41,42], HVAC optimization, retrofit M&V, and EPC data, and community-scale energy governance, thereby enabling verifiable net-zero trajectories at the district level [43]. This dual gap is particularly acute given the EPBD recast mandate for machine-readable building

energy performance data and the simultaneous push toward smart-ready buildings capable of demand response participation within energy community configurations [44,45].

The present scoping review addresses this gap through the PRISMA-ScR framework [45–47], guided by three research questions:

- RQ1 (Architectures and Technologies): What is the current state of research on DT architectures for building-scale and community-scale energy management within REC configurations, and what are the dominant architectural patterns, enabling technology stacks, building physics integration approaches, and technology readiness profiles?
- RQ2 (AI/ML and Building Performance): How are artificial intelligence and machine learning integrated within DT architectures for building and REC energy management, and what functional roles do they serve in building energy optimization (HVAC control, occupancy prediction, and fault detection), grid flexibility, demand response, and net-zero KPI monitoring?
- RQ3 (Gaps, Scalability and Policy): What technological capability gaps and implementation barriers characterize the current body of DT-for-building-and-REC research, particularly in data interoperability, UX design for non-technical prosumers, and EPC/building data integration, and what are the implications for platform designers, public administrations, and energy policy actors implementing net-zero building strategies under the EPBD recast?

This scoping review was guided by the Population–Concept–Context (PCC) framework. The population comprised individual buildings, building clusters, and Renewable Energy Communities (RECs), treated as interconnected energy units. The concept focused on Digital Twin architectures, enabling digital technologies, and the capabilities required to monitor, manage, and optimize energy performance [48]. The context was defined by the international scientific literature on buildings and community-scale energy systems, interpreted against the evolving EU regulatory framework, particularly RED II (Directive (EU) 2018/2001) for RECs and the recast EPBD (Directive (EU) 2024/1275) for net-zero and smart-ready building objectives [9,49–64].

More specifically, this review contributes to the present Special Issue by examining building energy monitoring and management tools, AI-based optimization approaches, the integration of renewable energy at building and community scales, and the operation of buildings and building clusters as demand-response-ready energy systems.

2. Materials and Methods

2.1. Literature Classification Criteria and Analytical Framework

The identified literature was classified along three macro-thematic dimensions:

1. Digital Twin Architectures for Energy Systems;
2. AI and Data-Driven Approaches for REC Management;
3. Enabling Technologies and Infrastructure for RECs.

Each article was further classified along cross-cutting dimensions:

1. REC lifecycle phases (Planning and Design, Implementation and Commissioning, Operation and Maintenance, and Monitoring and Evolution);
2. Digitalization objectives (Grid Integration and Flexibility, Energy Optimization, Community Governance, Energy Management, Data Forecasting, and Economic and Financial Benefits);
3. Specific enabling technologies;
4. Digital Twin Consortium technological capabilities (DS, IR, IA, UX, MN, and TW) [39].

To make the synthesis more transparent for a building-focused readership, the narrative interpretation also distinguished studies with direct building-scale relevance from

contributions framed at the generic microgrid or community-system levels. This interpretive distinction supports the revised building-centered reading of the corpus, but it does not alter the original quantitative coding matrix.

2.2. Literature Selection Process

2.2.1. Keyword Analysis and Search String Development

The literature identification process combined two complementary approaches: (1) systematic validation on Scopus of keywords derived from preliminary domain-specific literature analysis and (2) formulation of Boolean search strings through iterative testing and refinement. An initial pool of keywords was derived from a preliminary review of the domain-specific literature, subsequently validated and expanded through exploratory searches on Scopus, identifying synonyms and related concepts. Four complementary search strings (SS1–SS4) were formulated, each targeting a specific research dimension, as reported in Table 1. All search strings were applied to the TITLE-ABS-KEY Scopus field (title, abstract, and keywords) using the Advanced Search interface, with document type restricted to "Article" and "Conference Paper" and publication language set to English or Italian. The complete Boolean syntax for each string is reported in Table 1 to enable independent replication. Screening was performed on metadata exported from Scopus, including title, abstract, author keywords, index keywords, source title, document type, publication stage, and open-access metadata. Records retained after metadata screening underwent full-text assessment whenever the contribution appeared to include an explicit DT architecture, a building- or REC-relevant energy management use case, or an enabling digital infrastructure component. Forward and backward citation chaining was then used as a complementary recovery strategy for conceptually aligned papers not fully captured by keyword variability.

Table 1. Search strings used in Scopus.

Results	Boolean Query	String
63	(Digital Twin OR DT) AND (Renewable Energy Communit* OR Energy Communit* OR REC)	SS1
512	(Digital Twin OR DT) AND (Microgrid OR Smart Grid OR Distributed Energy OR Virtual Power Plant) AND (Communit* OR Local Energy)	SS2
400	(Artificial Intelligence OR Machine Learning OR Deep Learning) AND (Renewable Energy Communit* OR Energy Communit*) AND (Digital OR Platform OR Architecture)	SS3
127	(IoT OR Internet of Things OR Blockchain OR Cloud Computing OR Edge Computing) AND (Renewable Energy Communit* OR Energy Communit* OR Microgrid)	SS4

2.2.2. Sources and Time Frame

The structured queries were executed on Scopus on 25 March 2026. The structured search covered the period 2018–2025. The starting year, 2018, was selected because it marks the adoption of RED II, which established the European regulatory framework for Renewable Energy Communities. The end year, 2025, was selected as the latest complete bibliographic year available at the time of the search, while acknowledging that coverage of the most recent 2023–2025 literature may remain partial due to indexing and corpus finalization effects. To avoid excluding conceptually foundational studies, seminal pre-2018 contributions (2012–2017) were additionally recovered through forward and backward citation chaining and purposive sampling, as detailed in Section 2.2.2. These papers were retained because they provide foundational architectural and methodological contributions

not fully captured by keyword-based retrieval yet necessary for contextualizing the development trajectory of the field. The final corpus comprises 102 articles. Disciplines included Engineering, Computer Science, Energy, Environmental Science, Decision Sciences, and Business and Management. Publication language was restricted to English and Italian. Given the technological novelty of the field, both journal articles and conference papers were retained when they met the inclusion criteria, allowing the review to capture both consolidated analyses and early-stage demonstrators.

2.2.3. Eligibility, Classification, and Validation Criteria

Explicit criteria for inclusion and exclusion were defined across four dimensions: document type, language, thematic focus, and substantive content (Table 2). Eligibility was applied sequentially at title/metadata screening, abstract screening, and full-text review. Records were excluded at the full-text stage when the contribution lacked an explicit DT component, focused exclusively on market design without digital infrastructure, or remained too generic to support the building- and REC-oriented analytical framework adopted in this review.

Table 2. Inclusion and exclusion criteria.

Exclusion	Inclusion	Criterion
Review, Editorial, Book Chapter, Policy Report	Article, Conference Paper	Document type
Other languages	English, Italian	Language
Commercial applications without scientific validation	DT/AI/IoT applied to RECs or distributed energy systems	Thematic focus
Simulation-only without DT; energy trading without digital infrastructure	Architecture, framework, methodology, case study with DT component	Content
Before 2018 (exception: seminal pre-2018 contributions retained via citation chaining; see Section 2.2.2)	2018–2025	Period

Each included article was then assessed for its relevance to the three research questions according to the classification and validation criteria summarized in Table 3. To enhance consistency, a 10% reliability subsample was independently double-coded, yielding a Cohen's kappa of k = 0.78, which indicates substantial agreement. Disagreements were resolved through iterative discussion and re-reading of the full text until consensus was reached. For thematic coding, a traffic-light system was adopted: green indicated clear operational implementation, yellow indicated limited or implicit reference, and red indicated the absence of the component under examination.

Table 3. Classification and validation criteria adopted for the included studies.

Dimension	Criterion/Rule
Relevance to research questions	Each included article was assessed for its relevance to RQ1, RQ2, and RQ3
Thematic coding system	Green = clear operational implementation; yellow = limited or implicit reference; red = absence of component
Reliability procedure	A 10% subsample was independently double-coded
Inter-coder agreement	Cohen's kappa = 0.78, indicating substantial agreement
Disagreement resolution	Disagreements were resolved through iterative discussion and re-reading of the full text until consensus was reached

2.3. Thematic Matrix Structure

The thematic coding matrix was structured across eight principal dimensions:

A. Article identifier;
B. Contribution type (Applied Study, Simulation-Based, Methodological, and Prototype);
C. Enabling technologies;
D. DTC capabilities (DS, IR, IA, UX, MN, and TW);
E. REC lifecycle phases;
F. Digitalization objectives;
G. Relevance assessment per RQ;
H. Data realism classification.

Dimension (H) is introduced in this study as an original analytical extension to the standard PRISMA-ScR coding protocol. It classifies each article according to the type of data underpinning the DT architecture or validation study, distinguishing three categories: (H1) Synthetic/Simulated data, in which the DT operates on artificially generated or model-derived input without grounding in real building or energy system measurements; (H2) Historical/Archival data, in which real-world datasets (energy consumption records, metering archives, and EPC databases) are used in a static, retrospective mode; and (H3) Real-Time Sensor/Operational data, in which the DT ingests live data streams from IoT sensors, smart meters, or BMS in operational deployments.

This classification enables a structured assessment of the critical gap between DT architectures designed for idealized or simulated environments and architectures capable of functioning under the heterogeneous, data-incomplete conditions that characterize actual building stocks and energy community deployments. Figure 1 presents a representative excerpt of the coding matrix applied to the analytical corpus, illustrating the eight coding dimensions. DTC capabilities are color-coded using a traffic-light system (green: clear and operational; yellow: limited presence or mentioned; and red: absent or not relevant), consistent with the approach adopted in D'Alberto et al. [1].

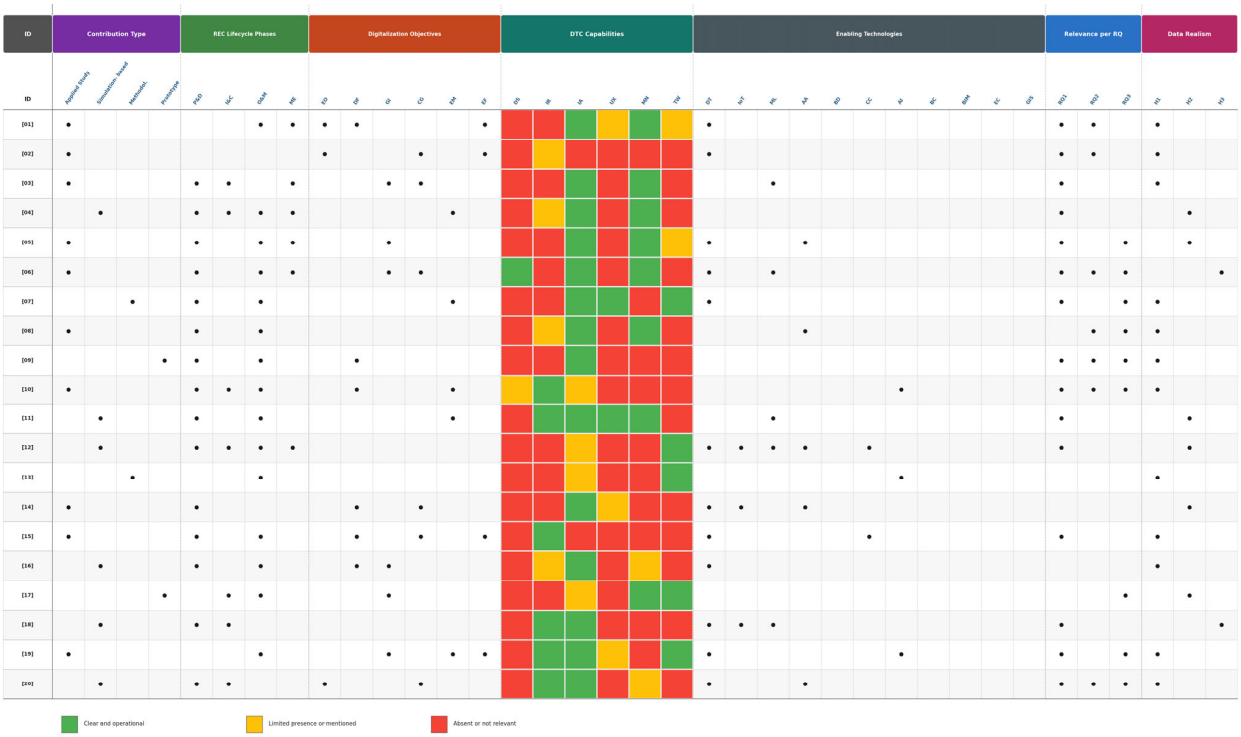

Figure 1. Extract from the thematic coding matrix (n = 102 articles). Columns represent the eight coding dimensions: contribution type (Applied Study, Simulation-Based, Methodological, and

Prototype); REC lifecycle phases (P&D, I&C, O&M, and ME); digitalization objectives (EO, DF, GI, CG, EM, and EF); DTC Capabilities (DS, IR, IA, UX, MN, and TW); enabling technologies (DT, IoT, ML, AA, BD, CC, AI, BC, BIM, EC, and GIS); relevance per RQ (RQ1, RQ2, and RQ3); data realism (H1, H2, and H3). DTC capabilities are color-coded: green = clear and operational; yellow = limited presence or mentioned; and red = absent or not relevant. Full matrix available from the corresponding author upon request.

With respect to enabling technology categories, "artificial intelligence" (AI), "machine learning" (ML), and "advanced analytics" (AA) were coded as distinct dimensions to ensure category independence: AI was assigned when the study referenced AI-based reasoning or knowledge systems in general; ML was coded when explicit supervised, unsupervised, or reinforcement learning algorithms were deployed; AA was coded when statistical or data-mining techniques were applied without an explicit ML framing. Studies could receive multiple codes where different paradigms coexisted within the same architecture.

The search process yielded 974 unique records after deduplication (128 duplicates removed), as illustrated in Figure 2. These records underwent metadata screening and abstract review, followed by full-text assessment of potentially eligible studies. In parallel, a complementary recovery strategy based on purposive sampling and backward/forward citation chaining identified 491 candidate references. The overlap between the structured Scopus search and the citation-chaining pathway was limited to 6 articles. Citation chaining was thus employed to complement, rather than replace, the structured search process. After combining both retrieval pathways and removing overlaps, the final analytical corpus consisted of 102 articles.

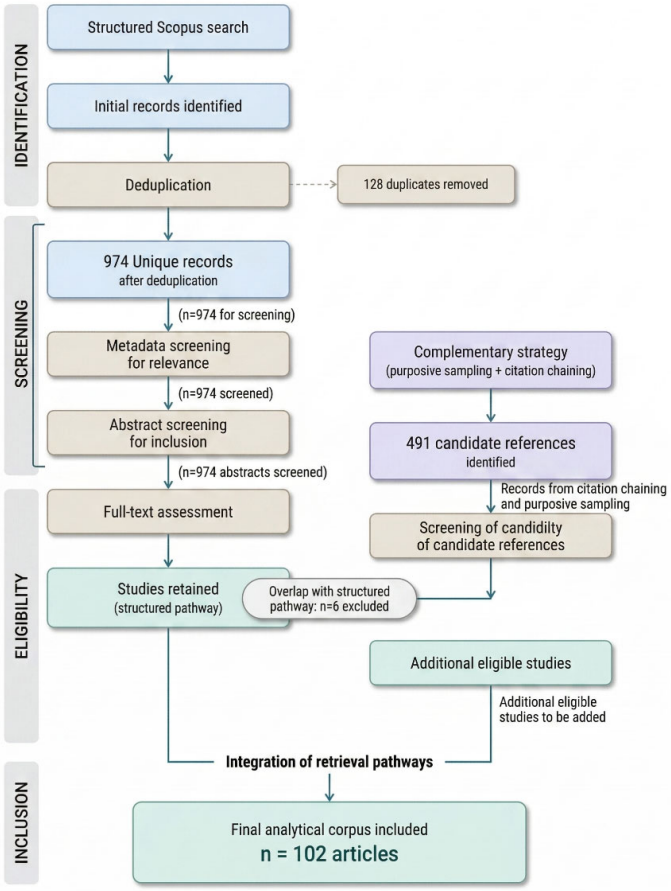

Figure 2. PRISMA-ScR flow diagram illustrating the article selection process for DT-REC architectures (n = 102).

The completed PRISMA-ScR checklist is provided in Appendix A.

3. Results

3.1. Matrix Overview and General Trends

The thematic matrix analysis coded 102 articles. Results reveal that the literature was strongly oriented toward concrete applications: 42% (43 contributions) address Applied Studies or Case Studies, 31% (32 articles) Simulation-Based Studies, 18% (18 articles) Methodological Contributions, and 9% (9 articles) Prototypes or Proof of Concept. This pattern indicates an empirical and applicative orientation consistent with early-to-mid technology readiness levels (TRL 4–6). Cross-dimensional analysis reveals the Core DT Stack (DT + IoT + ML) as the primary enabling combination, present in 14.7% of the corpus. When reread through a building-centered lens, the most directly relevant contributions cluster around smart-home energy management, public- and school-building demonstrators, multi-building self-consumption platforms, and district-scale coordination studies that explicitly model building loads. By contrast, a substantial share of the corpus operates at generic microgrid or community-system level, offering transferable architectural insight but not always reporting building-specific performance evidence. This distinction is important for the present article because it shows that the literature already supports monitoring, forecasting, and flexible operation at the building scale, while remaining comparatively weak on retrofit verification, commissioning protocols, and standardized post-occupancy net-zero metrics.

3.2. Temporal and Geographical Distribution of Publications

Figure 3 illustrates the temporal distribution of publications across the final analytical corpus (2012–2025; n = 102). The corpus exhibits accelerated growth from 2019 to 2020, peaking in 2020–2021 (46.1% of the total corpus). In 2020, 25 articles were published (24.5%), followed by 22 in 2021 (21.6%) and 16 in 2022 (15.7%). The 2023–2025 period accounts for 17 articles (16.7%)—4 in 2023 (3.9%), 5 in 2024 (4.9%), and 8 in 2025 (7.8%)—reflecting sustained research activity in the most recent years of the corpus. Pre-2018 contributions (2012–2017; n = 7) were recovered through citation chaining and represent seminal methodological references. This growth pattern is consistent with global post-COVID energy digitalization trends and the intensification of EU-level REC policy implementation following RED II transpositions.

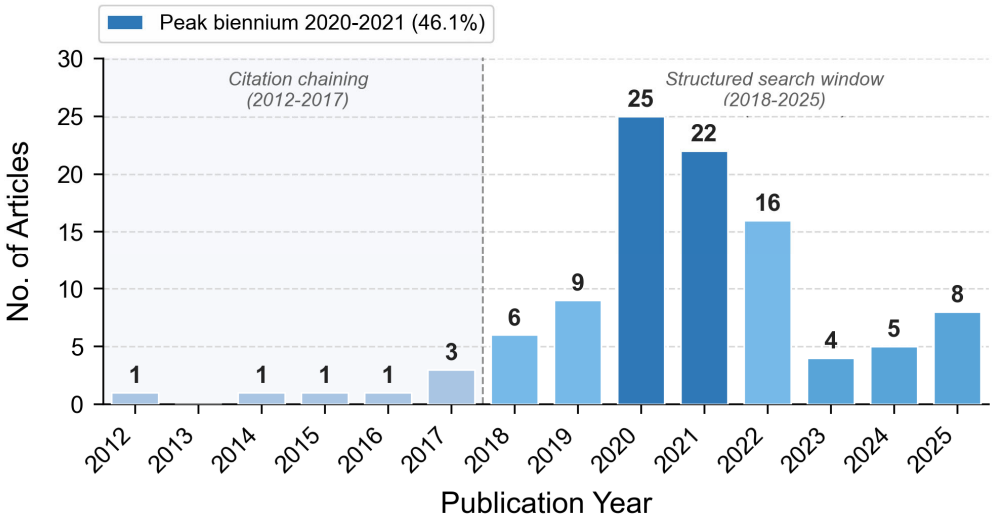

Figure 3. Temporal distribution of selected articles by publication year (n = 102; 2012–2025). The highlighted 2020–2021 biennium accounts for 46.1% of the total corpus. Structured search window: 2018–2025; pre-2018 contributions recovered via citation chaining. Table 4 summarizes the indicative

geographical distribution of the included articles. Analysis of the geographical distribution reveals a predominance of European and East Asian contributions, consistent with global renewable energy research clusters. Because author affiliations were not uniformly reported or equally granular across all eligible records, this mapping should be interpreted as a contextual distribution rather than as a fully reproducible bibliometric count. Even with this caution, Italy, Germany, Spain, and Nordic countries lead European contributions, while the significant Chinese presence (19.6%) reflects national investment in smart grid and Digital Twin research.

Table 4. Geographical distribution of included articles (indicative estimate).

Country/Region	Geographic Area	% (est.)	Articles (est.)
Italy	Europe	17.6%	18
Germany	Europe	11.8%	12
Spain	Europe	8.8%	9
Nordic Countries	Europe	7.8%	8
France	Europe	5.9%	6
Other EU countries	Europe	9.8%	10
China	Asia	19.6%	20
Other Asian countries	Asia	7.8%	8
USA	Americas	5.9%	6
Other/Undetermined	Other	4.9%	5

3.3. Technological Landscape of RECs: Enabling Technologies, DTC Capabilities, and Co-Occurrence Patterns

Figure 4 reveals a clear technology hierarchy: Digital Twin is the most frequently cited technology (57 articles, 55.9%), followed by IoT/sensor networks (24 articles, 23.5%) and machine learning (23 articles, 22.5%), the Core DT Stack. Second-tier technologies include advanced analytics (9.8%), Big Data (8.8%), Cloud Computing (7.8%), and artificial intelligence generics (7.8%). Blockchain, BIM, and Edge Computing are minority technologies (2.0% each), while GIS appears in only one article (1.0%). The complete absence of 5G and Common Data Environment (CDE) is a notable gap.

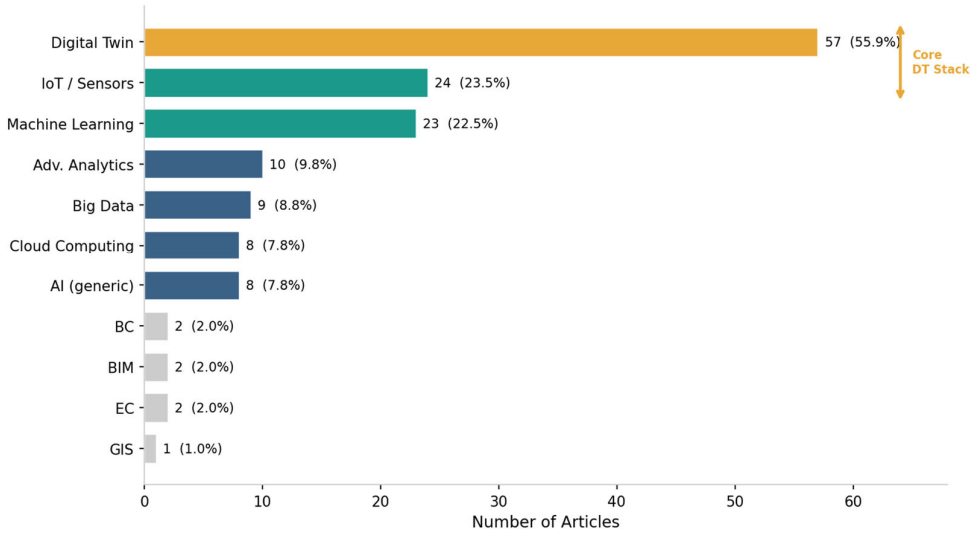

Figure 4. Frequency of enabling technologies in the analyzed corpus (n = 102 articles). The Core DT Stack (DT + IoT + ML) is highlighted. Horizontal bars indicate article count; percentages refer to corpus share.

Table 5 presents the distribution of the enabling technologies identified in the reviewed literature, indicating their frequency, percentage incidence, and corresponding solution/application area. It complements the hierarchy outlined above by showing not only how often each technology appears but also the main operational function it performs within the selected studies.

Table 5. Enabling technologies and technological solutions.

Solution/Application	Technology	%	Freq.
Digital Twin for REC, microgrid, VPP	Digital Twin (DT)	55.9%	57
Field data acquisition, smart metering, control	IoT/Sensor Networks	23.5%	24
Demand/production forecasting, optimization	Machine Learning (ML)	22.5%	23
KPIs, historical data analysis, decision support	Advanced Analytics (AA)	9.8%	10
Management of large energy data volumes	Big Data (BD)	8.8%	9
DT platform hosting, service scalability	Cloud Computing (CC)	7.8%	8
Generic AI systems, reinforcement learning	Artificial Intelligence (AI)	7.8%	8
P2P energy trading, smart contracts, governance	Blockchain (BC)	2.0%	2
Building information modeling within RECs	BIM	2.0%	2
Local IoT data processing, low latency	Edge Computing (EC)	2.0%	2
REC territorial planning	GIS	1.0%	1

Figure 5 illustrates the co-occurrence heatmap between enabling technologies and DTC capabilities, revealing a clear concentration around two dominant capability domains: Intelligence and Analytics (IA), and Management (MN). Digital Twin (DT) is primarily associated with IA (28 co-occurrences) and MN (27 co-occurrences), whereas machine learning (ML) exhibits its strongest linkage with IA (21 co-occurrences). In contrast, Data Services (DS) appears substantially underrepresented, with only 8 aggregate co-occurrences (7.8%), while User Experience (UX) remains comparatively limited, with 19 aggregate co-occurrences (18.6%). As highlighted by the red outlines in Figure 5, these results point to significant capability gaps within the current literature. Trustworthiness (TW) is represented by 33 co-occurrences (32.4%), indicating a non-negligible presence, yet one that still appears modest in relation to the cybersecurity and reliability requirements of digitally enabled operational energy platforms.

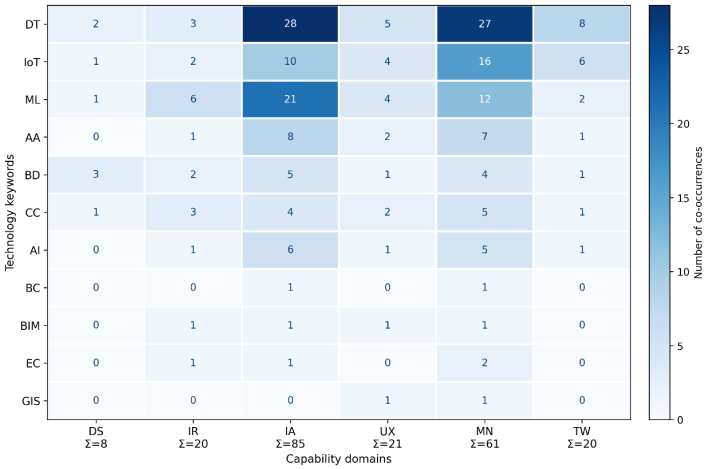

Figure 5. Co-occurrence heatmap: enabling technologies × DTC capabilities (n = 102). Red borders highlight critical gaps (DS and UX). Color intensity proportional to co-occurrence frequency.

Figure 6 synthesizes the principal combinations of enabling technologies identified in the reviewed literature, while Table 6 provides their detailed frequency distribution.

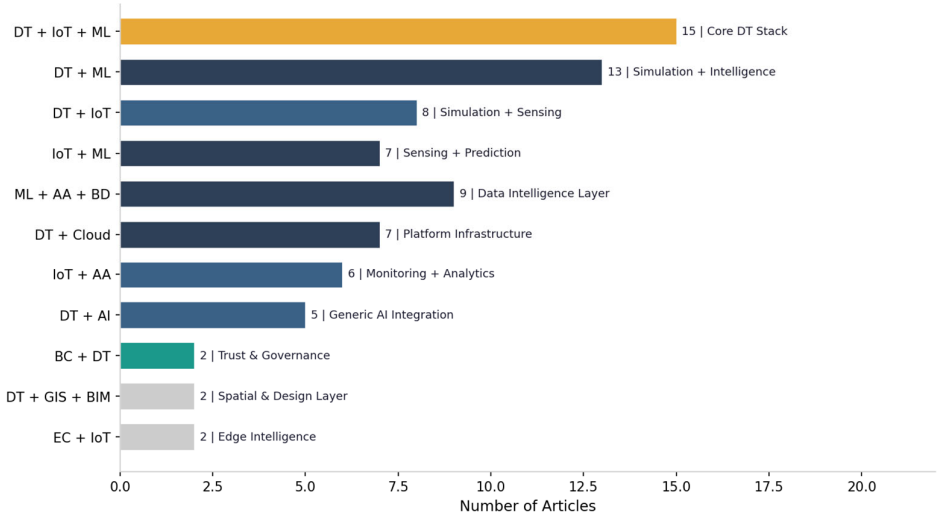

Figure 6. Principal technology co-occurrence combinations ranked by frequency (n = 102 articles). Labels indicate cluster membership and article count.

Table 6. Technology co-occurrence analysis.

Cluster	%	Freq.	Combination
Core DT Stack	14.7%	15	DT + IoT + ML
Simulation + Intelligence	12.7%	13	DT + ML
Simulation + Sensing	7.8%	8	DT + IoT
Sensing + Prediction	6.9%	7	IoT + ML
Data Intelligence Layer	8.8%	9	ML + AA + BD
Platform Infrastructure	6.9%	7	DT + Cloud
Monitoring + Analytics	5.9%	6	IoT + AA
Generic AI Integration	4.9%	5	DT + AI
Trust and Governance	2.0%	2	BC + DT
Spatial and Design Layer	1.96%	2	DT + GIS + BIM
Edge Intelligence	1.96%	2	EC + IoT

The Core DT Stack, consisting of Digital Twin (DT), IoT, and machine learning (ML), is the most recurrent configuration, occurring in 15 articles (14.7%), and can therefore be regarded as the dominant architectural pattern in the current literature. Other relevant combinations include DT + ML (13 articles, 12.7%) and DT + IoT (8 articles, 7.8%), which confirm the pivotal role of DT as the integrative core of these technological configurations. The Data Intelligence Layer cluster (ML + AA + BD) appears in nine articles (8.8%), underlining the growing importance of advanced analytics and data-driven intelligence in digital energy systems. Conversely, the Trust and Governance cluster (BC + DT) is observed in only two articles (2.0%), indicating a still limited but promising line of research, particularly with respect to transparency, traceability, and governance mechanisms in RECs.

3.4. REC Lifecycle Phases and Digitalization Objectives

As illustrated in Figure 7 and detailed in Table 7, the reviewed literature is strongly concentrated in the Planning and Design (P&D) phase, which is addressed in 79 articles

(77.5%). Operation and Maintenance (O&M) follows with 60 articles (58.8%), while Monitoring and Evolution (ME) appears in 23 articles (22.5%). In contrast, Implementation and Commissioning (I&C) is addressed in only 17 articles (16.7%). This pattern reveals a structural design-to-operation imbalance, with comparatively limited attention paid to the transition from system conception to field deployment. Digital Twin (DT) is particularly prominent in the P&D and O&M phases, appearing in 42 and 37 articles, respectively, which confirms its strong architectural and operational relevance. However, the underrepresentation of the I&C phase, as highlighted in Figure 7, is a critical issue for practical deployment, since commissioning procedures, validation protocols, and go-live frameworks remain only marginally addressed in the existing body of research.

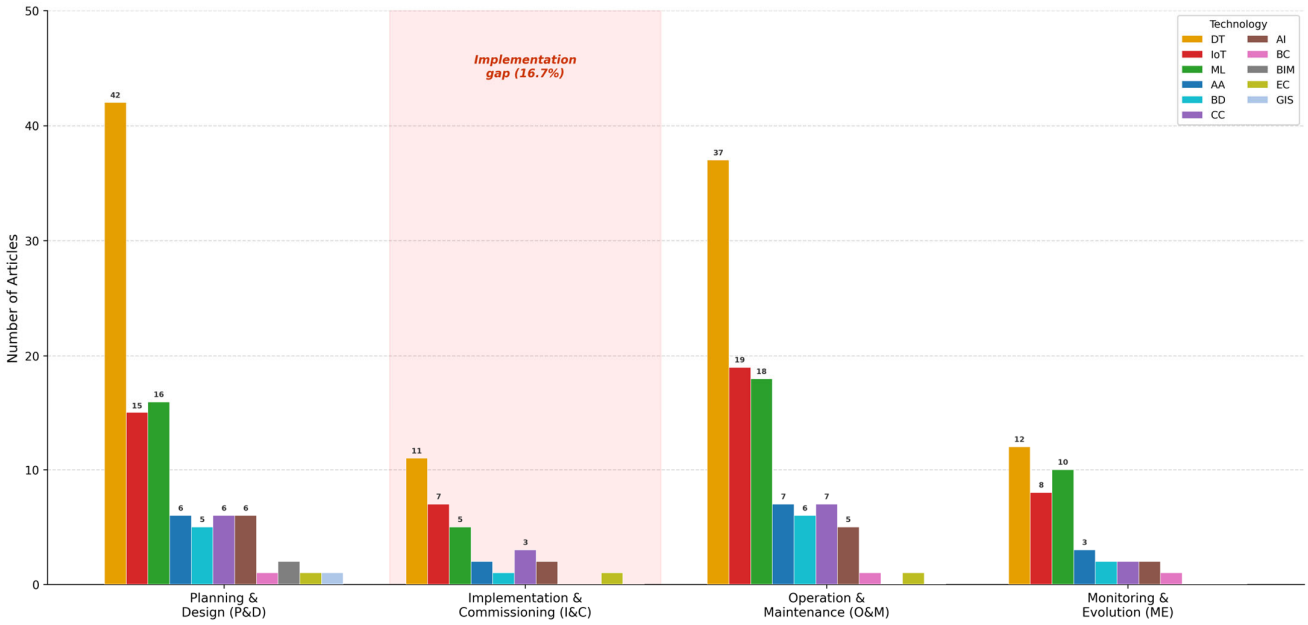

Figure 7. Distribution of enabling technologies across REC lifecycle phases (n = 102). The highlighted Implementation and Commissioning phase (I&C) represents the critical design-to-operation gap (16.7% of the corpus).

Table 7. Technology distribution by REC lifecycle phase.

Technology	P&D	I&C	O&M	ME
DT	42	11	37	12
IoT	15	7	19	8
ML	16	5	18	10
AA	6	2	7	3
BD	5	1	6	2
CC	6	3	7	2
AI	6	2	5	2
BC	1	0	1	1
BIM	2	0	0	0
EC	1	1	1	0
GIS	1	0	0	0

As illustrated in Figure 8 and summarized in Table 8, Grid Integration and Flexibility (GI) emerges as the leading digitalization objective, being addressed in 54 articles (52.9%).

This finding suggests that the integration of distributed renewable resources and the management of their variability constitute the primary focus of the current literature. Energy Optimization (EO) follows with 36 articles (35.3%), while Community Governance (CG) is identified in 32 articles (31.4%), indicating that governance is also gaining relevance as a recognized dimension of REC digitalization.

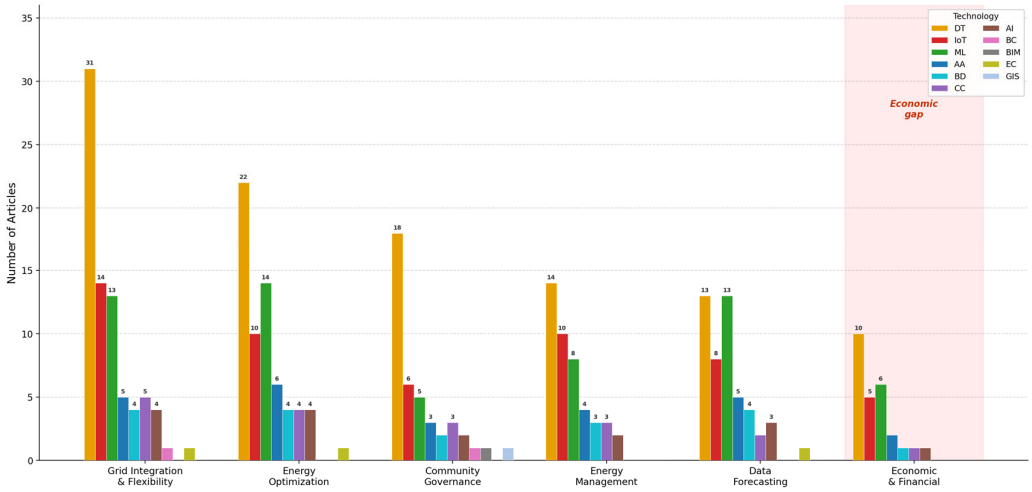

Figure 8. Technology distribution across REC digitalization objectives (n = 102). The highlighted Economic and Financial objective (EF) represents an underrepresented but critical research domain.

Table 8. Technology-objective co-occurrence (digitalization objectives).

Technology	GI	EO	CG	EM	DF	EF
DT	31	22	18	14	13	10
IoT	14	10	6	10	8	5
ML	13	14	5	8	13	6
AA	5	6	3	4	5	2
BD	4	4	2	3	4	1
CC	5	4	3	3	2	1
AI	4	4	2	2	3	1
BC	1	0	1	0	0	0
BIM	0	0	1	0	0	0
EC	1	1	0	0	1	0
GIS	0	0	1	0	0	0

In contrast, Economic and Financial Management (EF) occupies a comparatively marginal position, with only 17 articles (16.7%). As shown in Figure 8 and confirmed by the distribution reported in Table 8, this gap points to a limited treatment of benefit-allocation models, financial coordination mechanisms, and other economic dimensions that are essential for REC viability and long-term stability.

With regard to building performance, the literature is more consistent in reporting operational objectives, such as forecasting accuracy, self-consumption optimization, flexibility activation, cost optimization, anomaly detection, and comfort-aware control, than in documenting standardized whole-building performance indicators. Metrics such as kWh/m^2, kgCO_2/m^2, and pre-/post-retrofit verification outcomes appear only sporadically and without systematic comparability across studies. Taken together, these findings

indicate that the current body of literature is stronger in operational real-time optimization than in robust cross-case benchmarking of building energy performance.

3.5. Data Realism Classification: Synthetic, Historical, and Real-Time Data in DT Architectures

The data realism classification (Dimension H), introduced in Section 2.3 as an original analytical extension, reveals one of the most structurally significant findings of this review: the prevailing disconnection between the data environments assumed by DT research and the data conditions that characterize real-world building stocks and operational energy communities. Applying this classification to the corpus of 102 articles yields a distribution that exposes a systemic bias toward idealized, controlled data environments. Approximately 61% of the corpus (62 articles) relies predominantly on Synthetic/Simulated data (H1): DT architectures are validated against artificially generated load profiles, modeled building physics, or simplified grid representations without grounding in real energy or building data. A further 28% (29 articles) employ Historical/Archival data (H2), using metering archives or historical production datasets in a static mode that does not reflect the dynamic, incomplete, and heterogeneous data conditions of operational deployments. Only approximately 11% of the corpus (11 articles) documents DT architectures operating on Real-time Sensor/Operational data (H3), the data modality that is, by definition, required for any genuinely operational Digital Twin. Table 9 presents the complete data realism distribution by enabling technology and DTC capability.

Table 9. Data realism classification of the corpus (n = 102 articles) by data type and DTC capability coverage.

Operational Deployment Suitability	Dominant DTC Capabilities	Dominant Contribution Type	% Corpus	Articles (n)	Category
Not deployment-ready	IA (dominant), MN; DS and UX absent	Simulation-Based, Methodological	60.8%	62	H1: Synthetic/ Simulated Data
Partially transferable; validation gap	IA, MN; DS partial; UX largely absent	Applied Study (ML forecasting), Prototype	28.4%	29	H2: Historical/ Archival Data
Deployment-ready; represents TRL 6–8	IA, MN, IR, DS partial; TW elevated; UX present but limited	Applied Study (operational case study)	10.8%	11	H3: Real-time Sensor/ Operational Data

These results highlight one of the clearest patterns emerging from the review. The predominance of synthetic or historical data sources (89.2% of the corpus) indicates that most DT research for buildings and RECs is still based on data conditions that are only partially representative of real-world operation. Studies relying on real-time, incomplete, or noisy operational data remain comparatively limited. This aspect is particularly relevant for net-zero building management, where DT platforms are expected to integrate multiple heterogeneous data streams, including EPC-related energy data, occupancy signals, HVAC sensor data, and real-time grid price signals. Therefore, although the publication volume suggests growing research interest, the corpus points to a field in which real-world operational validation is still relatively limited.

4. Discussion

4.1. Architectural Maturity, Technology Readiness, and AI Integration in DT Architectures for RECs

The reviewed literature portrays a DT-for-REC research landscape characterized by a clear tension between architectural sophistication and real-world operational maturity [65]. On the one hand, Digital Twin (DT) emerges as a central framework, being explicitly cited in 55.9% of the corpus, which confirms its growing role as an integrative model

for energy management in Renewable Energy Communities [66,67]. On the other hand, this prominence appears to be concentrated mainly in computational, simulation-based, or planning-oriented contexts rather than in systematically documented operational deployments. In this sense, the field appears strategically focused, yet still more oriented toward architectural design and algorithmic innovation than toward implementation and validation under real operating conditions [68,69].

This pattern becomes particularly evident when the REC literature is compared with the building-management domain [70]. Unlike the more BIM-oriented trajectory often reported for building applications, REC research seems to have adopted the DT paradigm earlier as a unifying framework for distributed energy coordination [71]. However, the evidence reviewed here suggests that this conceptual advance has not yet been matched by an equally mature implementation base. At the same time, both domains show a similar internal imbalance: they concentrate primarily on Intelligence and Analytics (IA), and Management (MN) capabilities, while User Experience (UX) and Data Services (DS) remain comparatively weak [72]. For the purposes of this Special Issue, this is a relevant finding: the literature is already highly pertinent to energy-efficient building management, but it is still underdeveloped in precisely the layers that would be necessary to make DT solutions scalable, interoperable, and practically usable across heterogeneous building portfolios.

A similar conclusion emerges from the analysis of technology readiness. At first sight, the typological composition of the corpus, 42% Applied Studies, 31% Simulation-Based studies, and 9% Prototypes, might suggest a field at intermediate maturity. However, when these contribution types are interpreted together with the data realism classification, a more cautious picture emerges. Most simulation-based studies rely on fully synthetic data conditions, while a substantial share of the applied studies are based primarily on historical datasets rather than on live operational streams. This suggests that conventional classifications by contribution type may overestimate the actual deployment maturity of the field. Within the limits of the reviewed corpus, only a relatively small subset of studies appears to be validated under genuinely real-time operational conditions, whereas a much larger proportion remains anchored to historical or simulated environments.

The operational expression of this maturity gap is the pronounced imbalance between Planning and Design, and Implementation and Commissioning (77.5% vs. 16.7%, as documented in Section 3.4), which indicates that DT architectures are extensively conceptualized, modeled, and optimized, but far less frequently documented in terms of commissioning procedures, sensor-integration workflows, organizational adaptation, validation protocols, and the handling of real-world data-quality problems. In this context, deployment workflows, sensor-integration procedures, commissioning protocols, and go-live verification frameworks represent critical but largely absent contributions in the current literature. For building owners, public authorities, and REC operators, this imbalance translates into uncertainty regarding implementation risk, replicability, and deployment cost. In the building sector, this problem is amplified by the heterogeneity of the European building stock, particularly in Southern Europe, where a large share of the stock consists of older buildings with legacy heating systems, fragmented control infrastructures, and limited digital readiness. Under these conditions, DT architectures validated only on recent or highly instrumented reference buildings cannot yet be assumed to transfer directly to more constrained real-world contexts.

The role of artificial intelligence reinforces this interpretation. When machine learning (ML), advanced analytics (AA), and generic artificial intelligence (AI) references are considered together, explicit AI-related penetration reaches approximately 35% of the corpus. This indicates that a substantial proportion of proposed DT architectures still relies primarily on physics-based or rule-based approaches without an explicit predictive

intelligence layer. Where AI/ML is integrated, its application is concentrated mainly in data forecasting, energy optimization, and grid integration and flexibility, which confirms the strategic importance of predictive and adaptive control functions within REC-oriented DT systems [73]. Nevertheless, the prevailing configuration is typically a hybrid physics-driven plus data-driven architecture in which the two components are combined conceptually but not always fully integrated operationally [74]. Future DT architectures should prioritize dynamic self-calibration mechanisms enabling continuous bidirectional updating between the physical asset and its digital counterpart, with capacity to adapt to changing occupancy patterns, sensor degradation, and control-system drift over time.

More specifically, the reviewed studies often describe physics-based simulation and data-driven analytics as complementary modules, yet only rarely document continuous bi-directional updating between them [75,76]. As a result, many proposed DTs still fall short of the stronger interpretation of the paradigm, namely a system capable of adaptive self-calibration through continuous alignment between physical processes and observed data [77]. This limitation is particularly relevant in the context of energy-efficient building and REC management, where occupancy variability, control-system drift, partial sensing, and changing market signals require DT architectures to remain dynamically responsive over time [78]. Taken together, these findings suggest that the field has established a solid conceptual and architectural foundation, but that its transition toward robust, interoperable, and operationally validated DT ecosystems is still incomplete [79].

4.2. Cross-Sectoral Comparison and the Critical Gaps in UX, Data Services, and Implementation

A methodologically relevant contribution of this review lies in the cross-sectoral comparison between the DT-for-REC domain and the Digital Twin literature in the construction and building sector [80,81]. As illustrated in Figure 9, both domains exhibit a remarkably similar capability profile: Intelligence and Analytics (IA), and Management (MN) emerge as the dominant capabilities, whereas User Experience (UX) and Data Services (DS) remain consistently underrepresented [82]. This convergence suggests that such deficits are not domain-specific anomalies, but rather reflect a broader structural bias in DT research, which continues to privilege computational intelligence and control functions over human-centered design and data governance dimensions [83,84].

At the same time, the divergences between the two domains are equally informative. In the construction sector, BIM remains the dominant digital paradigm, with DT still emerging as an extension of model-based building information practices [85]. In contrast, in the REC domain, DT already appears as the primary integrative technology, without a comparable BIM-led transition [86]. Similarly, blockchain shows greater relative relevance in the REC literature than in the construction domain, reflecting its association with peer-to-peer energy transactions, traceability, and governance mechanisms [87]. The primary digitalization objective also differs substantially: whereas the REC literature is centered on Grid Integration and Flexibility, the construction domain is more strongly oriented toward Project Management, confirming that the two sectors are shaped by fundamentally different operational priorities despite convergent architectural limitations.

These cross-sectoral patterns are further clarified by the capability diagnostic presented in Figure 10. Among the identified gaps, the UX deficit is particularly significant in the REC context. Unlike many industrial DT applications, where the main users are technical professionals, REC governance necessarily involves non-technical actors, including households, prosumers, small businesses, and civil associations, whose participation is not merely desirable but intrinsic to the REC model itself. Under these conditions, an effective DT architecture must provide not only computational sophistication but also interfaces capable of translating complex energy and operational data into accessible and actionable

information. The persistent marginality of UX-related capabilities therefore represents more than a design weakness; it constitutes a potential barrier to inclusive governance and meaningful stakeholder participation.

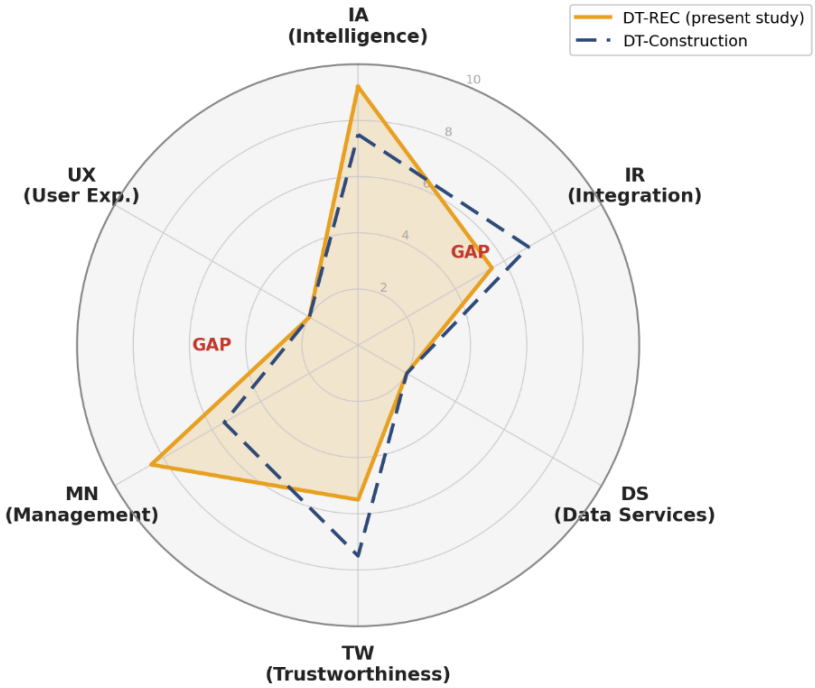

Figure 9. Cross-sectoral radar comparison of DTC capability distributions: DT-REC (present study, orange) vs. DT-Construction [39] (blue dashed). Both domains show convergent gaps in DS (Data Services) and UX (User Experience), marked with "GAP" labels.

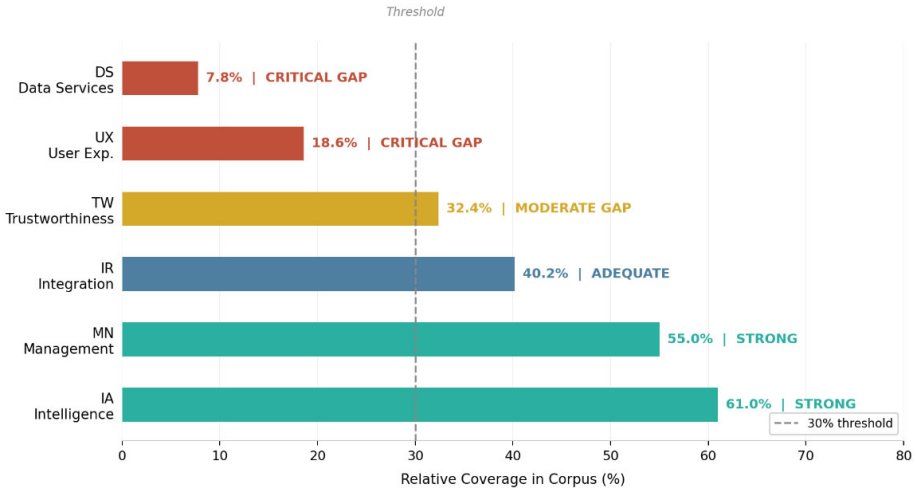

Figure 10. DTC capability coverage diagnostic (n = 102). Values represent relative coverage in the analyzed corpus. Critical gaps (DS and UX) are highlighted in red; the 30% threshold line marks minimum adequate coverage.

An even more structural limitation emerges in relation to Data Services (DS), which records the lowest coverage in the corpus. As shown in Figure 10, this gap points to a weak treatment of the data-governance layer that would be required for operational DT deployment. Semantic ontologies, standardized data models, API specifications, interoperability protocols, and data-quality management frameworks are all essential preconditions for integrating the heterogeneous information sources on which REC and building DTs depend. In this respect, the absence of references to enabling infrastructures such as 5G and

Common Data Environments (CDEs) is also telling, as it suggests that the literature has not yet engaged systematically with the infrastructural standards needed for interoperable, multi-source, district-scale DT architectures. In the building context, this challenge is further amplified by the fragmentation of EPC/APE databases across national, regional, and municipal registries, often characterized by inconsistent formats, uneven updating procedures, and limited machine-readability. Concrete pathways to address this structural deficit include the adoption of established interoperability frameworks such as the IFC/IDS (Industry Foundation Classes/Information Delivery Specification) standard for building data exchange, the BRICK Schema for semantic representation of building metadata and sensor relationships, and the SAREF (Smart Applications REFerence) ontology endorsed by ETSI for IoT semantic harmonization in energy systems. Aligning REC DT platforms with these open standards would substantially reduce integration barriers and improve the reusability and comparability of deployed architectures.

The Implementation and Commissioning gap reinforces this diagnosis. Even where advanced architectures are conceptually proposed, validated pathways for deploying them in real building and community contexts remain relatively scarce. This limited attention to implementation is not unique to the REC domain but appears as a broader weakness shared across DT-related research fields. Taken together, the DS and implementation gaps should not be interpreted as separate omissions. Rather, they collectively point to a coupled barrier between conceptual architectural development and scalable operational deployment. In other words, the current literature appears more advanced in defining what DT-enabled net-zero and REC systems should do than in documenting how such systems can be reliably integrated, commissioned, governed, and maintained in real-world conditions. It should also be acknowledged that operational REC and building DT implementations may exist in industrial, commercial, and institutional environments that are not systematically represented in the indexed academic literature. The grey literature, including technical reports, white papers, and proprietary pilot documentation, was not retrieved by the systematic search protocol and may document deployment experiences that complement the patterns identified here.

4.3. Implications for Policy, Platform Development, and the Twin Transition

The findings of this review carry important implications for both policy actors and technology developers operating at the intersection of the two converging EU regulatory trajectories represented by RED II for Renewable Energy Communities and the recast EPBD for net-zero and smart-ready buildings [9].

In particular, the recast EPBD marks a significant shift in EU building policy by requiring not only improvements in physical energy performance but also interoperable digital infrastructures, including machine-readable EPC databases, Building Renovation Passports, and the Smart Readiness Indicator (SRI) as a standardized measure of a building's capability for smart energy management and grid interaction. In this sense, the regulatory framework implicitly calls for the same DT capability stack identified in this review, namely Data Services (DS) for data integration; Integration (IR) for multi-system connectivity; Intelligence and Analytics (IA) for predictive and adaptive optimization; and User Experience (UX) for interaction with prosumers, operators, and building managers.

Within this perspective, the gaps identified in DS and UX are not merely academic limitations. Rather, they indicate areas in which the current DT evidence base remains only partially aligned with emerging regulatory and operational requirements. For public administrations, housing managers, and public building owners, this misalignment has practical consequences: procurement choices, retrofit sequencing, data-governance strategies, and digital-platform investments often need to be made before a sufficiently mature

body of deployment-ready evidence is available. Policy intervention should therefore concentrate on four priority areas: data standardization and interoperability, implementation support, inclusive digital governance, and building-scale DT readiness. In particular, the absence of semantic ontologies, standardized data models, and interoperable governance frameworks continues to generate fragmentation; the limited attention to Implementation and Commissioning highlights the need for structured pilot programs, technical assistance, and validation protocols; and the persistent weakness of UX-related capabilities risks undermining the participatory logic of RECs and the social-equity goals embedded in EU renovation policies.

These findings are equally relevant for platform designers and technology developers [49]. The dominance of the Core DT Stack confirms that DT, IoT, and ML already constitute the most established architectural basis for REC-oriented systems. However, differentiation is likely to arise less from adding further computational sophistication than from strengthening the currently underserved layers, especially DS, UX, and Trustworthiness (TW). In practical terms, this implies greater attention to semantic interoperability, data-quality management, explainable analytics, privacy-preserving processing, cybersecurity, and compliance-aware platform design [50]. A particularly important design implication concerns the relationship between physics-driven and data-driven components: many existing solutions remain hybrid only in a nominal sense, combining simulation and analytics without fully operationalizing continuous feedback between them [51,52]. DT architectures should therefore evolve toward continuous calibration loops, in which physical models are updated through observed operational data and uncertainty is explicitly managed over time [53]. At the same time, the most transferable solutions are unlikely to be those developed only for newly instrumented demonstrators, but rather those capable of functioning under conditions of partial sensing, legacy infrastructures, and heterogeneous building portfolios, while still offering understandable workflows and interfaces for non-specialist users [54,55].

Interpreted within the twin transition framework, these findings highlight both the progress achieved and the structural distance that still separates current DT research from the operational deployment required by net-zero building and energy-community objectives [56]. The rapid expansion of DT-for-REC research confirms the growing recognition of RECs as a priority application domain, while the emergence of the Core DT Stack reflects genuine progress toward a shared technical foundation [57,58]. At the same time, the persistent implementation deficit, the underdevelopment of UX, the weakness of data-governance layers, and the limited treatment of economic-benefit allocation suggest that the digital dimension of the twin transition remains more design-oriented than deployment-oriented [59,60]. This asymmetry is especially relevant in light of accelerating regulatory timelines associated with the EPBD recast and related building-renovation instruments [61,62]. Overall, the evidence points toward a research and innovation agenda centered on operational validation, commissioning documentation, building-stock integration, and inclusive governance design for households, cooperatives, and local public administrations.

4.4. Structural Mismatch and Deployment Implications: An Evidence-Informed Perspective

The corpus findings, read alongside official building stock data and regulatory frameworks, point to a structural mismatch between the implicit assumptions of the reviewed DT literature and the conditions that characterize real-world building and REC deployment contexts. Table 10 makes this mismatch explicit across four indicative dimensions.

The comparison in Table 10 indicates that the reviewed literature tends to assume well-instrumented, purpose-built buildings with clean data pipelines and technically proficient users, conditions that differ markedly from the heterogeneous pre-1980 building stock,

fragmented EPC databases, and non-technical prosumer populations that characterize real European deployment contexts, particularly those targeted by the EPBD recast [64,88]. A related observation concerns data resources: official datasets directly relevant to DT research for buildings and RECs, including SIAPE/APE (ENEA), ISPRA emission factors, and the EU Building Stock Observatory, appear largely absent from the reviewed corpus, despite being openly accessible and machine-readable [89,90]. Within the limits of this review, this suggests that barriers to their integration may be primarily methodological rather than technical and that incorporating such sources into future research could represent a tractable step toward more deployment-ready architectures [91,92].

Table 10. Structural mismatch: literature assumptions versus real-world deployment conditions in DT-for-building-and-REC research.

Dimension	Typical Assumption in Reviewed DT Literature	Deployment Condition	Indicative Mismatch
Building stock characteristics	The literature is dominated by modern, well-instrumented reference buildings or simplified residential models (97% of H1 + H2 corpus), with limited treatment of stock heterogeneity.	Around 65% of EU residential floor area is pre-1980, with heterogeneous envelopes, legacy HVAC systems, limited metering, and variable occupancy.	Critical
Data availability and quality	Complete, clean, high-resolution data are often assumed, while APIs and integration pipelines are treated as readily available; EPC/APE data are absent from most of the corpus (94%).	EPC databases remain fragmented, smart-meter access is uneven, and IoT coverage in existing stock is limited; missing and inconsistent data are common.	Critical
User profile and competency	DT solutions are mainly oriented toward technical operators, while UX is explicitly addressed in only 18.6% of the corpus.	REC users are largely households, small businesses, and civil associations, including vulnerable groups requiring accessible and trust-building interfaces.	Critical
Operational environment	Most studies rely on controlled simulation or laboratory conditions (89.2% H1 + H2), with limited treatment of failure modes, latency, and degraded data quality.	Real REC deployments face intermittent connectivity, variable meter quality, compliance checks, and grid variability of around ±15–20% intraday.	High

4.5. Limitations

The present scoping review was conducted in accordance with the PRISMA-ScR framework and is subject to the methodological boundaries inherent to this design. First, the search was conducted primarily in Scopus; while this database provides broad interdisciplinary coverage relevant to the energy–technology domain, multi-database integration would further strengthen retrieval completeness. In particular, IEEE Xplore and Web of Science Core Collection are complementary sources that may capture additional engineering-oriented contributions, particularly in smart grid, power systems, and embedded control domains. Second, the structured search window was bounded by the adoption of RED II (2018–2025); citation chaining was applied to recover foundational contributions predating this regulatory threshold, yielding a final corpus of 102 papers spanning 2012–2025. Third, the restriction to English- and Italian-language publications is consistent with the predominant language of the

indexed technical literature in this domain, though contributions published in other languages were not retrieved. Fourth, in keeping with the scope of PRISMA-ScR, no formal critical appraisal of individual study quality was performed; this is an intentional design choice of scoping reviews, which prioritize breadth of coverage over hierarchical quality ranking. Fifth, the geographical distribution analysis was based on institutional affiliation data as extracted from Scopus records, which were not uniformly complete; the resulting geographic overview should be interpreted as indicative rather than as a formal bibliometric mapping. Sixth, the exclusion of the grey literature is a standard limitation of database-driven systematic searches; operational REC implementations documented in technical and institutional reports may represent an underexplored segment, particularly with reference to the implementation gap documented in the results. These limitations do not affect the validity of the thematic synthesis but define the boundaries within which the findings should be interpreted. Seventh, the present review does not include a formal comparison of its methodological choices, search strategy, corpus size, and coding dimensions, with those of other systematic and scoping reviews addressing adjacent domains such as Digital Twins in construction or energy management more broadly. Such a comparison would further contextualize the methodological contribution of the data realism framework (Dimension H) and the DTC capability diagnostic introduced here.

5. Conclusions

This scoping review has mapped the state of the art in Digital Twin architectures for building-scale and community-scale energy management within Renewable Energy Community configurations, generating findings with implications for building physics integration, data governance, platform development, and energy policy [93]. Positioned at the intersection of RED II and the EPBD recast, this study indicates that DT architectures can function as enabling infrastructures for building- and district-scale net-zero management but that the supporting evidence remains uneven across deployment stages. Three contributions distinguish this work: (1) a multi-dimensional systematic mapping of the DT-for-building-and-REC research landscape calibrated to the DTC capability framework; (2) an evidence-informed gap map linking literature findings to official building stock datasets and operational deployment contexts; and (3) a policy-aligned interpretation of research gaps in relation to EPBD-driven building data interoperability and smart-readiness requirements [94].

In relation to RQ1, the landscape is characterized by rapid growth (46.1% of the corpus in 2020–2021), with DT consolidated as the dominant enabling technology (55.9%). The research is disproportionately oriented toward Planning and Design (77.5%), while Implementation and Commissioning remains underrepresented (16.7%), revealing a persistent design-to-operation gap. The strongest building-relevant evidence concerns monitoring, forecasting, self-consumption management, and flexible operation at the building or building-cluster scales, whereas commissioning workflows and post-retrofit verification remain comparatively thin. Technology readiness appears concentrated around TRL 4–6, with only a minority of clearly operational deployments [95,96].

In relation to RQ2, AI/ML penetration in the corpus reaches approximately 35% in aggregate. Where present, AI/ML is primarily deployed for data forecasting, energy optimization, grid flexibility, occupancy-aware control, and anomaly detection—functions that are directly relevant to energy-efficient buildings. However, the prevailing hybrid Physics-Driven + Data-Driven architecture remains operationally fragmented in many implementations, with limited evidence of continuous bi-directional model updating and relatively weak reporting of standardized building-performance KPIs.

In relation to RQ3, three critical capability gaps characterize the field: Data Services (7.8%, lowest absolute value), reflecting underinvestment in semantic interoperability and data governance; User Experience (18.6%), a barrier to inclusive prosumer and building participation [95,96]; and Trustworthiness (32.4%), present but still insufficient for operational platform cybersecurity demands. The absence of 5G and Common Data Environment references underscores the distance between many theoretical architectures and the infrastructure conditions required for deployment in existing building stock.

Overall, this study contributes analytically by clarifying where the literature already supports building-centered energy management and where it remains weak; methodologically by demonstrating a replicable PRISMA-ScR synthesis strategy enriched through a Data Realism lens; and strategically by identifying implementation, interoperability, and inclusivity gaps that matter directly for net-zero building deployment. For *Sustainability* and its Special Issue readership, the central message is not that DTs are already mature solutions for all building contexts but that they are emerging infrastructures whose value depends on whether future research can close the gap between simulation-rich design and deployment-ready building operation.

Future research directions include (1) the development and validation of semantic ontologies and open data standards enabling EPC/APE data ingestion into REC DT platforms, in alignment with EPBD recast data interoperability mandates; (2) systematic documentation of DT implementation methodologies through structured case studies in operational building clusters and RECs, with explicit reporting of commissioning, sensor integration, data quality management, and validation protocols; (3) the design and evaluation of prosumer-centric and building-manager-centric interface architectures for non-technical community members; (4) the integration of Blockchain and DT for transparent benefit allocation and energy governance in multi-building REC configurations; (5) the development of building archetype-specific DT calibration frameworks that leverage EPC databases and official building-stock observatories; (6) longitudinal studies tracking net-zero KPI trajectories such as kWh/m2, kgCO2/m2, self-sufficiency ratio, comfort, and flexibility activation across retrofit cycles; (7) the investigation of edge-cloud hybrid architectures for real-time HVAC control and community-scale dispatching under practical latency, privacy, and cybersecurity constraints; (8) comparative reporting frameworks that make building-performance outcomes more consistent across case studies, climates, and building types; and (9) the integration of standardized building energy performance indicators, including kWh/m^2, $kgCO_2/m^2$, and pre-/post-retrofit Measurement and Verification (M&V) protocols aligned with IPMVP, within DT operational dashboards, to enable cross-case comparison and policy-relevant performance benchmarking under EPBD recast requirements.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su18125869/s1, Table S1: Thematic coding matrix of the 102 included studies.

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Data Availability Statement: This review synthesizes publicly available data from the cited literature, the analytical tables reported in this manuscript, and the Scopus bibliographic exports used for screening (executed on 25 March 2026). No new primary dataset was generated. The thematic coding matrix for the 102 included studies and the completed PRISMA-ScR checklist are available in Supplementary Materials and Appendix A.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AA	Advanced Analytics;
AI	Artificial Intelligence;
APE	Attestato di Prestazione Energetica (Italian EPC);
BC	Blockchain;
BD	Big Data;
BIM	Building Information Modeling;
BMS	Building Management System;
CC	Cloud Computing;
CDE	Common Data Environment;
DT	Digital Twin;
DTC	Digital Twin Consortium;
DS	Data Services;
DR	Demand Response;
EC	Edge Computing;
EPC	Energy Performance Certificate;
EPBD	Energy Performance of Buildings Directive;
GIS	Geographic Information System;
HVAC	Heating, Ventilation, and Air Conditioning;
I&C	Implementation and Commissioning (REC lifecycle phase);
IA	Intelligence and Analytics (DTC capability);
IoT	Internet of Things;
IR	Integration
KPI	Key Performance Indicator;
LCA	Lifecycle Assessment;
MEPS	Minimum Energy Performance Standards;
ML	Machine Learning;
MN	Management;
M&V	Measurement and Verification;
nZEB	Nearly Zero-Energy Building;
P2P	Peer-to-Peer;
PCC	Population–Concept–Context;
PRISMA-ScR	Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Review;
REC	Renewable Energy Community;
RED II	Renewable Energy Directive II;
SRI	Smart Readiness Indicator;
TRL	Technology Readiness Level;

TW	Trustworthiness;
UX	User Experience;
VPP	Virtual Power Plant;
XAI	Explainable Artificial Intelligence

Appendix A

PRISMA-ScR Checklist [45].

Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
TITLE			
Title	1	Identify the report as a scoping review.	1
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	1
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	1-4
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	3-4
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	4
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	6-7
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	5-6
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	5
Selection of sources of evidence	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	5-7
Data charting process	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	7 - 8
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	4-7
Critical appraisal of individual sources of evidence	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	N / A
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	7 - 8

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	9
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	9 - 1 5
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	N / A
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	9-16
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	9 - 1 5
DISCUSSION			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	16-23
Limitations	20	Discuss the limitations of the scoping review process.	23-24
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	24-25
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	25

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.
* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.
† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).
‡ The frameworks by Arksey and O'Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting.
§ The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018;169:467–473. doi: 10.7326/M18-0850.

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