# AI and Digital Twin Applications in Building Energy Management: A State-of-the-Art Review

1st Afrouz Ghaemi
*School of Engineering)*
*Cardiff university*
Cardiff, UK
ghaemia@cardiff.ac.uk

2nd Yacine Rezgui
*School of Engineering)*
*Cardiff university*
Cardiff, UK
rezguiy@cardiff.ac.uk

3rd Ioan Petri
*School of Engineering)*
*Cardiff university*
Cardiff, UK
petrii@cardiff.ac.uk

4th Thomas Beach
*School of Engineering)*
*Cardiff university*
Cardiff, UK
beachth@cardiff.ac.uk

5th Ali Ghoroghi
*School of Engineering)*
*Cardiff university*
Cardiff, UK
ghoroghi@cardiff.ac.uk

***Abstract*—Purpose: This paper examines the integration of Artificial Intelligence (AI) and digital twin technologies in commercial and residential buildings, focusing on self-learning systems and intelligent energy management solutions. Methods: A comprehensive review synthesizes recent developments in AI applications, digital twin architectures, and building automation systems, with emphasis on autonomous control and occupant-centric optimization. Results: The analysis reveals promising trends in AI-enhanced digital twins for building systems, highlighting their capability to learn from occupant behavior, make data-driven decisions, optimize performance in real-time, and seamlessly integrate with other building technologies to create an efficient, comfortable environment. Conclusions: The findings demonstrate the transformative potential of AI-driven digital twins in modern buildings, offering practical guidance for implementing these technologies while prioritizing occupant comfort, energy efficiency, and sustainability through self-learning building systems.**

***Index Terms*—Artificial Intelligence, AI-enhanced Digital Twins, Smart Buildings, Building Automation Systems, Autonomous Building Systems, Energy Management.**

## I. Introduction

The evolution of building automation and self-learning systems has accelerated the adoption of artificial intelligence (AI) and digital twin technologies in building management [1]. Traditional building management systems often fail to leverage the potential of real-time data analytics and autonomous decision-making [2], limiting their ability to optimize operations for occupant comfort and energy efficiency. The emergence of AI-enhanced digital twins presents new opportunities for advancing building automation [3].

*Building Automation Systems (BAS)* are rule-based systems to control HVAC, lighting, and security. *Smart Buildings* are BAS with AI, IoT, and digital twins for adaptive optimization. *Autonomous Building Systems* are smart buildings that self-optimize using real-time, self-learning algorithms.

This review addresses four key research questions:

1) How are AI techniques currently deployed in smart building systems?
2) What frameworks exist for implementing digital twins in autonomous building systems?
3) What challenges impact AI-driven digital twin integration in building automation?
4) Which pathways can ensure optimal implementation of self-learning building systems?

Recent advances in AI applications [4] and digital twin frameworks [3] have demonstrated significant potential for enhancing building operations. However, integrating these technologies into cohesive, autonomous systems remains challenging [5]. This review synthesizes current knowledge and implementation strategies, with particular focus on:

- AI-driven building automation and control systems [6]
- Digital twin architectures for smart buildings [1]
- Integration frameworks for autonomous building operation [7]
- Real-time optimization strategies for occupant comfort [4]

By examining advanced methods in AI implementation, digital twin development, and self-learning systems integration, this paper provides insights for developing robust smart building systems. The findings support practitioners and researchers in implementing AI-enhanced digital twins for autonomous building operations.

### A. Relevance to Digital Transformation and Building Automation

The integration of AI-enhanced digital twins in smart buildings represents a critical advancement in digital transformation and building automation. This review addresses several key aspects of modern building technology evolution: 1. *Smart Buildings and Autonomous Building Systems:* The analysis examines how AI-driven digital twins enable autonomous decision-making and intelligent building operations [1]. 2. *Digital Transformation:* The review explores how organizations can effectively implement and manage the transition to AI-enhanced building systems [6]. 3. *Innovation Integration:* The research investigates frameworks for integrating cutting-edge AI technologies with existing building management systems [4]. This comprehensive examination offers useful insights to both academic researchers and industry professionals working on digital transformation and smart building technologies.

### B. Research Contribution

This review makes several significant contributions to the field: 1. *Comprehensive Framework:* Provides a systematic framework for understanding and implementing AI-enhanced digital twins in smart buildings. 2. *Integration Roadmap:* Develops a detailed roadmap for integrating AI technologies with existing building systems, addressing both technical and organizational challenges. 3. *Future Directions:* Identifies critical research gaps and future development pathways in smart building automation, particularly focusing on self-learning systems and digital transformation. 4. *Practical Guidelines:* Offers concrete implementation guidelines and best practices for organizations undertaking digital transformation initiatives in building automation and control. Sections II and III discuss the research methodology and state-of-the-art review. Sections IV to IX discuss key findings and analysis, practical implementations and framework, sustainability and circularity integration, technology innovation framework, gaps and future works, and conclusions and implications, respectively.

### C. Thematic Roadmap Aligned with the Research Questions

The paper is structured into nine sections, with the research questions (RQs) addressed in the following key sections:

- *RQ1 - AI Techniques for Smart-Building Control* (Section III-B) reviews and critiques state-of-the-art learning algorithms.
- *RQ2 - Digital-Twin Frameworks* (Section III-C) synthesizes architectural patterns that enable autonomous operation.
- *RQ3 - Integration Challenges* (Section III-D) analyzes technical and organizational barriers.
- *RQ4 - Implementation Pathways* (Section V) proposes a phased roadmap linking theory to practice.

### D. Conceptual Integration Scheme

Figure 1 summarizes key findings from the literature in an intuitive, three-layer framework. This integrated framework helps synthesize diverse ideas into a clear, practical model to guide the analysis presented in later sections III–V.
Furthermore, Table I highlights the unique contributions of this review compared to previous ones.

## II. Research Methodology

This review employed a systematic approach to synthesize and analyze current literature on AI-enhanced digital twins in smart buildings. The literature search process encompassed multiple scientific databases including Scopus, Web of Science, and IEEE Xplore, supplemented by relevant industry publications and technical reports. Search criteria focused on publications from 2014-2024, using key terms including artificial intelligence, digital twins, smart buildings, and building automation systems. The analytical framework consisted of two primary components: content analysis and quality assessment. The analysis process involved categorizing research content into specific themes, enabling the identification of recurring patterns and research gaps across the literature.

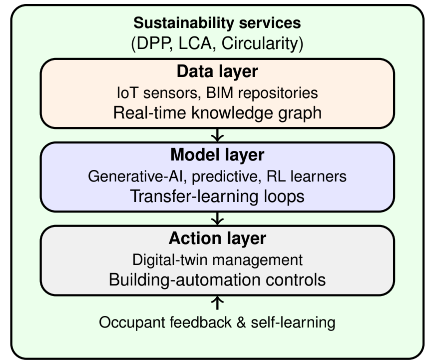


Fig. 1. A conceptual framework connecting the data, model, and action layers. The arrows highlight interactions and optimizations between these layers, while the outer circle emphasizes key sustainability considerations.

Each publication was evaluated based on its methodological rigor, technical depth, and implementation relevance. This systematic approach enabled comprehensive coverage of both theoretical developments and practical applications in the field. The review process paid particular attention to the intersection of AI technologies with digital twin implementations, focusing on: 1. Technical architectures and implementation frameworks. 2. Integration challenges and solutions. 3. Performance optimization strategies. 4. Future development pathways. This methodological approach ensured comprehensive coverage of the field while maintaining focus on practically relevant developments and emerging trends.

### A. Review Methodology

To increase methodological transparency we followed the PRISMA 2020 reporting guideline [12]. Figure 2 shows identification, screening, and inclusion flow (97 studies retained). While not following full PRISMA guidelines, our structured approach ensured a comprehensive and transparent research process. We implemented a detailed search strategy across three distinct databases, maintaining thorough documentation of our inclusion and exclusion rationale. The quality assessment process followed predefined criteria to ensure consistency and reproducibility of our review methodology.

### B. Selection Criteria

The literature review employed specific inclusion/exclusion criteria. For inclusion, we focused on four essential elements in our selection process: scholarly articles that underwent peer review between 2014-2024, research incorporating empirical validation methods, documented implementation case studies, and technical frameworks that demonstrated clear practical applications. Our exclusion protocol eliminated three categories of sources to maintain academic rigor: theoretical papers lacking implementation evidence, research without substantial validation data, and publications that had not undergone the peer review process.

### C. Quality Assessment Framework

Studies were evaluated using a structured assessment framework:

TABLE I
DIFFERENTIAL CONTRIBUTIONS OF THIS REVIEW RELATIVE TO RECENT SURVEYS

| **Prior review** | **Primary focus / window** | **Gap left open** | **Addressed here** |
|---|---|---|---|
| Adebowale *et al.* 2023 [8] | AI for improving productivity in the construction phase | Lacked discussion of digital twins or a comprehensive overview of building automation systems in the operational phase. Failed to address integration with AI and digital twins | ✓ |
| Liu *et al.* 2024 [9] | Applications and research trends of Digital Twin technology in the built environment | Does not delve into a holistic integration with building automation systems and AI | ✓ |
| Qiang *et al.* 2023 [10] | Building automation systems in green buildings for energy and comfort management | lack of detailed discussion on the integration of artificial intelligence and digital twins with these systems. | ✓ |
| Datta *et al.* 2024 [11] | AI and machine learning applications across the construction project lifecycle | lack of a holistic discussion of comprehensive building automation systems and their deep integration with AI and full building digital twins throughout the entire lifecycle | ✓ |

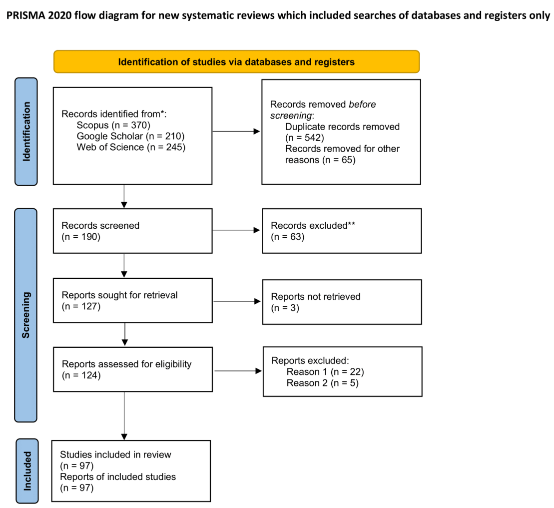


Fig. 2. PRISMA 2020 flow diagram for the literature-selection process.

TABLE II
QUALITY ASSESSMENT CRITERIA

| **Criterion** | **Assessment Metrics** |
|---|---|
| Methodological precision | Clearly defined methodology, reproducible results, statistical validity |
| Technical Depth | Detailed technical specifications, performance metrics, implementation details |
| Practical Relevance | Real-world application, scalability considerations, cost-benefit analysis |

## III. STATE-OF-THE-ART REVIEW

### A. Advanced AI Implementation Frameworks

*1) Deep Learning Architectures:* Recent developments in deep learning architectures have shown particular promise:

*a) Generative Models:* Advanced implementations encompass several sophisticated frameworks. GAN-based architectures have demonstrated significant capability in synthetic data generation [13], incorporating conditional GANs for scenario generation, robust model development through adversarial training, and adaptive model refinement via transfer learning approaches. Complementing these advances, variational autoencoders have proven instrumental in feature extraction [21], achieving this through latent space optimization, unsupervised feature learning mechanisms, and integrated anomaly detection capabilities.

*b) Reinforcement Learning Systems:* Key implementations have advanced along two primary trajectories. Multi-agent systems have emerged as powerful solutions for distributed control [4], incorporating cooperative learning frameworks, sophisticated policy optimization strategies, and real-time adaptation mechanisms. In parallel, deep Q-learning networks have demonstrated exceptional promise in optimal control applications [22], leveraging state-space optimization techniques, advanced action-value function learning, and sophisticated experience replay mechanisms for enhanced performance.

### B. AI Applications in Smart Buildings

AI techniques have transformed building automation and control systems, enabling advanced data analytics and self-learning decision-making [21]. Recent applications span predictive control, fault detection, and resource optimization [4]. Particularly notable are developments in:

*1) Machine Learning Integration:* Advanced machine learning approaches have demonstrated a significant impact in building automation. These approaches encompass sophisticated occupant-aware systems that leverage behavioral data analytics [23], comprehensive technical optimization frameworks utilizing deep neural networks [24], and advanced real-time analytics solutions for building control [25].

*2) Generative AI Applications:* Generative AI techniques serve as building system optimization tools with distinct approaches. Harell et al. [13] created synthetic data for occupant behavior modeling but lacked cross-building validation. Burgueño et al. [21] developed GAN frameworks offering 17% better prediction accuracy with higher computational costs, while Markus et al. [26] achieved better computational efficiency at lower accuracy, enhancing real-time viability. These complementary strengths suggest value in an integrated approach combining elements from each framework.

*3) Critical Analysis of Generative AI Applications:* While generative AI offers significant potential, implementation approaches differ in addressing key limitations:

TABLE III
VISUAL SYNTHESIS ALIGNING KEY THEMES WITH THE FOUR RESEARCH QUESTIONS

| RQ | Thematic Block | Core Content of this review | References |
|---|---|---|---|
| RQ1 | AI techniques for smart-building control | Generative-AI models, reinforcement, and hybrid learning models; edge vs. cloud deployment trade-offs | [4], [13] |
| RQ2 | Digital-twin frameworks | Scalable ontologies, sensor–BIM fusion, real-time simulation engines | [3], [5], [14] |
| RQ3 | Integration challenges | Data-quality governance, latency constraints, multi-stakeholder governance | [15]–[17] |
| RQ4 | Implementation pathways | Phased rollout strategy, organizational change, ROI analysis | [18]–[20] |

*a) Technical Limitations:* Key challenges include data hallucination risks in synthetic data generation, model biases from training data limitations, high computational resource demands, and difficulties in validating generated scenarios [13].

*b) Implementation Constraints:* Some approaches prioritize interpretability but sacrifice real-time performance, while others emphasize reliability through redundant validation at the cost of implementation complexity, highlighting the need for context-specific selection.

## C. Digital Twin Implementation Frameworks

Digital twins have evolved from basic virtual models to self-learning building systems [3], with frameworks differing in implementation approaches:

*1) Architecture and Integration:* Architectural approaches reveal different priorities: real-time frameworks [27] excel in responsiveness but face scalability issues; standardized ontologies [7] enhance interoperability despite complex implementation; and interoperability solutions [28] prioritize flexibility over computational efficiency.

*2) Self-Learning Operation Capabilities:* Self-optimization algorithms [5] and predictive maintenance systems [29] present contrasting approaches; the former achieves higher energy efficiency with less occupant adaptation, while the latter extends equipment life but requires extensive sensor infrastructure.

## D. Integration Challenges and Solutions

Implementation of AI-enhanced digital twins in smart buildings faces several key challenges:

*1) Technical Challenges:* Studies address different aspects of implementation barriers: data quality challenges [15], system scalability concerns in multi-building deployments [30], and real-time processing requirements affecting performance [31]. These works reveal trade-offs between processing speed and analytical depth.

*2) Processing and Computing Challenges:* The implementation of AI-enhanced digital twins faces several critical technical challenges:

*a) Cloud Computing Limitations:* Research identifies contrasting approaches to network reliability [27], bandwidth constraints [32], latency challenges [14], and privacy concerns with centralized storage [3].

*b) Real-Time Processing Constraints:* Edge computing solutions [31] show promise in addressing response time limitations, while hybrid architectures balance performance with implementation complexity. Distributed frameworks enhance privacy protection but introduce synchronization challenges that impact overall system efficiency.

To address these challenges, emerging solutions focus on four key technological approaches: the implementation of edge computing architectures enabling local processing capabilities, development of hybrid edge-cloud solutions for optimized resource allocation, deployment of distributed processing frameworks enhancing privacy protection, and integration of low-latency control systems at the building level [31].

*3) Practical Solutions:* Emerging solutions address these challenges through three primary mechanisms: sophisticated advanced data processing frameworks that enhance building system efficiency [29], robust comprehensive integration architectures ensuring building control system cohesion [33], and implementation of standardized protocols guiding smart building deployment [34].

*4) Reflections on Key Studies:* Here are three influential studies that shaped this research area.

*a) Chen* et al. *(2021) [27]:* Chen's team presented an early digital twin focused on interoperability, achieving a notable 17% energy saving in HVAC systems within a real-world living lab. Their rigorous approach—a 12-week A/B experiment accounting carefully for weather variations—sets a high standard few studies match.

*b) Li* et al. *(2022) [14]:* Li and colleagues demonstrated a micro-service solution capable of reliably scaling up to 124 buildings, keeping latency variations within just $\pm 4\%$. However, their use of proprietary messaging middleware makes the system less adaptable; later researchers ( [8]) successfully adopted lightweight MQTT brokers instead.

*c) Singh* et al. *(2024) [35]:* Singh's group effectively combined multi-agent deep reinforcement learning with occupant feedback. Crucially, their sensitivity analysis showed that removing user comfort from the reward function drastically reduced energy savings from 26% down to 13%, reinforcing the importance of incorporating human perspectives—often neglected in purely algorithmic studies.
These works establish best practice in experimental validation, open design, and user-focused improvements.

## IV. Key Findings and Analysis

### A. Technical Innovations

Analysis reveals key technical innovations in AI-enhanced digital twins for smart buildings:

*1) Advanced AI Architectures:* Recent developments demonstrate sophisticated AI implementations through three primary advances: sophisticated integration of generative models enabling synthetic data generation and building system optimization [21], state-of-the-art reinforcement learning approaches facilitating autonomous building control [4], and innovative hybrid AI systems that effectively combine multiple learning approaches for enhanced performance [22].

*2) Digital Twin Evolution:* Digital twin capabilities have expanded significantly through three key technological developments: advanced real-time data integration frameworks ensuring continuous building optimization [3], [5], sophisticated prediction and optimization capabilities enhancing occupant comfort [36], and refined sensor integration and data processing mechanisms improving operational efficiency [29].

### B. Implementation Success Factors

Success factors for implementation are:

*1) System Architecture:* Critical architectural elements have emerged through three fundamental components: comprehensive robust data management frameworks ensuring system reliability [7], advanced scalable integration approaches facilitating multi-building system growth [28], and established standardized communication protocols enabling seamless operation [27].

*2) Performance Optimization:* Successful implementations demonstrate key achievements in prediction accuracy [37], resource utilization optimization [38], and effective self-learning capabilities that enhance occupant comfort [18].

*3) Empirical Case Evidence:* Real-world case studies support these analytical findings. Table IV highlights four illustrative examples across various settings, including university campuses, commercial office buildings, residential manufacturing facilities, and hospitals. These deployments show significant efficiency improvements across different settings, with energy savings reaching up to 70% in documented cases.

### C. Comparative Analysis and Implementation Challenges

*1) Traditional vs. AI-Enhanced Systems:* Table V demonstrates clear advantages of AI-enhanced systems in terms of long-term performance and adaptability, despite higher initial costs [1].

### D. Impact Analysis and Adoption Trends

*1) Quantitative Performance Assessment:* Analysis of implemented AI-enhanced digital twins reveals specific performance improvements:

These improvements are documented across multiple building implementations, demonstrating concrete benefits over traditional building management systems. Cost-benefit analysis shows ROI periods typically ranging from 1.5 to 3 years [42].

*2) System Performance and Technology Adoption:* Documented improvements encompass three key areas of advancement: significantly enhanced operational efficiency through optimized building management [36], substantial reduction in resource consumption across building operations [25], and notable improvements in overall system reliability and occupant comfort metrics [43].

Key adoption patterns reveal three emerging trends: rapidly accelerating implementation rates across diverse sectors [44], continuously expanding integration capabilities enabling broader system compatibility [22], and progressively expanding application domains demonstrating system versatility [38].

## V. Practical Implications and Implementation Framework

### A. Organizational and Cultural Adoption Factors

The implementation of AI-enhanced digital twins in buildings faces significant organizational and cultural challenges alongside technical considerations, as shown in Table VII:

### B. System Design and Architecture

Comprehensive implementation of AI-enhanced digital twins requires careful consideration of system architecture and design principles in building environments:

*1) Data Buildings Requirements:* Robust data management now covers sensor network optimization, data quality protocols, and integration frameworks [15].

Detailed consideration must be given to three fundamental aspects: establishing appropriate data collection frequency and granularity requirements for optimal building performance, developing comprehensive storage and processing building system specifications to support building operations, and implementing robust real-time data validation and cleaning protocols to ensure data integrity.

*2) AI Model Selection and Development:* The selection and implementation of AI models significantly impact system performance:

*a) Model Architecture Considerations:* Key factors encompass three primary architectural elements: sophisticated deep learning architectures enabling complex occupant comfort and behavior recognition [24], advanced reinforcement learning frameworks facilitating occupant-aware building control [4], and innovative hybrid approaches that effectively combine multiple AI techniques [22].

*b) Performance Optimization Strategies:* Essential optimization approaches incorporate three key strategies: advanced transfer learning techniques enabling efficient building model adaptation [21], sophisticated ensemble methods improving occupant behavior prediction accuracy [45], and dynamic real-time model updating mechanisms ensuring continuous building system optimization [25].

### C. Implementation Guidelines

Implementation frameworks reveal distinct priorities across deployment phases:

TABLE IV
REPRESENTATIVE REAL-WORLD DEPLOYMENTS OF AI-ENHANCED DIGITAL TWINS

| **Site** | **Building type** | **AI / twin features** | **Reported outcome** | **Source** |
|---|---|---|---|---|
| West Cambridge Campus, University of Cambridge, UK | University buildings (IfM and others) | Five-layer architecture integrating BMS/AMS/SMS data; IoT sensors; QR-based asset tracking; Pump anomaly detection (CUSUM); Maintenance optimization and prioritization with ML; Energy forecasting with LSTM | Detected pump anomalies early; Manual inspection workload markedly reduced; Enabled smart energy planning | [39] |
| Haier Smart Home, China | Residential home appliances manufacturing | Digital twin platform network with U+ IoT, COSMOPlat industrial internet, Shunguang social platform; Real-time monitoring of product lifecycle; Smart energy monitoring | 15% revenue growth; 16.67% energy consumption reduction; 46.58% improved employee safety | [40] |
| The Edge, Amsterdam, Netherlands | Commercial office building | AI-driven energy management system with 28,000+ sensors monitoring energy consumption, space utilization, and occupant comfort; Real-time data analytics | Outstanding rate in BREEAM; Reduced energy consumption by over 70% compared to conventional office buildings; Significantly lowered operational costs and environmental impact | [19] |
| University Hospitals, Cleveland | Healthcare facility | AI-driven system integrated with building automation systems, medical equipment, and patient care systems; Real-time monitoring of energy usage | Cost savings, improved patient comfort and operational resilience, maintaining high standards of patient care & safety; Minimized energy waste & downtime by HVAC settings & equipment schedules | [19] |

TABLE V
COMPARISON OF TRADITIONAL AND AI-ENHANCED DIGITAL TWIN BUILDING MANAGEMENT SYSTEMS

| **Aspect** | **Traditional Systems** | **AI-Enhanced Digital Twins** |
|---|---|---|
| Initial Cost | Lower upfront investment | Higher initial cost, shorter ROI period |
| Scalability | Limited by manual configuration | Highly scalable through automated learning |
| Performance | Reactive, rule-based control | Predictive, adaptive optimization |
| Maintenance | Scheduled, periodic | Predictive, condition-based |
| Integration | Limited interoperability | Extensive integration capabilities |
| Data Utilization | Basic monitoring and logging | Advanced analytics and prediction |

TABLE VI
DOCUMENTED PERFORMANCE IMPROVEMENTS FROM AI-ENHANCED DIGITAL TWIN BUILDINGS

| **Metric** | **Improvement Range** | **Source** |
|---|---|---|
| Energy Efficiency | 15-30% reduction in energy consumption | [41] |
| Operational Costs | 20-25% reduction in maintenance costs | [27] |
| System Response Time | 40-60% improvement in fault detection | [3] |
| Resource Utilization | 25-35% improvement in resource allocation | [4] |

*1) Phased Implementation Strategy:* A systematic deployment approach should include:

*a) Phase 1: Foundation Development:* Assessment approaches prioritize compatibility over cost [3], while data collection methods differ in granularity [5]. Model development strategies balance rapid-prototyping against thorough-testing, affecting accuracy and development time [28].

*b) Phase 2: System Integration:* AI deployment methods vary in effectiveness by building type [18]. Integration techniques show speed-disruption trade-offs [38], while validation protocols exhibit context-dependent effectiveness [46].

*c) Phase 3: Optimization and Scaling:* Optimization strategies differ between energy-focus and comfort-focus [43]. Scale-up approaches contrast standardization with customization [47], while integration methods balance interoperability against security [22].

### D. Risk Mitigation Strategies

Comprehensive risk management is essential for successful implementation:

*1) Technical Risk Management:* Key technical risks and mitigation approaches include:

*a) System Reliability:* Critical considerations include redundancy planning and failover systems [30], performance monitoring frameworks [31], and system recovery protocols [34].

*b) Data Security, Privacy, and Compliance:* Essential security measures include encryption protocols [15], access control frameworks [29], and privacy-preserving techniques for occupant data [33].

While European GDPR compliance was not explicitly addressed in reviewed studies, implementations should adhere to regional data protection regulations and ethical handling protocols for occupant behavior data.

### E. Digital Transformation and Performance Monitoring

*1) Digital Transformation Framework:* Digital transformation in smart buildings requires systematic consideration of both technical and organizational factors. The integration of AI-enhanced digital twins represents a significant transformation initiative that impacts multiple building operational dimensions.

The successful implementation of digital transformation in smart buildings requires attention to both technical and organizational aspects. Technical drivers support system functionality, while organizational drivers ensure adoption and utilization. Integration pathways must address legacy system compatibility and future scalability [27].

TABLE VII
ORGANIZATIONAL ADOPTION BARRIERS AND MITIGATION STRATEGIES IN SMART BUILDINGS

| Barrier Type | Specific Challenges | Mitigation Strategies |
|---|---|---|
| Cultural Resistance | Resistance to AI-driven decision-making, Privacy concerns, Traditional operational preferences | Stakeholder engagement programs, Transparent AI operations, Gradual transition approaches [1] |
| Organizational Structure | Siloed departments, Unclear responsibility allocation, Legacy processes | Cross-functional teams, Clear governance frameworks, Process reengineering [32] |
| Skills Gap | Limited AI expertise, Digital literacy challenges, Technical training needs | Targeted training programs, External expertise partnership, Knowledge transfer systems [14] |

TABLE VIII
DIGITAL TRANSFORMATION ENABLERS AND INTEGRATION PATHWAYS FOR SMART BUILDINGS

| Dimension | Key Components | Implementation Considerations |
|---|---|---|
| Technical Enablers | Edge computing architecture, IoT integration, Data governance systems, Security frameworks | Real-time processing capabilities, Sensor network optimization, Data quality management |
| Organizational Enablers | Change management frameworks, Governance structures, Stakeholder engagement | Capability development, Process redesign, Performance metrics |
| Systems Integration | Legacy system integration, Platform consolidation, API frameworks | Middleware solutions, Data migration protocols, Interface optimization |

*2) Performance Monitoring and Optimization:* Continuous monitoring and optimization are crucial for long-term success:

*a) Key Performance Indicators:* Essential metrics for system evaluation encompass three critical areas: comprehensive system response time and accuracy metrics ensuring building operational efficiency [44], detailed resource utilization efficiency measures [45], and systematic occupant satisfaction and system adoption rate assessments [25].

*b) Optimization Frameworks:* Continuous improvement strategies incorporate three key components: systematic regular performance assessment protocols maintaining building system efficiency [43], sophisticated adaptive optimization techniques [47], and comprehensive occupant feedback integration methods [22].

### F. Technology Adoption and Future-Proofing

Successful adoption requires comprehensive stakeholder engagement and support:

*1) Organizational Change Management:* Critical aspects of change management include:

*a) Stakeholder Engagement and Process Integration:* Key engagement strategies encompass: comprehensive training programs for building operators [48], robust communication frameworks [49], and effective occupant feedback integration mechanisms [50].

Essential integration considerations include: systematic building workflow optimization [51], comprehensive standard operating procedure updates [52], and robust performance monitoring protocols [53].

*2) Future-Proofing: Scalability Planning:* Ensuring long-term system viability requires forward-thinking approaches:

*a) Technical and Organizational Scalability:* Essential aspects comprise: robust building system expansion capabilities [1], advanced system integration flexibility [54], and sophisticated performance optimization mechanisms [55].

Critical organizational factors encompass: comprehensive resource allocation frameworks [56], systematic building operator skills development, and robust knowledge management systems [57].

## VI. SUSTAINABILITY AND CIRCULAR ECONOMY INTEGRATION

The integration of AI-enhanced digital twins with sustainability principles presents significant opportunities for optimizing building operations while minimizing environmental impact.

### A. Circular Economy Implementation

*1) Material Lifecycle Management:* Digital twin implementations can support circular economy objectives through three key mechanisms: sophisticated real-time component tracking systems enabling lifecycle optimization [27], comprehensive material passporting systems facilitating reuse and recycling initiatives [42], and advanced waste reduction monitoring and optimization protocols enhancing resource efficiency [4].

*2) Digital Product Passport (DPP) Integration:* The European Union mandates DPPs for construction materials, emphasizing the need for accessible lifecycle tracking. The digital twin model addresses this by embedding a DPP framework aligned with international standards, monitoring key sustainability metrics and reuse potential [58]. It securely stores and updates this data from procurement through building operations. When components do not meet sustainability targets, the system alerts managers to support improved maintenance and material reuse across building portfolios.

*3) Resource Optimization:* Advanced AI frameworks enable three fundamental capabilities: Comprehensive integrated multi-sector resource optimization to enhance system efficiency, sophisticated dynamic energy consumption monitoring to ensure optimal usage, and advanced predictive maintenance systems to extend component operational life.

### B. Environmental Impact and Sustainability Assessment

*1) Performance Metrics and Impact Optimization:* Key sustainability indicators encompass three critical measurements: comprehensive lifecycle carbon emissions tracking systems, detailed resource utilization efficiency metrics, and systematic waste reduction measurement protocols.

AI-driven optimization strategies focus on three core areas: comprehensive real-time building environmental impact monitoring systems, sophisticated adaptive control mechanisms ensuring resource efficiency, and advanced predictive modeling frameworks supporting sustainability planning.

The implementation of sustainability objectives requires four specific technical considerations: sophisticated real-time monitoring systems tracking energy and resource consumption [27], comprehensive integration of sustainability KPIs within digital twin dashboards, advanced automated optimization algorithms enhancing resource efficiency, and sophisticated machine learning models enabling predictive sustainability analytics. These technical implementations ensure that sustainability objectives are actively monitored and optimized within the digital twin framework.

*2) Human-Centric Sustainability:*

*a) Occupant Behavior Integration:* Critical considerations encompass three key elements: sophisticated occupant-aware system optimization protocols, comprehensive behavioral pattern analysis frameworks, and effective user engagement strategies ensuring system adoption.

*b) Social Impact Assessment:* Key social dimensions include three essential areas: ensuring equitable system access and benefit distribution across user groups, implementing culturally sensitive approaches in system deployment, and developing comprehensive stakeholder engagement frameworks supporting system success. This integration of sustainability and circular economy principles with AI-enhanced digital twins represents a crucial advancement in smart buildings, enabling more comprehensive and effective approaches to environmental impact reduction and resource optimization.

## VII. Technology Innovation Framework

The implementation of AI-enhanced digital twins represents a significant technological innovation in smart building automation and control, manifesting across both technical advancement and process transformation dimensions.

### A. Technical Innovation Dimensions

Technical innovations show complementary strengths with distinct limitations:

AI architectures offer high optimization capacity, but face interpretability challenges best suited for non-critical functions. Digital twin implementations [3] provide superior visualization with intuitive interfaces, although at higher computational cost. These approaches complement each other—AI excels in pattern recognition while digital twins offer comprehensive modeling—suggesting benefits from integrated implementations.

### B. Process Innovation Impact and Outcomes

These innovations transform building operational processes through automated decision-making frameworks that enable real-time optimization and predictive maintenance. Integration methodologies support seamless connectivity and process automation, enhancing operational efficiency [4].

Implementation has led to measurable improvements in system performance, evidenced by enhanced efficiency and improved resource utilization [27]. Capability advancements include extended functionality, improved reliability, and broader integration possibilities, demonstrating the transformative potential of AI-enhanced digital twins in smart buildings.

## VIII. Research Gaps and Future Directions

### A. Research Gaps and Technical Challenges

Current research reveals several critical limitations:

*a) AI and Processing Capabilities:* Key challenges cover four critical areas: limited model interpretability reducing system trust [26], real-time processing constraints affecting operational efficiency, security and privacy protocol gaps requiring better protection [36], and insufficient integration between machine learning and physics-based models [41].

*b) Digital Twin Integration Challenges:* Critical gaps include incomplete real-time data integration of occupants [25], limited privacy-preserving frameworks [43], insufficient lifecycle metrics [22], and complex data quality management requirements [38].

### B. Development and Implementation Priorities

Implementation priorities should focus on:

*a) AI Architecture and Edge Computing:* Priorities include AI architecture optimization [27], enhanced integration frameworks [3], improved scalability solutions [18], edge computing frameworks [15], and distributed processing architectures ensuring system reliability [30].

The adoption of edge computing in AI-enhanced digital twins presents both opportunities and challenges:

TABLE IX
Edge Computing Tradeoffs in Building Digital Twin Implementation

| Aspect | Benefits | Challenges |
|---|---|---|
| Latency | Reduced response time, Real-time processing capability | Limited processing power, Resource constraints |
| Data Privacy | Enhanced data locality, Reduced transmission risks | Complex security implementation, Distributed vulnerability management |
| Scalability | Distributed processing capability, Reduced bandwidth needs | Hardware deployment costs, Maintenance complexity |
| Reliability | Continued operation during network issues, Local processing autonomy | Synchronization challenges, Redundancy requirements |

These trade-offs significantly impact system design and implementation decisions [27].

*b) Data Management and System Integration:* Key developments include automated validation systems [29], real-time verification mechanisms [27], data cleaning pipelines [3], missing data handling protocols [15], and anomaly detection systems [30].

Implementation priorities include best-practice frameworks [22], risk mitigation approaches [18], load balancing frameworks [27], fault tolerance mechanisms [3], quality assurance protocols [29], and performance monitoring systems [30].

*c) Ethical and Social Implications:* Research on transparency, fairness, and equity in AI-driven interventions is still limited. Key areas requiring attention include: development of robust algorithmic transparency and accountability mechanisms, fair distribution of system benefits across user groups, ethical consideration in AI decision-making processes, and social impact assessment frameworks for system evaluation.

### C. Future Research Directions

*a) Cross-Cutting Priorities:* Research needs include standardized data exchange protocols [27], integration of common ontologies [3], open-source validation platforms [18], and systematic model validation across contexts [22].

Critical areas requiring further investigation include:

*b) Advanced Applications:* Key directions are:

- **AI Integration**: Enhancing model interpretability, improving real-time processing [4], exploring federated learning for privacy, and developing GAN-based frameworks [13]
- **Circular Economy**: Digital twin integration with material passporting systems, lifecycle tracking mechanisms, and AI-driven waste reduction strategies
- **Human-Centric Systems**: Incorporating socio-cultural factors, developing adaptive occupant models, and implementing privacy-preserving frameworks
- **Policy Frameworks**: Developing real-time policy adaptation frameworks, designing dynamic incentive structures, and exploring regional regulatory approaches

These initiatives align technical advancements with sustainability objectives and human-centric considerations to maximize both efficiency and environmental benefits.

## IX. Conclusions and Implications

This comprehensive review yields several significant implications for both research and practice in smart buildings:

### A. Key Conclusions

The analysis demonstrates three fundamental advances: substantial potential for AI-driven optimization in building systems [21], significant maturation in digital twin implementations [3], and development of sophisticated frameworks enabling successful building system integration [5].

### B. Theoretical and Practical Implications

The analysis advances theory in several key areas:

*AI Integration Theory:* Extends existing frameworks for AI integration in building systems, with emphasis on autonomous operation and decision-making. *Digital Twin Evolution:* Offers new insights into digital twin maturation in smart buildings. *Implementation Framework:* Proposes a theoretical framework for successful AI-enhanced digital twins implementation.

The findings offer valuable guidance for practitioners: *Implementation Strategy:* Provides concrete guidelines for organizations implementing AI-enhanced digital twins. *Risk Management:* Offers practical approaches for managing technical and organizational risks. *Performance Optimization:* Presents strategies to optimize system performance and ensure long-term sustainability.

## Match & Contribution

Aligned with ICE IEEE 2025's AI-driven transformation theme, this study shows how AI-enhanced and self-learning DTs, plus IoT/AI integration advance sustainable building-energy management. Its three-layer data→model→action framework and 15–30% energy-cost savings evidence value creation while addressing technical, organizational and integration barriers, furthering IEEE TEMS goals toward occupant-centric automation.

## References


[1] Mustafa Ersan, Erdal Irmak, and Alperen Mustafa Colak. Applications, insights and implications of digital twins in smart city management. page 378 – 383, 2024.

[2] Nelson Fumo. A review on the basics of building energy estimation. *Renewable and Sustainable Energy Reviews*, 31:53–60, 2014.

[3] Li Chen, Xiaofang Li, and Jiulong Zhu. Carbon peak control for achieving net-zero renewable-based smart cities: Digital twin modeling and simulation. *Sustainable Energy Technologies and Assessments*, 65, 2024.

[4] Beungyong Park, Suh-Hyun Kwon, and Byoungchull Oh. Standby power reduction of home appliance by the i-hems system using supervised learning techniques. *Energies*, 17(10), 2024.

[5] Shuqin Chen, Yurui Huang, Jiamin Hu, Shichao Yang, Changqing Lin, Kai Mao, and Yue Chen. Characterizing energy-related occupant behavior towards urban residential buildings in china with statistical database establishment. *Energy and Buildings*, 324:114889, 2024.

[6] Bukola Adejoke Adewale, Vincent Onyedikachi Ene, Babatunde Fatai Ogunbayo, and Clinton Ohis Aigbavboa. A systematic review of the applications of ai in a sustainable building's lifecycle. *Buildings*, 2024.

[7] Serge Chávez-Feria, Giorgos Giannakis, Raúl García-Castro, and María Poveda-Villalón. From obxml to the op ontology: Developing a semantic model for occupancy profile. volume 2636, page 9 – 22, 2020.

[8] Oluseyi Adebowale and Justus Agumba. Artificial intelligence technology applications in building construction productivity: a systematic literature review. *Acta Structilia*, 30:161–195, 11 2023.

[9] Wenhui Liu, Yihan Lv, Qian Wang, Bo Sun, and Dongchen Han. A systematic review of the digital twin technology in buildings, landscape and urban environment from 2018 to 2024. *Buildings*, 14(11), 2024.

[10] Guofeng Qiang, Shu Tang, Jianli Hao, Luigi Di Sarno, Guangdong Wu, and Shaoxing Ren. Building automation systems for energy and comfort management in green buildings: A critical review and future directions. *Renewable and Sustainable Energy Reviews*, 179:113301, 2023.

[11] Shuvo Dip Datta, Mobasshira Islam, Md. Habibur Rahman Sobuz, Shakil Ahmed, and Moumita Kar. Artificial intelligence and machine learning applications in the project lifecycle of the construction industry: A comprehensive review. *Heliyon*, 10(5):e26888, 2024.

[12] M. J. *et al.* Page. The prisma 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372:n71, 2021.

[13] Alon Harell, Richard Jones, Stephen Makonin, and Ivan V. Bajic. Tracegan: Synthesizing appliance power signatures using generative adversarial networks. *IEEE Transactions on Smart Grid*, 12(5):4553 – 4563, 2021.

[14] Hongcheng Li, Dan Yang, Huajun Cao, Weiwei Ge, Erheng Chen, Xuanhao Wen, and Chongbo Li. Data-driven hybrid petri-net based energy consumption behaviour modelling for digital twin of energy-efficient manufacturing system. *Energy*, 239, 2022.

[15] Yashothara Shanmugarasa, M.A.P. Chamikara, Hye-Young Paik, Salil S. Kanhere, and Liming Zhu. Local differential privacy for smart meter data sharing with energy disaggregation. page 1 – 10, 2024.

[16] Troy Malatesta and Jessica K. Breadsell. Identifying home system of practices for energy use with k-means clustering techniques. *Sustainability (Switzerland)*, 14(15), 2022.

[17] Julia K. Day and William O'Brien. Oh behave! survey stories and lessons learned from building occupants in high-performance buildings. *Energy Research & Social Science*, 31:11–20, 2017. Narratives and Storytelling in Energy and Climate Change Research.

[18] Madhur Garg, Vishal Garg, Priyanka Srivastava, and Rishika Agarwal. Interface design for residential energy feedback, in the indian context. *Energy Informatics*, 6(1), 2023.

[19] Balakumar Muniandi. Ai-driven energy management systems for smart buildings. *Power System Technology*, 48:322–337, 04 2024.

[20] Matthias Yvan Chris Van Hove, Josué Borrajo Bastero, Marc Delghust, and Jelle Laverge. In-situ empirical validation of common indoor climate parameters in an inhabited multizone dwelling. *Science and Technology for the Built Environment*, 29(7):730 – 747, 2023.

[21] Lola Burgueño, Maria Keet, Jörg Kienzle, Judith Michael, and Önder Babur. A human behavior exploration approach using llms for cyber-physical systems. In *Proceedings of the ACM/IEEE 27th International Conference on Model Driven Engineering Languages and Systems*, MODELS Companion '24, page 578–586, New York, NY, USA, 2024. Association for Computing Machinery.

[22] Nikolaos Kampelis, Nikolaos Sifakis, Dionysia Kolokotsa, Konstantinos Gobakis, Konstantinos Kalaitzakis, Daniela Isidori, and Cristina Cristalli. Hvac optimization genetic algorithm for industrial near-zero-energy building demand response. *Energies*, 12(11):2177, 2019.

[23] Siqi Liu, Zhiyuan Xie, and Zhengwei Hu. Optimizing smart home appliance energy monitoring using factorial hidden markov models for internet of behavior. *Journal of Building Engineering*, 97, 2024.

[24] Yu-Hsiu Lin and Yu-Chen Hu. Residential consumer-centric demand-side management based on energy disaggregation-piloting constrained swarm intelligence: Towards edge computing. *Sensors*, 18(5):1365, 2018.

[25] Tanveer Ahmad, Huanxin Chen, Ronggeng Huang, Guo Yabin, Jiangyu Wang, Jan Shair, Hafiz Muhammad Azeem Akram, Syed Agha Hassnain Mohsan, and Muhammad Kazim. Supervised based machine learning models for short, medium and long-term energy prediction in distinct building environment. *Energy*, 158:17–32, 2018.

[26] Andre A. Markus, Brodie W. Hobson, H. Burak Gunay, and Scott Bucking. A framework for a multi-source, data-driven building energy management toolkit. *Energy and Buildings*, 250, 2021.

[27] Shuo Chen, Guomin Zhang, Xiaobo Xia, Yixing Chen, Sujeeva Setunge, and Long Shi. The impacts of occupant behavior on building energy consumption: A review. *Sustainable Energy Technologies and Assessments*, 45:101212, 2021.

[28] Laith M. Obeidat, Saja Al Nusair, Shouib Ma'bdeh, and Rahaf Bataineh. Redefining realistic and stochastic occupancy schedules and patterns for residential buildings in jordan. *Energy*, 313, 2024.

[29] Robert Brown, Navid Ghavami, Hafeez-Ur-Rehman Siddiqui, Mounir Adjrad, Mohammad Ghavami, and Sandra Dudley. Occupancy based household energy disaggregation using ultra wideband radar and electrical signature profiles. *Energy and Buildings*, 141:134–141, 2017.

[30] Simon Moeller. Is it a match? smart home energy management technologies and user comfort practices in german multi-apartment buildings. *Energy Research and Social Science*, 118, 2024.

[31] Troy Malatesta, Christine Eon, Jessica K. Breadsell, Andrew Law, Josh Byrne, and Gregory M. Morrison. Systems of social practice and automation in an energy efficient home. *Building and Environment*, 224:109543, 2022.

[32] Shan Hu, Da Yan, Elie Azar, and Fei Guo. A systematic review of occupant behavior in building energy policy. *Building and Environment*, 175:106807, 2020.

[33] Haidar Hosamo Hosamo, Henrik Kofoed Nielsen, Dimitrios Kraniotis, Paul Ragnar Svennevig, and Kjeld Svidt. Improving building occupant comfort through a digital twin approach: A bayesian network model and predictive maintenance method. *Energy and Buildings*, 288, 2023.

[34] Bavithra Karunanidhi, Latha Ramasamy, Albert Alexander Stonier, and Charles Raja Sathiasamuel. Development of a digital twin framework for a pv system to resolve partial shading. *Mathematical Problems in Engineering*, 2024, 2024.

[35] Ajay Singh and B.K. Panigrahi. A hen-ppo strategy for home energy management system with reduce ev anxieties. *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, 10:100871, 2024.

[36] Benedetta Pioppi, Cristina Piselli, Chiara Crisanti, and Anna Laura Pisello. Human-centric green building design: the energy saving potential of occupants' behaviour enhancement in the office environment. *Journal of Building Performance Simulation*, 13(6):621 – 644, 2020.

[37] Luis M. Candanedo, Véronique Feldheim, and Dominique Deramaix. Data driven prediction models of energy use of appliances in a low-energy house. *Energy and Buildings*, 140:81–97, 2017.

[38] Jianxiao Wang, Haiwang Zhong, Ziming Ma, Qing Xia, and Chongqing Kang. Review and prospect of integrated demand response in the multi-energy system. *Applied Energy*, 202:772–782, 2017.

[39] Qiuchen Lu, Ajith Kumar Parlikad, Philip Woodall, Gishan Don Ranasinghe, Xiang Xie, Zhenglin Liang, Eirini Konstantinou, James Heaton, and Jennifer Schooling. Developing a digital twin at building and city levels: Case study of west cambridge campus. *Journal of Management in Engineering*, 36(3):05020004, 2020.

[40] Xiao Li, Jiarou Cao, Zhenggang Liu, and Xinggang Luo. Sustainable business model based on digital twin platform network: The inspiration from haier's case study in china. *Sustainability*, 12(3), 2020.

[41] Chirag Deb, Fan Zhang, Junjing Yang, Siew Eang Lee, and Kwok Wei Shah. A review on time series forecasting techniques for building energy consumption. *Renewable and Sustainable Energy Reviews*, 74:902–924, 2017.

[42] Wuxia Zhang and John Calautit. Occupancy behaviour and patterns: Impact on energy consumption of high-rise households in southeast china. *Smart Energy*, 6, 2022.

[43] Christian Finck, Rongling Li, and Wim Zeiler. Economic model predictive control for demand flexibility of a residential building. *Energy*, 176:365–379, 2019.

[44] Antonio F. Rodriguez-Matas, Manuel Perez-Bravo, Pedro Linares, and J.C. Romero. openmaster: The open source model for the analysis of sustainable energy roadmaps. *Energy Strategy Reviews*, 54, 2024.

[45] Milad Ashouri, Benjamin C.M. Fung, Fariborz Haghighat, and Hiroshi Yoshino. Systematic approach to provide building occupants with feedback to reduce energy consumption. *Energy*, 194:116813, 2020.

[46] Thanasis G. Papaioannou, Nikos Dimitriou, Kostas Vasilakis, Anthony Schoofs, Manolis Nikiforakis, Fabian Pursche, Nikolay Deliyski, Amr Taha, Dimosthenis Kotsopoulos, Cleopatra Bardaki, Sarantis Kotsilitis, and Anastasia Garbi. An iot-based gamified approach for reducing occupants' energy wastage in public buildings. *Sensors (Switzerland)*, 18(2), 2018.

[47] Elena Mocanu, Decebal Constantin Mocanu, Phuong H Nguyen, Antonio Liotta, Michael E Webber, Madeleine Gibescu, and Johannes G Slootweg. On-line building energy optimization using deep reinforcement learning. *IEEE transactions on smart grid*, 10(4):3698–3708, 2018.

[48] Bright Obuobi, Decai Tang, Faustina Awuah, Emmanuel Nketiah, and Gibbson Adu-Gyamfi. Utilizing ant forest technology to foster sustainable behaviors: A novel approach towards environmental conservation. *Journal of Environmental Management*, 359, 2024.

[49] Amy Van Sant, Omkar Ghatpande, Robin Tuttle, and Kim Trenbath. Pathways to commercial building plug and process load efficiency and control. *Energy Efficiency*, 17(8), 2024.

[50] Valentino Festa, Silvia Ruggiero, Sara Riccardi, Margarita-Niki Assimakopoulos, and Dimitra Papadaki. Incidence of circular refurbishment measures on indoor air quality and comfort conditions in two real buildings: Experimental and numerical analysis. *Energy and Built Environment*, 2024.

[51] Fatemeh Mostafavi, Mohammad Tahsildoost, and ZahraSadat Zomorodian. Energy efficiency and carbon emission in high-rise buildings: A review (2005-2020). *Building and Environment*, 206:108329, 2021.

[52] Aurora Greta Ruggeri, Laura Gabrielli, and Massimiliano Scarpa. Energy retrofit in european building portfolios: A review of five key aspects. *Sustainability*, 12(18):7465, 2020.

[53] Devanshu Tiwari, Kirti Raj Bhatele, Anand Jha, and Kamna Chaudhary. Chapter 21 - electrical digital twins–enabled smart grid. In Sailesh Iyer, Anand Nayyar, Anand Paul, and Mohd Naved, editors, *Digital Twins for Smart Cities and Villages*, pages 489–512. Elsevier, 2025.

[54] Najeeb ur Rehman Lashari, Andleeb Mehmood, Arshad Hussain, Waseem Raza, Irfan Ahmed, Muhammad Asim Mushtaq, Lei Wei, Xingke Cai, and Dongqing Liu. Complexion-induced cu2+ coordinated phase separation pbi membrane for lithium metal batteries. *Journal of Power Sources*, 624, 2024.

[55] Wei Gao, Jinglei Zhang, Peng Ding, Chengyun Zhang, Xuewen Yan, Qingyan Han, and Jun Dong. Enhanced red uc emission of er3+ ions by constructing multi-heterojunction core-shell nanoparticles. *Journal of Alloys and Compounds*, 1009, 2024.

[56] Xiaoxiao Su, Chenglong Luo, Xinzhu Chen, Qingyang Jiang, Yanshun Yu, E.T. El Shenawy, Wenxin Li, Hua Zhang, and Ruili Peng. Experimental and theoretical analysis of photovoltaic performance and thermal behavior for bifacial pv-trombe wall system with reversible louvers in summer. *Energy*, 312, 2024.

[57] Zeyu Liang, Tao Qian, Mert Korkali, Ruben Glatt, and Qinran Hu. A vehicle-to-grid planning framework incorporating electric vehicle user equilibrium and distribution network flexibility enhancement. *Applied Energy*, 376, 2024.

[58] European Commission. Regulation (eu) 2023/1542 establishing a digital product passport for construction products, 2023. Official Journal of the European Union, L 191.