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Augmented Green Twin for Building Energy Optimization

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Abstract

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Optimizing energy use in buildings has become critical as global sustainability and carbon reduction goals accelerate. This study explores the potential of an innovative framework, Augmented Green Twin (AGT), which combines digital twin technology with augmented intelligence to enhance the operational energy efficiency of buildings. Specifically, it investigates AGT as a transformative approach to optimizing building energy consumption, focusing on technical performance and user engagement. Traditional building management systems face significant limitations, including static energy modelling, poor real-time adaptability, disconnected system integration, and oversight of human behavioural factors. These challenges often result in inefficient energy use and suboptimal occupant comfort. This study develops a conceptual AGT framework to guide future energy optimization strategies based on insights from a comprehensive literature review and stakeholder interviews. The framework is designed to leverage real-time data and augmented intelligence to enable adaptive, dynamic

monitoring and energy usage adjustment in response to traditional systems' identified limitations. By incorporating a variety of data inputs, such as sensor data, weather data, occupancy patterns, and user feedback, AGT can provide a more responsive and personalized energy management solution. AGT integrates predictive analytics, enabling the system to anticipate future energy demands and proactively address potential issues. It emphasizes a human-in-the-loop approach, ensuring that occupant preferences, behaviours, and comfort are actively incorporated into energy optimization strategies. It also identifies potential challenges to the practical implementation and scalability of the proposed AGT framework. It is identified that despite its potential, successful deployment of the framework will require addressing challenges regarding the integration of legacy systems, data security, and user acceptance. This study contributes to the body of knowledge by offering valuable insights into the potential and challenges of AGT for building energy optimization.

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Chapter 1: Introduction

1.1 Background and Context

Globally, buildings account for an estimated 40% of total energy consumption and nearly 30% of greenhouse gas (GHG) emissions, significantly contributing to climate change (IEA, 2022). Urbanization, changing climate conditions, and evolving occupant needs push the building industry toward more intelligent and sustainable energy management practices. As cities grow and adopt net-zero emission targets, optimizing energy consumption in the built environment is increasingly urgent. While traditional energy-saving measures such as retrofitting insulation or replacing inefficient equipment have had measurable impacts, the operational phase of buildings still presents untapped opportunities for dynamic, adaptive optimization.

The emergence of intelligent buildings, equipped with advanced sensing, control, and analytics systems, has given rise to more data-driven energy management. While effective in some domains, Building Energy Management Systems (BEMS) still operate based on pre-configured schedules, static assumptions, and isolated subsystems (Ahmad et al., 2021). Their limitations are most evident in environments where occupancy fluctuates, such as offices with hybrid work patterns or public buildings with varying usage. In such cases, rigid systems overcompensate or underperform, leading to energy waste and occupant discomfort.

Digital twin (DT) technology has been upgraded significantly by enabling real-time simulation and building performance monitoring. Digital twins serve as virtual representations of physical systems and are updated continuously using live data from IoT sensors (Tao et al., 2018). Although DTs have revolutionized monitoring, they alone are insufficient for optimizing performance unless coupled with intelligent analytics and user interaction. This shortfall has led to the development of

the Augmented Green Twin (AGT), a novel paradigm that integrates digital twins with augmented intelligence and human-in-the-loop engagement (Shneiderman, 2020; Wang et al., 2022).

1.2 Theoretical Justifications

The AGT concept builds on several interrelated theoretical domains. First, it draws from cyber-physical systems theory, which explores how integrated computational and physical processes interact to achieve system-level optimization. Second, it leverages concepts from human-centered AI, emphasizing transparency, adaptability, and shared control between humans and machines (Shneiderman, 2020). Finally, it aligns with digital ecosystem theory, which focuses on digital entities' interoperability and dynamic behavior across interconnected systems. Together, these frameworks provide a basis for understanding how AGT systems can continuously learn, predict, and adapt within the operational environment.

1.3 Problem Statement and Research Gap

Traditional BEMS and digital twin implementations are hindered by critical shortcomings: static models, siloed system integration, limited user engagement, and the absence of predictive capabilities (Ahmad et al., 2021). These constraints reduce their effectiveness in addressing modern energy optimization needs, especially in buildings with dynamic occupancy or environmental variability (Li et al., 2020). The integration of augmented intelligence - a symbiotic relationship between AI and human insight - has yet to be fully realized in building energy systems. AGT systems aim to address these limitations by combining real-time data collection, predictive analytics, and human-in-the-loop optimization. Specifically, AGT moves beyond static models by enabling adaptive learning algorithms; it breaks down system silos by integrating data streams across HVAC, lighting, and occupancy systems; and it incorporates user behavior and preferences directly into energy decision-making through interactive feedback loops.

Additionally, the lack of empirical models that combine real-time feedback loops with human decision-making underscores the need for research on AGT systems. This study addresses this gap by conceptualizing and proposing the AGT framework as a holistic, intelligent alternative to traditional BEMS.

1.4 Research Aim and Objectives

1.4.1 Aim

This study aims to evaluate and conceptualize AGT as a comprehensive model for optimizing building energy consumption.

1.4.2 Objectives

1. To identify the key challenges associated with current practices in optimizing building operational energy.
2. To develop a conceptual framework for using AGT to optimize building operational energy.

1.5 Conceptual Preview of AGT Framework

The AGT framework consists of five integrated layers: (1) Real-time data input through IoT sensors (Tao et al., 2018); (2) Digital Twin simulations that mirror building conditions (Kwon et al., 2022); (3) Predictive analytics driven by AI algorithms (Agostinelli et al., 2021); (4) Human-in-the-loop mechanisms enabling user input (Shneiderman, 2020); and (5) Feedback loops allowing continuous learning (Petri et al., 2023). These layers form a dynamic control system capable of proactive and reactive energy optimization. AGT differentiates itself from BEMS by emphasizing adaptability, occupant-centered performance, and long-term learning from historical data.

1.6 Significance of Study

This research contributes significantly to advancing the field of smart buildings and sustainable energy management. While digital twins have increasingly been applied in building operations for real-time monitoring and performance visualization (Tao et al., 2018; Kwon et al., 2022), their utility is often constrained by limited decision-making capabilities and the absence of integrated user interaction. The proposed Augmented Green Twin (AGT) framework offers a novel approach by embedding augmented intelligence and human-centered design into the digital twin ecosystem. This advancement enables AGT systems not only to monitor but also to learn from building performance data, adapt to user preferences, and engage stakeholders in real-time optimization strategies (Shneiderman, 2020; Petri et al., 2023)

The study contributes to both academic knowledge and practical applications, particularly for building owners, facility managers, and policymakers seeking to reduce energy consumption, enhance occupant satisfaction, and support broader sustainability objectives. By proposing a conceptual framework for AGT and examining its potential implementation, this thesis provides valuable insights into how emerging technologies can reshape the future of energy optimization in buildings. In addition to proposing solutions, the study also contributes by systematically identifying the existing limitations in traditional BEMS and digital twin models - such as their inability to adapt in real time, poor integration across subsystems, and limited engagement with human behavior. Recognizing these challenges not only informs the theoretical development of AGT but also serves as a foundational step for future empirical investigations and practical innovation in smart building technologies.

1.7 Overview of Methodology

This study adopts a qualitative, exploratory research methodology to investigate the feasibility and conceptualization of the Augmented Green Twin (AGT) framework in building energy optimization. This approach is justified by AGT's novelty and interdisciplinary nature, which integrates digital twin technologies, artificial intelligence, predictive analytics, and human-in-the-loop mechanisms.

Data was collected through semi-structured interviews with five domain experts, including professionals from engineering consultancy, building operations, and sustainability sectors. These interviews provided in-depth insights into technical, behavioral, and policy aspects of AGT adoption. In addition, the same interview protocol was applied to five generative AI models (e.g., ChatGPT, Bard, Claude) to compare human and synthetic expert perspectives.

A systematic literature review preceded the interviews to establish a conceptual foundation, identify thematic gaps, and inform the development of the interview protocol. This review synthesized 55 peer-reviewed sources covering digital twins, energy systems, occupant engagement, and AI in the built environment.

For data analysis, thematic analysis was conducted using Braun and Clarke's (2006) six-phase framework. Both inductive and deductive coding techniques were applied, using NVivo software to identify emergent themes across the dataset. AI-generated responses were analyzed separately and compared against human expert insights to evaluate alignment and reveal knowledge gaps.

This multi-source, qualitative design supports the development of a grounded, context-sensitive AGT framework and ensures the findings are both theoretically informed and practically relevant.

1.8 Structure of the Thesis

This thesis is structured as follows:

Chapter 1 introduces the research background, objectives, and significance.

Chapter 2 presents a comprehensive literature review covering BEMS and their current challenges, digital twins, AI, and human-centered design.

Chapter 3 outlines the qualitative methodology, data sources, and interview protocols.

Chapter 4 presents and analyzes the empirical findings from AI and human expert interviews.

Chapter 5 discusses results and develops the AGT conceptual framework.

Chapter 6 concludes the study and offers recommendations for further research.

Chapter 2. Literature Review

2.1 Chapter Introduction

This chapter comprehensively reviews scholarly literature on the intersection of digital twin technologies, augmented intelligence, and building energy optimization. It evaluates the evolution of traditional Building Energy Management Systems (BEMS), the shortcomings of current energy optimization methods, and how the Augmented Green Twin (AGT) model addresses these gaps. As buildings contribute significantly to global carbon emissions and energy consumption, there is growing emphasis on designing intelligent systems that go beyond fixed rule-based controls and integrate real-time data with human-in-the-loop feedback. This literature review sets the foundation for the conceptual framework developed in this research by exploring academic debates, empirical findings, and technological innovations.

2.2 Limitations of Traditional Building Energy Management Systems

Traditional BEMS have evolved from simple, time-based scheduling systems to rule-based control architectures to manage core subsystems such as heating, ventilation, air conditioning (HVAC), and lighting. Despite these developments, BEMS often suffer from three core limitations: static configuration, limited user engagement, and siloed subsystem operation (Yang et al., 2017). Static configurations refer to their reliance on pre-defined control logic, which fails to accommodate real-time variations in building occupancy, environmental conditions, or system degradation (Wang et al., 2019). These inflexible assumptions lead to inefficiencies, especially in buildings with dynamic occupancy patterns such as offices and educational institutions.

Ahmad et al. (2021) emphasize that this rigidity results in excessive energy use, such as HVAC systems operating in unoccupied zones or lighting remaining on in naturally lit areas. Moreover,

BEMS have historically excluded behavioral dimensions from their optimization logic. Sartori et al. (2016) argue that traditional systems' lack of behavioral modeling often results in user dissatisfaction, frequent manual overrides, and ultimately, reduced system efficiency.

Additionally, traditional BEMS frameworks treat subsystems - HVAC, lighting, and plug loads - as independent entities. This fragmented approach results in missed opportunities for integrated energy savings (Li et al., 2020). For instance, an HVAC system may cool a room without considering occupancy schedules derived from lighting or security systems.

Previous studies have developed BEMS-based optimization frameworks using model predictive control (MPC), fuzzy logic, or rule-based systems. For example, Afram and Janabi-Sharifi (2014) reviewed MPC applications in building energy systems. They found that while MPC enhances control over predefined objectives, it still requires static models and often lacks responsiveness to unexpected occupancy changes. Similarly, Mahdavi et al. (2008) proposed a simulation-assisted BEMS framework that uses historical data for energy optimization. However, their approach assumed stable occupant patterns and could not account for behavioral feedback or fluctuating user preferences.

Another example is the work of Nassif (2012), who developed a demand-controlled ventilation system using CO₂ sensors. While this method improved ventilation efficiency, it operated isolated from lighting and thermal comfort systems and did not integrate predictive forecasting or user input.

These studies highlight the limitations of traditional optimization models, which rely on rigid rules, static assumptions, or isolated control schemes. The AGT framework proposed in this study addresses these gaps by integrating real-time sensor data, predictive analytics, and human-in-the-

loop feedback, thereby creating a more responsive, adaptive, and holistic energy optimization system.

2.3 The Emergence of Digital Twin Technology

DTs have emerged as a transformative technology in building operations by offering real-time virtual representations of physical assets. Tao et al. (2018) define a digital twin as a cyber-physical system that dynamically reflects the state of physical systems using data from sensors, building automation systems, and IoT devices. Applying DTs in buildings enables performance monitoring, fault detection, and optimization through real-time simulation. However, most digital twin applications in the building sector are confined to visualizations and lack decision-making intelligence. Integrating machine learning into digital twins has given rise to what scholars now call 'intelligent digital twins' (Grieves, 2022). These systems are capable of pattern recognition, anomaly detection, and even autonomous control decisions. However, as Agostinelli et al. (2021) noted, current implementations remain technically focused and overlook socio-behavioral elements critical for sustainable performance. This is where AGT offers a broader paradigm.

2.4 Concept of Augmented Green Twin (AGT)

The AGT builds on digital twin technology by integrating augmented intelligence, predictive analytics, and human-centered design principles. AGT enables adaptive energy optimization by reacting to data inputs and learning from them to predict and adjust building operations proactively. The term 'augmented intelligence' emphasizes the collaboration between humans and machines rather than replacing human decision-making (Shneiderman, 2020). In AGT systems, human-in-the-loop engagement plays a central role. Occupants can interact with interfaces to provide feedback on comfort levels. At the same time, facility managers can fine-tune control strategies using Augmented Reality/Virtual Reality (AR/VR) visualization tools (Böhm et al., 2021). This engagement ensures that AI-generated optimization strategies remain contextually

relevant and socially acceptable. AGT thus bridges the technical potential of AI with the lived experience of building occupants.

2.5 Real-Time Data Integration and Predictive Analytics

AGT platforms continuously collect data from building automation systems, environmental sensors, smart meters, and external sources such as weather APIs. This data is streamed into the digital twin, enabling dynamic updates of building states. Predictive analytics, often based on neural networks or decision trees, then use this data to forecast energy loads, equipment failure risks, or comfort level deviations (Francisco et al., 2020). By applying these forecasts, AGT systems can initiate pre-emptive actions, such as reducing HVAC load before peak energy prices or triggering early maintenance. This not only enhances energy efficiency but also contributes to operational resilience. Agostinelli et al. (2021) found that buildings equipped with predictive models saw a 15-25% reduction in unplanned maintenance events and up to 30% improvement in energy performance.

2.6 Human-in-the-Loop Optimization and Behavior Modelling

A unique feature of AGT is its human-in-the-loop optimization capability. Traditional systems often neglect the influence of human actions on energy consumption, but AGT recognizes the variability of human behavior and incorporates user feedback into system operations. Petri et al. (2023) demonstrated that models incorporating occupant feedback consistently outperform automated-only models in terms of both energy savings and user satisfaction. AGT systems use interfaces that allow occupants to provide real-time feedback, which is analyzed and weighted in optimization algorithms. These systems are especially important in flexible-use buildings, such as offices with hybrid schedules, educational institutions, or hospitals, where energy demand cannot be pre-defined accurately.

2.7 Barriers and Enablers of AGT Implementation

Despite its promise, AGT adoption faces several barriers: integration with legacy systems, cybersecurity risks, high upfront costs, and organizational resistance to change (Opoku et al., 2021; Teisserenc & Sepasgozar, 2021). Retrofitting older buildings with IoT infrastructure and edge computing capabilities can present technical and financial challenges. Additionally, the high volume of data generated by AGT frameworks raises concerns regarding privacy, ownership, and long-term cybersecurity management.

However, enabling conditions for AGT implementation are steadily emerging. Decreasing sensor and computing costs, increasing regulatory momentum for smart infrastructure, and growing public awareness of energy efficiency and climate resilience are driving institutional interest in intelligent energy management. Countries like Singapore, Germany, and Canada have implemented national or regional strategies that support the integration of smart building technologies, such as digital twin platforms and AI-enhanced building management systems, as part of broader smart city or energy transition initiatives.

For instance, Singapore's Smart Nation initiative promotes digital transformation in infrastructure and buildings, creating a supportive environment for technologies aligned with AGT (Smart Nation and Digital Government Office, 2021). In Germany, the “Energiewende” (Energy Transition) policy framework and investment in smart grids and building automation projects serve as foundational platforms for AGT-aligned systems, even if AGT itself has yet to be fully deployed (BMWK, 2022). Through programs like the Green Infrastructure Fund and smart city pilots in Toronto and Vancouver, Canada has also advanced the use of real-time monitoring and predictive analytics in building operations (Natural Resources Canada, 2021).

Although direct case studies showcasing AGT systems specifically achieving a quantifiable percentage of energy reductions are limited, these countries' enabling technological and regulatory frameworks provide a strong foundation for future AGT adoption and pilot studies. These international examples illustrate how policy, funding, and stakeholder collaboration can be critical enablers for transitioning toward more intelligent, adaptive, and human-centered energy optimization systems in buildings.

2.8. Knowledge and Research Gaps

The preceding literature review highlights substantial theoretical and empirical gaps that form the basis for this study's research focus. Despite notable advancements in BEMS, DT applications, and AI-driven energy tools, the convergence of these technologies into a comprehensive, adaptive, and user-centered energy optimization framework remains underexplored.

First, existing BEMS architectures continue to rely on static configurations, operate in subsystem silos, and marginalize occupant behavior in energy modeling. Although model predictive control (MPC) and rule-based systems have improved certain aspects of optimization, they remain limited by their inability to incorporate real-time variability and multi-system coordination (Afram & Janabi-Sharifi, 2014; Mahdavi et al., 2008; Nassif, 2012). These methods fail to address behavioral nuances, adaptability to unpredictable usage patterns, and feedback-driven performance refinement.

Second, while Digital Twins offer real-time visibility into building operations, their practical energy optimization deployment remains primarily observational rather than prescriptive. As Tao et al. (2018) and Grieves (2022) suggest, many DT implementations function as advanced dashboards without embedded intelligence to autonomously adapt or optimize systems. The concept of intelligent digital twins has emerged in recent discourse. However, integrating AI-

driven decision-making with behavioral input - hallmarks of the AGT model - has yet to be operationalized at scale.

Third, although recent literature acknowledges the significance of user behavior in energy performance (Sartori et al., 2016; Petri et al., 2023), mainstream optimization models ignore or undervalue human feedback loops. AGT addresses this gap by prioritizing human-in-the-loop mechanisms, incorporating occupant comfort preferences and adaptive user engagement in real time.

Fourth, predictive analytics have succeeded in specific use cases, such as fault detection or demand forecasting (Francisco et al., 2020; Agostinelli et al., 2021). However, these applications are not embedded within a unified control framework that includes feedback and simulation. The synthesis of predictive capabilities with operational decision-making, user-centered controls, and continuous learning, as AGT proposes, has not been fully investigated.

Fifth, the reviewed literature lacks a conceptual model integrating real-time data streams, intelligent learning, and occupant feedback into a single operational loop. AGT addresses this need by positioning augmented intelligence as the bridge between digital infrastructure and behavioral adaptability. Despite growing interest in smart buildings and human-AI collaboration, few empirical or conceptual studies articulate how this integration functions in practice.

Sixth, practical deployment challenges - such as integrating with legacy infrastructure, ensuring cybersecurity, managing data ownership, and overcoming organizational resistance - have been mentioned in passing across various studies (Opoku et al., 2021; Teisserenc & Sepasgozar, 2021), but no unified approach has addressed them in the context of a next-generation energy framework. Moreover, while initiatives in countries like Singapore, Germany, and Canada suggest institutional

momentum for smart technologies, there is little documentation of AGT-style models being evaluated or adopted.

Finally, the literature does not formally define or structure the AGT concept. This study is among the first to propose a conceptual framework that unifies these fragmented research strands. This study fills a critical void in theory and practice by identifying, synthesizing, and integrating themes across BEMS, DTs, predictive modeling, and behavioral energy research.

Thus, this research contributes by:

- Synthesizing disparate technological and behavioral frameworks into an integrated AGT model;
- Providing a conceptual basis for empirical testing and future pilot studies;
- Highlighting implementation barriers and proposing design principles for scalable AGT deployment;
- Elevating user-centric design as a core component of the energy optimization strategy.

These contributions directly address the identified knowledge gaps, reinforcing the study's relevance to smart building research, energy policy, and AI-augmented decision-making in the built environment.

2.9 Chapter Summary

This chapter has critically examined the evolution and current limitations of traditional Building Energy Management Systems (BEMS), the emergence and application of Digital Twin (DT) technologies, and the conceptualization of the Augmented Green Twin (AGT) model as a next-generation approach to building energy optimization. It identified that while traditional BEMS

frameworks provide foundational control over HVAC and lighting systems, they remain static, fragmented, and inattentive primarily to occupant behavior and real-time variability. Past optimization models, including rule-based and model predictive control systems, have been unable to fully account for dynamic operating conditions or integrate user feedback in meaningful ways.

Digital Twin technologies have made notable strides in enabling real-time visualization and monitoring of building systems. However, most implementations remain observational and lack embedded intelligence or actionable adaptability. The literature reveals a growing interest in "intelligent digital twins" that integrate AI capabilities, but few practical frameworks exist that synthesize digital twins with predictive analytics and human-in-the-loop engagement as AGT proposes.

The AGT model emerges as a response to these shortcomings. By combining real-time data from IoT devices, AI-driven predictive control, and behavioral feedback mechanisms, AGT introduces a holistic and adaptive strategy for energy optimization that evolves with user needs and system performance. The chapter has shown that human-centered design, such as interfaces allowing occupant feedback and AR/VR-based visualizations, enhances system responsiveness and user trust, filling a key gap in traditional BEMS and DT approaches.

Barriers to AGT implementation, including legacy system integration, cybersecurity, cost, and institutional resistance, were also reviewed alongside enabling factors such as declining sensor costs and increasing policy support. International initiatives in Singapore, Germany, and Canada offer a glimpse into the institutional readiness for smart building transformations, although AGT-style models remain largely theoretical.

Finally, Section 2.8 outlined key knowledge gaps that justify this study. These include the lack of unified models that integrate behavioral dynamics, predictive analytics, and adaptive learning into building energy systems; limited empirical evaluation of human-AI collaborative frameworks; and insufficient exploration of AGT's feasibility in existing building contexts. These gaps provide the foundation for the current research, which seeks to develop and conceptualize AGT as a scalable, human-centered energy optimization paradigm.

Together, the insights presented in this chapter establish the academic and practical significance of AGT and justify the study's research questions, methodology, and conceptual framework explored in the following chapters.

Chapter 3: Methodology

3.1 Chapter Introduction

This chapter outlines the methodological framework adopted to investigate the feasibility, conceptual development, and implementation challenges of the Augmented Green Twin (AGT) model for building energy optimization. Given AGT's interdisciplinary and emerging nature, an integration of digital twin technologies, augmented intelligence, and human-in-the-loop feedback systems, a qualitative research methodology was selected. This approach allows for exploring expert insights, interpretive patterns, and contextual dynamics critical to understanding complex, real-world applications of novel energy technologies.

The chapter begins by detailing the research design and philosophical approach, followed by a description of the systematic literature review that informed the conceptual framework and interview instrument. It then elaborates on data collection methods, expert recruitment strategies, and the development of the semi-structured interview protocol. A comprehensive account of the data analysis strategy is also presented, including thematic analysis and the integration of AI-generated responses. Finally, ethical considerations and methodological limitations are addressed to ensure transparency and validity throughout the research process.

This chapter establishes the empirical foundation upon which the AGT conceptual framework is built and contextualized, bridging the theoretical insights discussed in Chapter 2 and the findings that will be analyzed in Chapter 4.

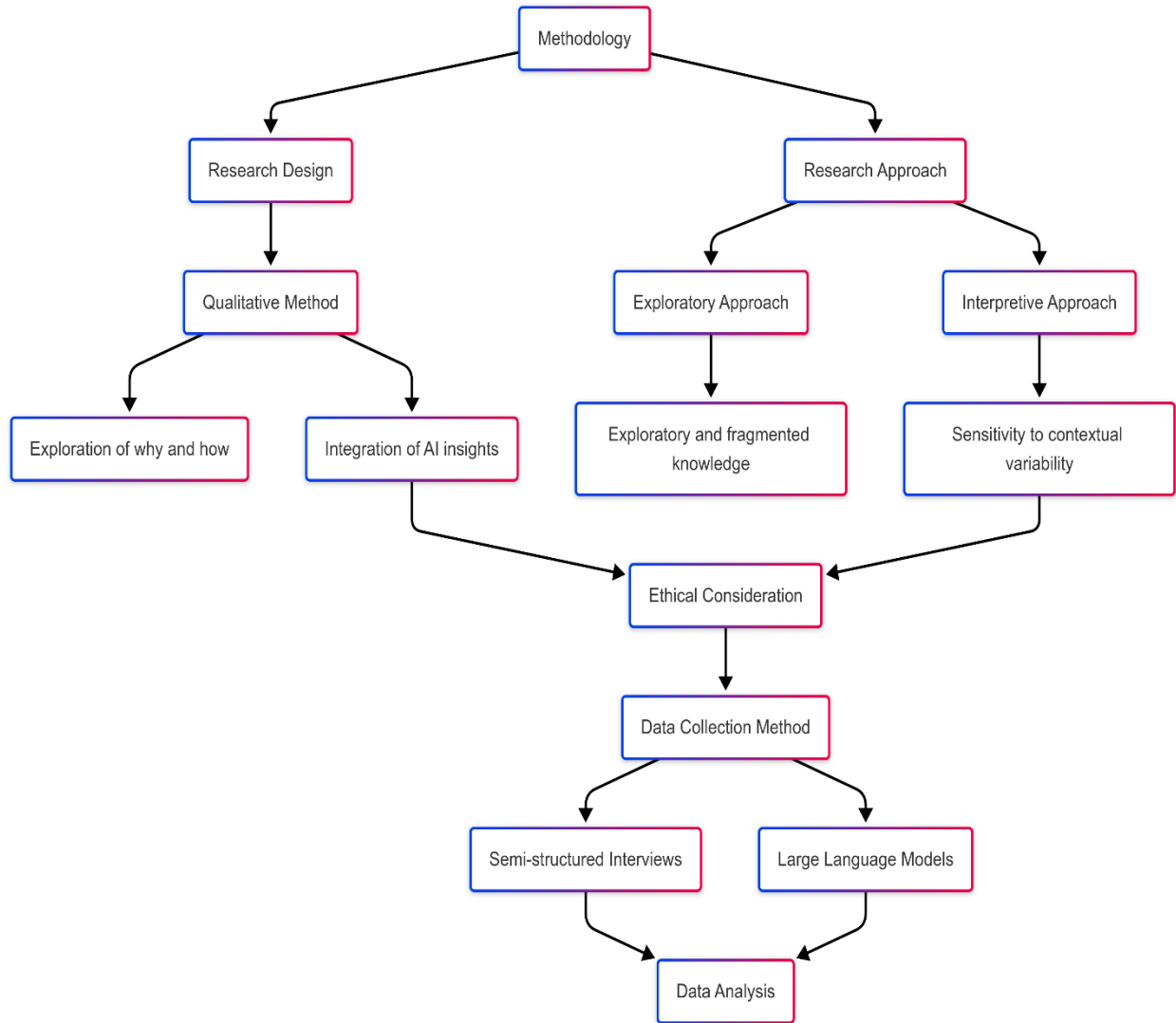


FIGURE 3.1 FLOWCHART OF THE METHODOLOGY

3.2 Research Design

This study adopts a qualitative research design, guided by the aim of understanding the AGT framework's feasibility, implementation strategies, and contextual applicability in optimizing building operational energy efficiency. The qualitative approach was selected not only for its appropriateness in exploring complex, interdisciplinary phenomena - such as AGT's convergence of DT technology, augmented intelligence, predictive analytics, and human-in-the-loop feedback

- but also for its capacity to capture rich, context-specific insights that are often inaccessible through quantitative methods (Denzin & Lincoln, 2018; Miles, Huberman, & Saldaña, 2014).

Qualitative research is particularly effective when investigating emergent technologies and systems-level innovations, as it allows researchers to explore the meanings, assumptions, and contextual conditions that shape adoption and implementation (Creswell & Poth, 2018; Merriam & Tisdell, 2015). AGT represents a novel integration of socio-technical systems, where energy modeling, behavioral feedback, and machine learning algorithms intersect in real-time environments. Such multifaceted systems defy simple variable-based models, necessitating an approach that accommodates interpretive depth, narrative detail, and emergent categories - core strengths of qualitative inquiry (Patton, 2015).

Furthermore, qualitative designs are well-suited for early-stage conceptual development and theory building (Yin, 2016). At the time of this research, AGT generally remains a largely conceptual innovation with limited empirical implementation and virtually no standardized framework. As such, a qualitative design enables constructing a grounded conceptual model by systematically engaging stakeholders through semi-structured interviews, literature synthesis, and cross-case thematic comparison (Ritchie et al., 2014). These methods facilitate a deeper understanding of the real-world variables that shape AGT deployment, including technological compatibility, organizational readiness, regulatory constraints, and occupant behavior.

Another important justification for using qualitative design lies in its suitability for exploring "how" and "why" questions, especially in under-theorized contexts (Maxwell, 2013). Rather than testing predefined hypotheses, this study seeks to answer open-ended questions about AGT's rationale, potential, and limitations from the perspective of industry experts, technologists, and

sustainability practitioners. Such knowledge would be difficult to obtain through quantitative surveys or statistical models, which are better suited for hypothesis testing in mature fields.

The design choice also reflects the study's commitment to contextual validity, as energy optimization in buildings varies greatly across settings, depending on climate, building typology, occupancy patterns, regulatory environments, and digital infrastructure. By prioritizing expert interviews over numerical datasets, the study allows participants to share experiential knowledge that incorporates these real-world complexities (Tracy, 2010). This aligns with the constructivist paradigm, which holds that reality is socially constructed and best understood through the perspectives of those embedded within it (Lincoln & Guba, 1985).

Moreover, a qualitative approach enables the integration of AI-generated insights (from GPT-4, Claude, Bard, and others) with human expertise, thereby facilitating a dialogic evaluation of human-AI knowledge systems. This methodological innovation enhances the robustness of the conceptual model by exposing epistemological gaps between algorithmic and human reasoning in AGT design - a task unsuited for traditional quantitative paradigms. This methodological foundation provides the flexibility, depth, and reflexivity required to advance a rigorous, practice-oriented understanding of AGT in intelligent building energy optimization.

3.2 Research Approach

This study adopts an exploratory and interpretive research approach in response to the early-stage development and limited empirical grounding of the AGT concept. AGT represents an innovative integration of digital twin systems, artificial intelligence, and occupant-driven energy feedback mechanisms - elements that, though independently studied, have not yet been comprehensively examined as a unified framework in building energy optimization. Given the absence of established models or widely accepted theoretical constructs in this area, the research does not

begin with hypotheses to be tested. However, it seeks to discover, define, and clarify key phenomena through inductive reasoning. Inductive reasoning refers to drawing general conclusions or theoretical insights from specific observations or patterns found in qualitative data (Thomas, 2006). In this study, using inductive reasoning allowed for building a conceptual understanding of the AGT framework based on insights gathered from expert interviews, rather than testing a pre-established theory.

Exploratory research is appropriate for investigations where knowledge is fragmented, speculative, or emergent (Babbie, 2020; Stebbins, 2001). In the case of AGT, no standard methodology or operational taxonomy yet exists, and limited documentation is available on real-world implementation, as highlighted in the justifications of this study. Thus, the exploratory approach allows for flexible, responsive engagement with expert participants and supports the generation of novel insights into AGT's structure, functionality, and adoption barriers. It accommodates unexpected findings and helps illuminate previously overlooked dimensions of intelligent building optimization, such as behavioral feedback loops, system adaptability, and AI-human collaboration in decision-making.

Additionally, this study is informed by an interpretivist epistemology, which asserts that reality is socially constructed and best understood through the meanings attributed by individuals within their specific contexts (Schwandt, 2015; Burrell & Morgan, 1979). By prioritizing expert interviews over abstract theorization or numerical measurement, the study positions experts as co-constructors of knowledge, allowing their lived experiences, organizational realities, and disciplinary perspectives to shape the understanding of AGT feasibility and application

The interpretive approach also enables sensitivity to contextual variability - a critical consideration in energy systems research, where factors such as climate, infrastructure, building codes, user

behavior, and organizational culture interact in highly localized ways. Through dialogue with domain professionals from various sectors (engineering, architecture, building management, sustainability), the research probes how AGT might be understood, valued, and applied differently depending on stakeholder goals, market readiness, and technical infrastructure. These insights are foundational for developing a conceptual framework that is theoretically sound and responsive to practice-based complexities.

By combining exploratory and interpretive perspectives, the research approach supports the development of a grounded, practice-informed conceptualization of AGT that is sensitive to both emerging technological possibilities and the socio-organizational realities that shape their use. The outcome is a richly contextualized foundation for subsequent empirical inquiry and policy guidance.

3.3 Literature Review - Methodology

To establish a robust conceptual foundation for this study and guide the development of its data collection instruments, a systematic literature review (SLR) was undertaken. The review was designed to synthesize existing knowledge at the intersection of digital twin systems, augmented intelligence, predictive analytics, energy performance, and human-centric optimization in building operations. This structured approach ensured transparency, reproducibility, and methodological rigor in identifying, selecting, and synthesizing relevant sources in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Moher et al., 2009).

The literature review process began with formulating explicit inclusion and exclusion criteria. Eligible publications included peer-reviewed journal articles, academic conference proceedings, technical white papers, and published authoritative industry reports. These were selected for their

empirical, conceptual, or theoretical relevance to the study's central themes. The primary inclusion criteria were:

- Focus on building energy optimization, particularly during the operational phase.
- Application or assessment of digital twin technologies in the built environment.
- Integration of augmented intelligence, machine learning, or predictive analytics.
- Emphasis on human-in-the-loop systems, occupant feedback, or behavioral modeling in energy systems.

The literature search was conducted across multiple reputable academic databases, including Scopus, ScienceDirect, and Google Scholar, to ensure comprehensive coverage of multidisciplinary research. Boolean keyword combinations were developed using terms such as:

- Digital twin buildings
- Augmented intelligence
- Predictive maintenance AND energy optimization
- Occupancy behavior AND building systems
- Human-in-the-loop AND smart buildings
- AI-driven energy management

An initial pool of sources was identified. After deduplication and a two-stage screening process (title/abstract and full-text review), a final selection of 55 highly relevant sources was included in the review. These sources span engineering, environmental design, computer science, and

architecture disciplines, highlighting the inherently interdisciplinary nature of the AGT research landscape.

Each source was thematically analyzed using qualitative content analysis techniques. This process enabled the identification of key thematic trends, such as:

- Persistent reliance on static energy models in traditional BEMS
- The underutilization of real-time data integration and predictive algorithms.
- Fragmented understanding of occupant behavior and comfort in optimization strategies.
- Emerging interest in AI-enhanced decision-making tools, though rarely integrated with digital twins or user feedback mechanisms.

The SLR also revealed significant knowledge gaps, particularly in the synthesis of technical and human-centered approaches to energy management. Most existing studies treat digital twin models, predictive analytics, and behavioral adaptation as separate research silos, rather than components of an integrated framework. This lack of convergence provides a justification and a strategic opportunity for the AGT model proposed in this study, which seeks to unite these domains into a cohesive and responsive system for building energy optimization.

Moreover, the literature review directly informed the development of the interview protocol, helping to shape the semi-structured questions around real-world implementation barriers, data integration challenges, occupant engagement mechanisms, and the role of AI in operational energy decisions. It also provided the initial conceptual structure upon which the AGT model was built and validated.

The systematic literature review was critical to grounding the study in existing academic discourse while simultaneously identifying the conceptual blind spots that AGT aims to address. By applying rigorous inclusion criteria, drawing from high-impact databases, and triangulating interdisciplinary sources, the review ensured that the subsequent stages of this research were theoretically sound, methodologically justified, and aligned with emerging trends in smart building energy management.

3.4 Data Collection Methods

This study employed semi-structured expert interviews as its primary data collection method, enabling the exploration of nuanced, context-specific insights into the feasibility and implementation of the AGT framework in building energy optimization. The interview approach was selected to align with the interpretive and exploratory nature of the research, which sought to understand expert interpretations, lived experiences, and systemic challenges associated with AGT adoption.

Semi-structured interviews offer a balanced methodological advantage: they provide consistency and structure across participants while allowing for flexibility and depth through open-ended questions and adaptive probing (Kallio et al., 2016; DiCicco-Bloom & Crabtree, 2006). This format is especially valuable for complex topics such as AGT, where technological, organizational, behavioral, and regulatory dimensions intersect uniquely across contexts.

Five domain experts participated in the study. These individuals were selected through purposive sampling, a strategy well-suited for qualitative inquiries that gathers rich, context-specific insight from those with specialized knowledge and strategic relevance to the research problem (Patton, 2015).

In qualitative research - especially within exploratory, theory-building studies - depth of understanding is prioritized over generalizability (Creswell & Poth, 2018). As such, smaller, purposefully selected samples are considered appropriate when the aim is to extract in-depth insights from individuals with direct experience and expertise. The selected sample of five experts is justified based on three key criteria:

1. Information Power: According to Malterud et al. (2016), the more relevant and specific the participants are to the study's objectives, the fewer participants are needed. All five experts possess direct professional experience in smart building technologies, energy analytics, digital twin deployment, or AI integration, giving them high information power relevant to the study.
2. Thematic Saturation: Although saturation is more fluid in interpretive qualitative research, recurring patterns and themes emerged by the fourth interview. The fifth interview reinforced these patterns and introduced only marginally new perspectives, indicating that thematic saturation was effectively achieved.
3. Exploratory Nature of the Study: Since the AGT framework is a novel and under-theorized concept, the goal was not statistical representation but rather to explore emergent insights, barriers, and enablers from those at the forefront of technological innovation. This aligns with guidance from Guest et al. (2006), who found that inhomogeneous expert groups with as few as six participants can yield meaningful thematic depth.

Participants were drawn from 2 key sectors:

1. Engineering and Construction Firms (3 participants): Practitioners involved in energy and digital retrofit projects and data-driven facility upgrades.

2. Facility and Operations Managers (2 participants): Practitioners responsible for real-time management of commercial buildings' energy, HVAC, and maintenance.

To maximize accessibility and accommodate participants across geographical locations, interviews were conducted through in-person meetings and virtual platforms such as Zoom and Microsoft Teams. Each session lasted approximately 60 to 90 minutes, depending on participant availability and engagement. All interviews were transcribed verbatim to ensure an accurate, comprehensive representation of expert responses.

- The interview protocol was structured around six core themes from the literature review and aligned with the study's research objectives. These included:
- Definitions and Expectations of AGT: Experts were asked to describe AGT in their own terms and discuss its conceptual potential in energy optimization.
- System Integration Challenges in Traditional BEMS: Participants reflected on the limitations of existing building energy systems, particularly about data silos and lack of interoperability.
- Potential of Predictive Analytics in Building Operations: Discussions on how machine learning and forecasting tools can enhance decision-making in real-time control systems.
- User Engagement and Human-in-the-Loop Optimization: Experts shared insights on the role of occupant behavior, feedback mechanisms, and the social acceptance of innovative technologies.
- Technical and Organizational Barriers to AGT Implementation: Infrastructure readiness, stakeholder alignment, cost implications, and change management challenges.

- **Regulatory Readiness and Market Acceptance:** Questions explored the role of codes, certifications, data governance, and policy incentives in supporting or hindering AGT deployment.

Throughout the interviews, participants were encouraged to share project case studies, practice examples, and projections for future trends. The conversational format facilitated the emergence of new insights not initially anticipated, particularly in areas such as AI model explainability, cybersecurity concerns, and occupant comfort personalization.

This data collection method provided rich, empirical grounding for the development of the AGT conceptual framework and ensured that the findings reflected both academic understanding and industry realities.

3.5 Expert Selection and Recruitment

Purposive sampling, a well-established qualitative strategy designed to ensure the inclusion of information-rich cases that directly address the research questions (Patton, 2015), guided the selection of participants. Given the exploratory and interdisciplinary nature of this study, centered on integrating AGT technology into real-world building operations, engaging with experts possessing deep domain knowledge and first-hand experience in the design, deployment, or strategic planning of energy optimization systems in buildings was essential.

To ensure credibility, relevance, and diversity of perspectives in the data collected, experts were selected based on the following criteria:

1. Minimum of five years of professional experience in building energy performance, sustainability consulting, digital twin deployment, or AI-driven building analytics.

2. Demonstrated familiarity with intelligent building systems, including predictive control platforms, real-time monitoring technologies, and energy management frameworks incorporating occupant feedback.
3. Active involvement in strategic, design, or operational roles, such as research leadership, product development, policy advisory, or facility operations, where decision-making on energy technologies is part of the expert's mandate.

This selection strategy aligns with recommendations from Moser and Korstjens (2018), who emphasize that qualitative studies benefit most when participants are positioned to offer conceptual, experiential, and contextual insights, especially in early-stage innovation research.

Experts were identified through a combination of methods:

- Professional academic networks: Conference proceedings, journal co-authorship, and faculty directories were used to identify scholars in digital twins, sustainability, and AI in the built environment.
- Professional platforms: LinkedIn was used to locate practitioners in engineering consultancies, technology firms, and building operations who met the criteria.
- Referral and snowball sampling: Initial participants were asked to recommend colleagues with specialized knowledge or complementary perspectives, expanding the expert pool and improving trust in participant-researcher relationships.

The participant pool was deliberately curated to reflect a balance across technological expertise, implementation experience, and organizational decision-making roles, ensuring that insights

captured technical feasibility, practical constraints, stakeholder dynamics, and institutional readiness.

Before participation, each expert received a formal informed consent form outlining the study's purpose, confidentiality assurances, voluntary participation terms, and data handling protocols. Participants were assured that identifying details would be anonymized in the reporting phase to protect confidentiality and support open, candid dialogue.

This carefully structured expert recruitment process allowed for a well-rounded, multi-perspective exploration of the opportunities and barriers associated with AGT deployment in real-world building environments.

3.6 Interview Protocol Development

The development of the interview protocol was critical to ensuring the methodological rigor and thematic alignment of the study's qualitative inquiry. As the core data collection instrument, the interview guide was carefully crafted to reflect the theoretical gaps identified in the literature review and the exploratory aims of the research. Its design followed established principles for qualitative research instrumentation, including construct alignment, question sequencing, and adaptability for open-ended exploration (Turner, 2010; Kallio et al., 2016).

The initial draft of the guide was developed based on the thematic categories emerging from the systematic literature review (see Section 3.3), which highlighted key gaps and challenges in existing Building Energy Management Systems (BEMS), the role of human feedback in intelligent energy systems, and the growing interest in predictive and AI-driven control frameworks. The goal was to ensure that the interview questions could surface expert perspectives on the technical feasibility and socio-organizational dimensions of implementing the Augmented Green Twin (AGT) concept.

To refine the guide's structure, clarity, and relevance, two pilot interviews were conducted with industry experts not included in the final sample. These pilot sessions were instrumental in assessing question phrasing, time allocation, and the prompts' ability to elicit rich, narrative responses. Feedback from these pilots led to several modifications, including simplifying technical jargon, better sequencing of thematic blocks, and adding follow-up prompts to encourage deeper reflection on behavioral, regulatory, and interoperability issues.

The finalized interview guide consisted of a semi-structured format, incorporating core questions and adaptive probes that could be modified in real time depending on the participant's expertise and emerging lines of discussion. The questions were organized around the following four thematic categories:

Background and Definitions: These questions explored how experts conceptualize AGT and its differentiation from conventional BEMS and digital twin systems.

Example: "What potential do you see for AGT in addressing gaps in traditional energy systems?"

Technical Integration and Predictive Capabilities: This section probed insights into the feasibility of real-time data integration, AI-driven forecasting, and interoperability challenges.

Example: "What types of data or systems would need to be integrated for an AGT model to function effectively?"

Human-AI Interaction and Behavior Modeling: These questions explored user feedback, occupant comfort, and the human-in-the-loop dimension of energy optimization.

Example: "How should user behavior be incorporated into future building energy models?"

Implementation Barriers, Policy, and Market Readiness: This category focused on external factors such as institutional policies, industry standards, and market receptivity to AGT frameworks.

Example: “What policy or regulatory changes would facilitate the wider adoption of AGT technologies?”

Open-ended questions were prioritized to allow participants the freedom to elaborate, share experiences, or bring forward novel ideas that the researcher might not have anticipated. Probing and clarifying questions were used strategically to encourage depth without leading responses (Rubin & Rubin, 2012).

The flexibility of the semi-structured format proved essential for tailoring the conversation to each expert’s background while maintaining thematic coherence across the dataset. This structure supported a balance between comparative analysis across participants and the emergence of new categories and insights, contributing to the study’s overall trustworthiness and analytical richness.

A copy of the interview protocol is attached as an appendix.

3.7 Data Analysis Strategy

This study’s qualitative data analysis was conducted using thematic analysis, a flexible and widely accepted approach for identifying, analyzing, and reporting patterns within qualitative data sets (Braun & Clarke, 2006). This method was selected for its suitability for studies seeking to interpret experiential, conceptual, and contextual meanings derived from in-depth interviews. Thematic analysis is particularly effective in exploratory research, as it allows researchers to construct nuanced themes that emerge from participant narratives and theoretical constructs (Nowell et al., 2017). The process followed the six-phase analytical framework outlined by Braun and Clarke (2006), ensuring methodological transparency and reliability:

Familiarization with the Data: The interviews were transcribed verbatim and carefully reviewed multiple times to ensure deep immersion and familiarity with the content.

Generating Initial Codes: Deductive (theory-driven) and inductive (data-driven) techniques were employed using a hybrid approach. Deductive codes were derived from existing literature, including terms such as “predictive analytics,” “occupant feedback,” “system interoperability,” and “human-AI collaboration.” Inductive codes emerged directly from participant discourse, capturing contextual concepts like “legacy systems resistance,” “AI model bias,” “data privacy concerns,” and “organizational inertia.”

Searching for Themes: Initial codes were grouped into broader thematic categories that captured recurring patterns across interviews. These themes aligned closely with the study's research questions, including AGT feasibility, barriers to adoption, user engagement, and regulatory readiness.

Reviewing Themes: The provisional themes were reviewed to assess internal coherence and distinctiveness. Transcripts were re-examined to ensure that identified themes were well-supported by the data and did not overlap or overly broadly.

Defining and Naming Themes: Each theme was clearly defined and labeled to reflect its underlying narrative or concept. Descriptive and interpretive labels were used to ensure conceptual clarity and analytical depth.

Producing the Report: Finally, the themes were synthesized and interpreted according to the study's objectives, supported by illustrative quotations, and linked to the theoretical framework in subsequent chapters.

All transcripts were imported into NVivo 12, a qualitative data analysis software that enhances analytical efficiency and transparency to facilitate systematic coding and data organization. NVivo's tools were used to assign codes, track code frequencies, generate thematic visualizations, and cross-compare thematic intersections among participants.

To enhance the reliability and credibility of the coding process, a second cross-code of 20% of the transcripts was done. This assessed inter-coder reliability, an important quality criterion in qualitative analysis. The resulting agreement rate was 85%, within acceptable thresholds for qualitative studies (Miles & Huberman, 1994). Thematic analysis in this study was not merely a process of categorizing content but a means of developing interpretive insight into how domain experts conceptualize AGT systems' integration, value, and challenges. This method supported the emergence of a grounded, empirically validated conceptual framework that informs the conclusions and recommendations of this thesis.

3.8 Integration of AI Model Responses

In addition to the primary dataset obtained from expert interviews, this study adopted an innovative comparative qualitative approach by incorporating insights generated from five leading generative artificial intelligence (AI) models: ChatGPT (OpenAI), Bard (Google), Claude (Anthropic), Copilot (Microsoft), and Perplexity AI. These models were selected based on their wide accessibility, advanced reasoning capabilities, diverse training corpora, and relevance to interdisciplinary knowledge domains such as sustainability, AI systems, and smart buildings.

Four main considerations guided this selection:

1. Domain coverage: All five models are trained on expansive datasets, including technical, architectural, and environmental content relevant to building energy systems.

2. Architectural diversity: The models represent different foundational architectures and training philosophies, offering a more comprehensive perspective when triangulated.
3. Public accessibility and reproducibility: Each model was freely or commercially available at the time of research, allowing transparent replication of the methodology.
4. Performance in reasoning and summarization tasks: Recent literature benchmark comparisons (OpenAI, 2023; Google DeepMind, 2023; Anthropic, 2023) suggest these LLMs outperform earlier models in technical domains.

Each LLM used in this study is briefly described below:

- ChatGPT (OpenAI): A transformer-based language model optimized for dialogue and reasoning tasks. Known for its contextual awareness, nuanced output, and ability to simulate domain expertise in technical subjects.
- Bard (Google): Developed on Google’s Pathways Language Model (PaLM), Bard integrates real-time search capabilities with language generation, making it well-suited for topics that involve emerging trends or regulatory developments.
- Claude (Anthropic): Focused on “constitutional AI,” Claude emphasizes alignment, transparency, and user intent. It tends to offer cautious, balanced reasoning and is designed to reduce hallucinations and misleading content in complex domains.
- Copilot (Microsoft/OpenAI): Embedded within Microsoft’s productivity tools, Copilot leverages OpenAI’s models with enhanced contextual integration, particularly in applied technical tasks. It was helpful for simulating structured responses with practical framing.

- Perplexity AI: A retrieval-augmented generation (RAG) model that cites real sources and emphasizes evidence-backed answers. Its inclusion enabled cross-checking of knowledge verifiability in AGT-related queries.

The models were prompted with the same semi-structured interview guide administered to human participants to evaluate their ability to simulate domain expertise on the subject of Augmented Green Twin (AGT) frameworks in building energy optimization.

The inclusion of AI-generated responses served three key methodological purposes: To evaluate the current conceptual capacity of large language models (LLMs) in articulating a complex, interdisciplinary topic such as AGT; To identify gaps or biases in AI-generated knowledge, particularly in areas that require nuanced contextual or experiential understanding; To assess the potential for AI models to act as co-design partners or knowledge support tools in the future development of energy optimization systems.

The decision to include AI model analysis was informed by emerging research on human-AI collaborative systems and the role of generative AI in knowledge work (Shneiderman, 2020; Seeber et al., 2020). These models increasingly function as decision support tools, creative partners, and content generators in various professional domains. In the context of smart building design, understanding how AI perceives and proposes solutions for integrated, human-centric energy optimization systems offers valuable insight into the readiness and limits of AI-enabled innovation. Each AI model was queried using consistent prompts derived from the original interview protocol, covering themes such as: Definitions and framing of AGT; Technical feasibility of integrating digital twins and AI in BEMS; Real-time adaptability and predictive analytics; Role of occupant feedback in optimization strategies; Policy and implementation barriers. The responses were treated as synthetic expert outputs and subjected to thematic analysis

using the same coding framework applied to human interview transcripts (see Section 3.7). However, AI-generated responses were analyzed separately and comparatively, enabling the identification of:

Conceptual alignment or divergence between AI and human experts; Areas where AI models demonstrated strong synthetic reasoning (e.g., articulating system interoperability benefits); Blind spots or oversimplifications (e.g., limited appreciation for human factors, regulatory complexity, or implementation trade-offs); Patterns in output variation across different AI platforms, revealing differences in training data, model bias, and reasoning depth.

Thematic cross-comparison revealed that while AI models were generally proficient at describing technical architectures and potential benefits of AGT systems, they lacked contextual specificity, real-world implementation insight, and critical reflection on socio-organizational dynamics. For example, most AI responses emphasized the efficiency gains from predictive analytics but did not address issues such as user resistance, organizational change management, or data privacy, which were key concerns for human experts.

This methodologically distinct layer of analysis offered a dual benefit: it provided a benchmark for current generative AI capabilities in a specialized knowledge domain and underscored the importance of human-AI symbiosis in the design and governance of future smart building systems. The findings from this component are synthesized in the discussion and conclusion chapters, where recommendations are made for strategically integrating AI reasoning into collaborative design processes without over-relying on autonomous outputs.

The integration of AI model responses thus represents a novel methodological extension within the qualitative research paradigm. It offers insight into the epistemic boundaries of artificial

intelligence in expert-driven domains and informs the trajectory of human-in-the-loop AGT system development.

3.9 Ethical Considerations

This study was conducted in full compliance with ethical research standards and protocols, as reviewed and approved by the Institutional Review Board (IRB). Given the study's qualitative nature, its engagement with human participants, and its integration of AI-generated responses, particular attention was paid to ensuring the protection of participants' rights, the confidentiality of data, and the integrity of analysis.

Before data collection, all expert participants received a detailed informed consent form outlining the study's purpose, procedures, anticipated risks and benefits, and their rights as participants. Consistent with the Belmont Report's principles of respect for persons, beneficence, and justice (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979), participants were informed of the voluntary nature of their involvement and their right to withdraw from the study at any time without consequence.

Each participant consented to the Audio recording of their interview session, the use of anonymized excerpts in published materials, and the secure storage and handling of all personal and professional information shared during interviews.

All interviews were conducted confidentially and securely in private physical spaces or via virtual conferencing. To protect participant identity and promote candid expression, all interview transcripts were de-identified, with names, organizations, and other identifying information removed or replaced with pseudonyms. Digital audio files, transcripts, and consent forms were stored on password-protected devices and backed up on encrypted drives, accessible only to the principal researcher.

In addition, ethical protocols were extended to address the inclusion of artificial intelligence (AI) models as supplementary contributors to the study. AI-generated content was:

Clearly labeled and distinguished from human participant data; Not treated as a replacement for expert knowledge but rather as a complementary analytical perspective; Evaluated separately to avoid conflating synthetic and experiential insights, thereby preserving epistemological transparency and analytic validity.

The study also considered the ethical implications of AI model usage, particularly regarding the potential reproduction of bias present in training data (Binns, 2018), the lack of contextual awareness in LLMs when generating insights about real-world implementation, and the researcher's responsibility to interpret AI-generated data critically and not present it as factually or contextually equivalent to lived expert experience.

Chapter 4: Data Analysis and Interpretation

4.1 Chapter Introduction

This chapter presents a comprehensive analysis of the data collected from two primary sources: semi-structured expert interviews and responses from five leading generative AI large language models (LLMs) - ChatGPT (OpenAI), Bard (Google), Claude (Anthropic), Copilot (Microsoft), and Perplexity AI. These dual data sources provided complementary perspectives on the feasibility, potential, and barriers to implementing the Augmented Green Twin (AGT) framework for building energy optimization.

The chapter is structured thematically, guided by the hybrid coding framework described in Chapter 3. Key insights from domain experts are synthesized with LLM responses and cross-referenced with the literature to construct a holistic and practice-informed conceptualization of AGT. While sections 4.2 through 4.8 focus on themes derived from expert perspectives, section 4.9 introduces and compares the findings obtained from the AI models, illuminating the extent to which LLMs can replicate domain expertise and where they fall short.

These sources enrich the study's understanding of AGT, showcasing human-centered and AI-simulated interpretations that shape the broader conclusions and framework proposed in Chapter 5.

4.2 Thematic Analysis Methodology

Thematic analysis served as the primary analytical tool for interpreting qualitative data in this study. Interview transcripts were analyzed using NVivo 12 software, enabling systematic coding, theme development, and content categorization. A hybrid coding strategy was employed, combining deductive codes - rooted in themes identified during the literature review - and inductive codes, emerging organically from the interview data. This approach ensured both

theoretical grounding and empirical richness. The themes were iteratively refined and cross-validated by a second data analysis to enhance interpretive reliability.

4.3 Interpretation and Synthesis of Expert Insights

The expert insights were synthesized with findings from the literature to construct a multidimensional AGT conceptual framework. Five core themes were identified: (1) AGT superiority over traditional BEMS, (2) multi-source data integration and predictive capabilities, (3) human-AI collaboration, (4) challenges to AGT implementation, and (5) future directions for AGT application in building energy optimization in the industry.

4.4 Comparative Perceptions of AGT and Traditional BEMS

Experts consistently perceived that AGT significantly outperforms traditional BEMS due to its adaptability, real-time responsiveness, and capacity for dynamic learning. AGT was described as a next-generation paradigm capable of transcending the static, rules-based logic of conventional BEMS by leveraging AI, machine learning, and occupant data to provide predictive, context-aware optimization.

Participants noted that where BEMS typically operate on predefined schedules, AGT enables continuous recalibration based on real-time occupancy, environmental inputs, and user preferences. This capability was seen as critical for enhancing building performance, especially in dynamic-use settings such as office environments with hybrid work schedules. Experts also pointed out that AGT's capacity to integrate cross-domain data sources provides a holistic view of building systems, enabling optimization not possible within siloed BEMS infrastructures.

4.5 Real-Time Data Integration and Predictive Analytics

One of AGT's most frequently discussed benefits was its ability to merge diverse data sources - including IoT sensors, weather forecasts, grid signals, and occupant feedback - into a unified

energy optimization engine. Experts emphasized that this data fusion capability allows AGT to move beyond reactive control toward predictive and preemptive energy management.

The interviewees highlighted how predictive analytics could enable AGT to anticipate peak energy loads, adjust setpoints preemptively, and provide maintenance forecasts before system failures occur. Literature supports this view, with Francisco et al. (2020) and Agostinelli et al. (2021) demonstrating that predictive control can reduce operational costs while improving user comfort and system longevity.

4.6 Human-AI Collaboration and User Engagement

Experts widely supported a human-in-the-loop model for AGT, wherein AI acts as a decision-support system rather than a fully autonomous controller. This perspective aligns with Shneiderman's (2020) advocacy for reliable, safe, and human-centered AI systems. Participants emphasized that facility managers must remain transparent, interpretable, and overridable by AGT's recommendations.

User engagement was also considered crucial. Interactive dashboards, gamified energy challenges, and real-time feedback tools were identified as effective ways to influence occupant behavior and enhance energy awareness. This participatory approach was viewed as a energy-saving strategy and a means to increase user satisfaction and buy-in.

4.7 Implementation Barriers and Deployment Challenges

Despite their enthusiasm for AGT systems' potential, interviewed experts consistently pointed to several critical barriers that could hinder their adoption and scalability in real-world building operations.

1. Integration with Legacy Systems: A central technical barrier identified by experts was the difficulty of interfacing AGT frameworks with legacy building systems, particularly

outdated HVAC, lighting, and building energy management systems (BEMS). Many commercial office buildings - especially those built before 2000 - operate on fragmented, proprietary platforms lacking the data interoperability and processing bandwidth required for real-time sensor integration and AI-driven analytics (Teisserenc & Sepasgozar, 2021; Li et al., 2020). For example, while AGT relies on continuous streams of sensor data from IoT devices and cloud-based computing environments, legacy BEMS often operate on static rule-based logic with minimal integration capabilities. Experts noted that retrofitting such buildings would require significant infrastructure upgrades, including rewiring, installing sensor networks, and updating communication protocols - activities that could disrupt ongoing operations.

2. **Financial Constraints and Cost-Benefit Uncertainty:** Another prominent concern was financial feasibility, especially for small-to-medium building owners lacking access to significant capital reserves. The upfront investment in AGT-enabling technologies - such as IoT sensor arrays, predictive analytics software, cloud-based storage, and occupant feedback platforms - was seen as prohibitively expensive (Opoku et al., 2021; Ghaffarian-Hoseini et al., 2013). Experts pointed out that return on investment (ROI) remains difficult to quantify for AGT, as benefits such as occupant comfort, predictive maintenance, or system adaptability are less tangible than energy savings. Moreover, building owners often prioritize short-term financial performance over long-term sustainability gains, which deters adoption unless supported by public incentives or clear regulatory mandates.
3. **Data Privacy, Cybersecurity, and Governance:** AGT systems require extensive data collection on occupant behavior, building operations, and external conditions, raising significant concerns around data privacy, ownership, and cybersecurity. Experts

highlighted the growing challenge of complying with international data protection laws such as the General Data Protection Regulation (GDPR) in the EU or the California Consumer Privacy Act (CCPA) in the U.S., especially when using cloud-based platforms and AI-driven analytics (Cheng et al., 2021). Cybersecurity was also a persistent concern as buildings become increasingly digitized, cyber intrusions or system manipulation risk grows, particularly when operational systems are remotely accessible. Without robust encryption, user authentication, and security protocols, AGT systems may become vulnerable entry points for attackers, potentially jeopardizing critical building functions.

4. **Organizational Resistance and Cultural Inertia:** Experts emphasized that organizational culture remains one of the most stubborn barriers to AGT implementation. In many facility management teams, there is limited exposure to data-driven optimization systems. AI technologies are often viewed with skepticism due to perceived complexity, job displacement fears, or lack of training (Ahmad et al., 2021; Petri et al., 2023). In particular, change management challenges arise when AGT requires shifting operational routines, engaging occupants as active participants in energy decisions, or reconfiguring maintenance protocols based on predictive models. Resistance to change is often most substantial in institutional settings where hierarchical decision-making or conservative budgeting dominates. Experts also noted that a lack of skilled personnel familiar with AI deployment further complicates AGT adoption.

These concerns mirror those discussed in the literature, including Ahmad et al. (2021) and Petri et al. (2023), who note that systemic fragmentation and institutional inertia continue to impede the scaling of smart energy technologies.

4.8 Scalability, Cloud Deployment, and Future Directions

Experts agreed that AGT's broader implementation depends on its ability to scale across multiple facilities and building types. Cloud-based architectures, edge computing, and modular design were cited as critical enablers for scalability.

Participants also discussed the potential of AGT to integrate renewable energy assets, such as rooftop photovoltaics and battery storage, into building operations, aligning with sustainability goals and net-zero energy targets. They argued that the future of AGT lies in creating open-source platforms, standardized data ontologies, and policy incentives that foster interoperability and collaborative development.

The data analysis demonstrates that AGT is perceived as a powerful, future-ready solution for building energy optimization. While challenges remain, particularly around integration, costs, and institutional readiness, expert opinion converges around AGT's unique value proposition: a responsive, AI-augmented, human-centered platform capable of driving substantial improvements in energy performance, occupant comfort, and sustainability.

The insights gathered in this chapter directly inform the development of the AGT conceptual model and underpin the practice recommendations presented subsequently.

4.9 Comparative Insights from Large Language Models (LLMs)

To complement the expert interviews, this study analyzed the responses of five generative LLMs - ChatGPT, Bard, Claude, Copilot, and Perplexity AI - prompted with the same semi-structured interview guide administered to human participants. This methodological innovation allowed for a comparative evaluation of how well current AI systems can simulate domain expertise in the emerging field of intelligent building energy optimization.

4.9.1 Justification for Using LLMs

These five LLMs were selected due to their accessibility, popularity, and reputational prominence in research and applied AI contexts. Each of them offers distinct strengths:

- ChatGPT (OpenAI): Known for its high coherence, domain versatility, and extensive training on both scientific and general knowledge corpora.
- Bard (Google): Strong at integrating real-time web-based information and contextual elaboration from broader digital sources.
- Claude (Anthropic): Designed to focus on ethical reasoning and context-aware dialogue, especially in technical and interdisciplinary conversations.
- Copilot (Microsoft): Built for code synthesis and domain-specific applications, often used in industry scenarios like data science and systems modeling.
- Perplexity AI: It is optimized for concise, evidence-supported answers and document summarization, making it helpful in synthesizing multi-source knowledge.

These models were selected because LLMs represent the current frontier of human-AI collaboration. They can engage in semi-structured dialogue, generate novel insights, and reason across disciplines.

4.9.2 Summary of LLM Contributions

The LLM-generated responses largely mirrored the thematic categories identified in expert interviews, including:

- The limitations of traditional BEMS (e.g., static rule-based logic, lack of integration),
- The benefits of predictive analytics, including load forecasting and maintenance,

- The role of occupant behavior and the value of human-in-the-loop design,
- Implementation barriers, including cybersecurity, data ownership, and cost,
- Future directions, such as cloud-based scalability and integration with renewables.

However, key distinctions emerged, which are highlighted in the table below:

TABLE 4.1 DISTINCTIONS BETWEEN LLM RESPONSES AND EXPERT-INTERVIEW RESPONSES

Theme	LLM Responses	Human Expert Responses
Technical Accuracy	Accurate in system design concepts, AI roles, and predictive analytics	Same, with more contextual depth and implementation nuance
Human Behaviour	Conceptually acknowledged, but lacked rich examples of occupant dynamics	Described detailed real-world feedback, resistance, and comfort preferences
Implementation Challenges	Surface-level treatment, general concerns about cybersecurity and costs	Nuanced discussion of organizational inertia, policy barriers, skill gaps
Novelty and Innovation	Strong on emerging trends (e.g., digital twins, cloud edge computing)	Provided practical insights on readiness, vendor interoperability, etc.
Real-world Case Integration	Absent or speculative	Grounded in lived experiences and current projects

4.9.3 Observed Limitations of LLMs

While the LLMs provided technically coherent and sometimes innovative responses, several limitations were observed:

- Lack of contextual specificity: Most responses were generalized and lacked localization to specific building types or stakeholder needs.

- Shallow treatment of human factors: While they identified human behavior as important, they rarely elaborated on engagement mechanisms, cultural barriers, or training needs.
- Blind spots in institutional dynamics: Procuring, liability, and interdepartmental coordination were almost entirely missing.
- No experiential learning: Unlike human experts, LLMs do not draw from direct project experience or tacit knowledge.

4.9.4 Contribution of LLMs to the Research

Despite their limitations, the LLMs helped in three significant ways:

1. Benchmarking the state of AI-generated domain knowledge and identifying its boundaries.
2. Complementing human insights by reinforcing recurring themes and occasionally introducing new angles (e.g., the potential for real-time carbon pricing).
3. Highlighting the need for robust human-AI collaboration in AGT system design, where synthetic reasoning is enhanced by human judgment, context, and experience.

Chapter 5: Discussion

5.1 Chapter Introduction

This chapter interprets the findings presented in Chapter 4, linking them with existing literature and theoretical frameworks to articulate the broader implications of the AGT framework for building energy optimization. The discussion critically evaluates how AGT addresses key limitations in current BEMS, explores the human and technological factors influencing implementation, and assesses AGT's potential contribution to sustainable building operations. It also reflects on the research's theoretical contributions, introduces the AGT framework, and identifies new directions for future inquiry.

5.2 AGT and the Evolution of Energy Management Systems

The comparison between AGT and traditional BEMS highlights a shift in energy management thinking. Traditional BEMS are typically designed around static schedules, deterministic rule sets, and siloed subsystems, which limit their responsiveness to real-time changes in occupancy, weather, and system performance. AGT, by contrast, represents an evolution toward adaptive, data-driven, and occupant-responsive systems.

This shift mirrors broader digital twin literature trends, emphasizing simulation, feedback loops, and predictive intelligence (Tao et al., 2018). By merging these capabilities with AI and real-time data streams, AGT can learn from historical performance, forecast future demands, and continuously optimize building operations. These findings align with Francisco et al. (2020), who highlight the potential of predictive analytics and IoT integration in reshaping operational efficiency.

5.3 Human-in-the-Loop: Repositioning the User in Energy Optimization

One of the most distinctive features of AGT is its human-centric approach. While conventional systems often treat occupants as passive variables or sources of uncertainty, AGT repositions them as active participants in energy decision-making. This aligns with Shneiderman's (2020) vision of reliable, human-centered AI, where technology augments rather than replaces human judgment.

Experts in this study emphasized the value of user feedback systems, gamified dashboards, and adaptive interfaces that personalize comfort and enhance energy awareness. This perspective challenges the long-standing dichotomy between comfort and efficiency, suggesting that informed and engaged users can contribute to both goals simultaneously. Moreover, integrating behavioral modeling into AGT design represents a methodological advancement, bridging engineering models with social science insights on motivation, feedback, and user agency.

5.4 Implementation Realities: Barriers and Enablers

Despite its promise, AGT faces significant implementation challenges. Interviewees identified financial constraints, interoperability issues, legacy system compatibility, and organizational resistance as key barriers. These findings mirror those in Ahmad et al. (2021) and Li et al. (2020), who note that technical innovation in the building sector often outpaces institutional and policy readiness.

The discussion also highlights critical enablers of AGT adoption. Phased deployment strategies, government incentives, and cloud-based architectures were frequently cited as mechanisms to reduce risk and build stakeholder confidence. These align with Petri et al. (2023), who argue for modularity and scalability in deploying AI-enhanced systems.

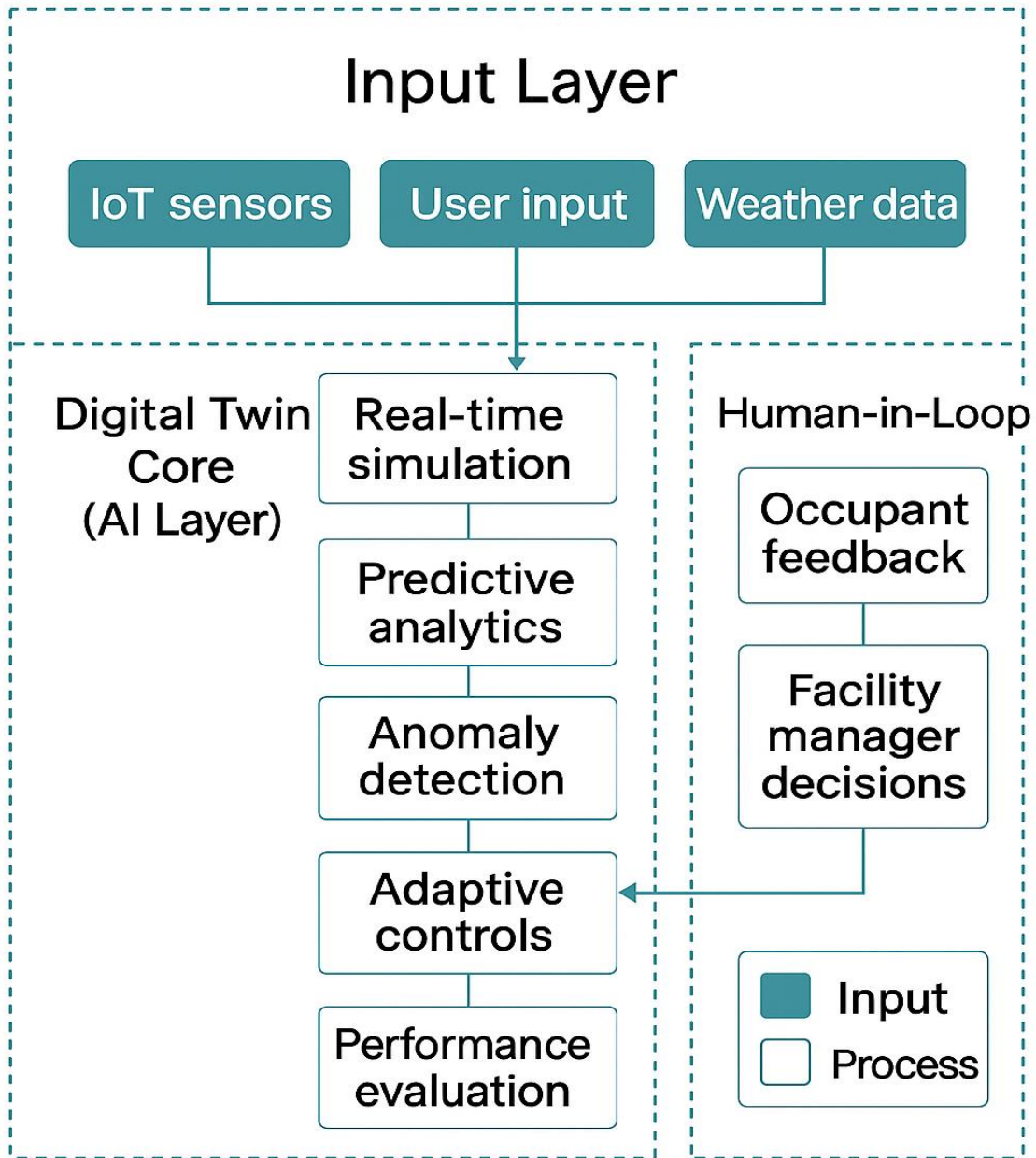
Importantly, the need for multi-stakeholder engagement emerged as a cross-cutting theme. Facility managers, IT teams, designers, and occupants must all be integrated into the implementation process to ensure alignment of goals, proper training, and shared ownership. Without such collaboration, AGT systems risk becoming technically sophisticated but underutilized.

5.5 Theoretical Contributions and Conceptual Innovation

This research theoretically advances the discourse on digital twin applications by introducing the AGT model as a hybrid socio-technical system. Unlike traditional digital twins, which focus predominantly on physical and operational modeling, AGT integrates behavioral, organizational, and AI-driven layers. This multidimensionality allows a more holistic understanding of how energy optimization unfolds within complex, inhabited environments.

The study contributes to emerging debates on explainable AI (XAI) and AI-assisted decision support in the built environment. Experts' insistence on interpretability, transparency, and override functions reflects growing concerns about algorithmic opacity. AGT, therefore, presents an opportunity to prototype systems where AI augments human agency rather than substituting for it.

5.6 The AGT Conceptual Framework



AGT Framework

FIGURE 5.1 THE AGT CONCEPTUAL FRAMEWORK

The conceptual framework in **Figure 5.1** was developed through an integrated synthesis of the systematic literature review (Chapter 2), expert interviews, and AI-generated responses (Chapters 3 and 4). It embodies the core architecture of the AGT model, structured into interdependent layers that reflect this study's empirical findings and research objectives.

The framework comprises three core layers: the Input Layer, the Digital Twin Core (AI Layer), and the Human-in-the-Loop, each playing a unique role in enabling adaptive and intelligent building energy optimization. This section defines the key components and explains how their interaction forms a dynamic and user-centered control system.

1. Input Layer

This layer gathers essential real-time and contextual data that fuels all downstream processes within the AGT system. It includes:

- **IoT Sensors:** These devices provide real-time data on building conditions, including temperature, humidity, occupancy, lighting levels, and equipment status.
- **User Input:** Occupant feedback on thermal comfort, lighting preferences, or manual overrides is collected through interfaces like dashboards or mobile apps.
- **Weather Data:** External environmental inputs, such as temperature forecasts, humidity, and solar radiation, are integrated to enhance prediction accuracy.

Function: This layer ensures that the AGT system remains contextually aware and can reflect both internal building states and external environmental changes.

2. Digital Twin Core (AI Layer)

The core computational engine of the AGT framework simulates, predicts, and adapts building behavior in real time. Its five interconnected components include:

- **Real-Time Simulation:** Virtually replicates the current operational state of the building using incoming data to maintain situational awareness.
- **Predictive Analytics:** Leverages historical and contextual data to forecast energy demand, user comfort needs, and system performance.
- **Anomaly Detection:** Monitors system outputs for irregularities or inefficiencies and flags them for corrective action.
- **Adaptive Controls:** Automatically adjusts building control systems (e.g., HVAC, lighting) based on predictive models and user preferences to optimize performance.
- **Performance Evaluation:** Compares expected outcomes against real-world results to refine algorithms and improve accuracy over time.

Function: This layer transforms raw data into actionable intelligence, enabling real-time decisions that strike a balance between energy efficiency and user comfort.

3. Human-in-the-Loop

Recognizing the value of human judgment, this layer ensures that system optimization is informed by user behavior and managerial oversight. It includes:

- **Occupant Feedback:** Users contribute qualitative data regarding their comfort levels and operational satisfaction, enabling the system to tailor its responses.
- **Facility Manager Decisions:** Operational staff can intervene, validate, or override system suggestions based on institutional policies or safety concerns.

Function: This layer embeds user agency into automated processes, fostering a socio-technical ecosystem where human and machine intelligence co-evolve.

Interaction Between Components

The AGT framework operates as a closed-loop system, with dynamic interaction across all layers:

1. The Input Layer delivers continuous, real-time information to the Digital Twin Core, enabling up-to-date simulation and forecasting.
2. The Digital Twin Core processes this data, detects anomalies, and deploys adaptive control strategies to building systems.
3. The Human-in-the-Loop both informs and reacts to the system through feedback and strategic oversight, creating a loop of participatory optimization.
4. The Performance Evaluation mechanism further refines the loop by learning from deviations between expected and observed results.

5.7 Comparison of AGT and Traditional BEMS

To further illustrate the conceptual advantages of the AGT framework, Table 5.1 offers a comparative summary between AGT and conventional BEMS. This comparison highlights the distinctive attributes of AGT in terms of adaptability, human integration, data responsiveness, and overall system intelligence. It highlights how AGT improves operational efficiency through predictive analytics and real-time responsiveness and enhances occupant engagement and comfort through human-in-the-loop optimization. By addressing the critical limitations of traditional BEMS, AGT emerges as a forward-looking, AI-augmented, and user-centric paradigm for building energy optimization.

TABLE 5.1 COMPARATIVE SUMMARY BETWEEN AGT AND TRADITIONAL BEMS

Feature	Traditional BEMS	AGT
Model Adaptability	Static, based on fixed assumptions	Dynamic, real-time adjustments based on live data
Human Integration	Minimal; users are often not considered in optimization	Strong, human-in-the-loop with occupant feedback
System Integration	Siloed (HVAC, lighting, energy systems isolated)	Holistic integration across all building systems
Data Utilization	Limited use; delayed response	Real-time analytics and predictive decision-making
Responsiveness	Reactive, slow	Proactive and predictive adjustments
Visualization Tools	Basic dashboards (if any)	Advanced AR/VR visualization for user engagement
Occupant Comfort	Often overlooked	Actively optimized based on real occupant feedback
Learning Capabilities	Rare or manual tuning	AI-powered learning and continuous improvement
Maintenance Approach	Scheduled or reactive	Predictive and preventive maintenance
Overall Efficiency	Limited by rigid programming	Continuously optimized for peak performance

5.8 Expert Reflections on AGT’s Relevance and Utility

Across the interviews, several experts expressed optimism about the AGT framework and its potential to address long-standing challenges in building energy management. Many acknowledged that the concept of integrating real-time data streams, predictive analytics, and human-centric feedback into a unified system resonates with the industry's shift toward smart, adaptive buildings.

Specifically, participants highlighted that AGT could help mitigate the rigidity of traditional BEMS by introducing dynamic and context-aware control mechanisms. One participant noted that such a system could “bridge the gap between technical systems and human behavior,” which remains a critical challenge in achieving sustained energy efficiency. Others appreciated AGT’s emphasis on occupant engagement and feedback integration, arguing that this approach aligns well with the growing demand for personalized comfort and user-responsive design.

While some experts cautioned that full-scale implementation may face integration and cost-related barriers, the consensus was that AGT represents a forward-looking and practical evolution of current practices. They saw value in the potential to test AGT through pilot projects or modular retrofits before wider adoption.

Overall, the expert feedback affirmed that the AGT model is not only conceptually sound but also well-aligned with both current pain points and future directions in building energy optimization.

Chapter 6: Conclusions and Recommendations

6.1 Chapter Introduction

This final chapter presents the overarching conclusions derived from the study. It offers practical and theoretical recommendations for deploying, developing, and future investigation of the Augmented Green Twin (AGT) framework in building energy optimization. Grounded in the findings from expert interviews, AI model assessments, and a comprehensive literature review, this chapter synthesizes the research contributions. It outlines a pathway for advancing the scholarship and practical implementation of AGT technologies.

6.2 Summary of Key Findings

The expert interviews confirm that AGT has high potential for improving energy efficiency in office buildings by addressing the shortcomings of traditional BEMS. Key benefits include predictive analytics, adaptive controls, and real-time multi-source data integration. However, legacy system compatibility, cost barriers, and data security concerns must be addressed for successful implementation.

The study also sought to investigate how an AGT framework could transform operational energy optimization in commercial buildings by integrating digital twin technology, augmented intelligence, and human-in-the-loop interaction. The research yielded several key insights:

- AGT provides a dynamic alternative to traditional Building Energy Management Systems (BEMS) by incorporating real-time data streams, predictive analytics, and adaptive control.
- Human-AI collaboration is central to AGT's success, offering the potential to bridge technological capabilities with user needs and behavioral feedback.

- Implementation challenges remain around system integration, financial feasibility, and organizational resistance. However, phased deployment and stakeholder engagement were identified as effective mitigation strategies.
- Scalability and sustainability are achievable through cloud-based architecture, open-source frameworks, and policy support mechanisms.

These findings confirm AGT as a compelling framework for future smart building systems, capable of driving operational efficiency, enhancing occupant comfort, and supporting decarbonization efforts.

6.3 Revisiting Research Objectives

This section revisits the research objectives outlined in Chapter 1 and discusses how each objective was addressed through the study, highlighting the key findings that emerged.

Objective 1: To identify the key challenges associated with current practices in optimizing commercial building operational energy.

This objective was achieved through an extensive literature review (Chapter 2) and semi-structured interviews with domain experts (Chapter 4). The findings confirmed that traditional BEMS suffer from several limitations, including:

- Static system configurations that cannot adapt to dynamic occupancy and environmental changes (Wang et al., 2019);
- Siloed subsystems, which hinder integrated optimization across HVAC, lighting, and plug loads (Li et al., 2020);

- Limited user engagement, leading to manual overrides and reduced system performance (Sartori et al., 2016);
- Lack of predictive capabilities, which results in reactive rather than proactive energy management (Ahmad et al., 2021).

Experts further emphasized barriers such as poor interoperability with legacy systems, cybersecurity and data governance risks, organizational resistance, and cost-related uncertainties as ongoing impediments to energy optimization. These insights are detailed in Section 4.7.

Objective 2: To develop a conceptual framework for using AGT to optimize building operational energy.

This objective was fulfilled by synthesizing insights gathered from the literature review, expert interviews, and AI-generated responses. A five-layer **AGT** framework was developed and presented in Chapter 5. The model integrates:

1. Real-time IoT data inputs
2. Digital twin simulation environments
3. Predictive analytics via AI
4. Human-in-the-loop engagement, and
5. Continuous feedback learning loops.

The framework distinguishes itself from traditional BEMS by offering a dynamic, adaptive, and user-centered system capable of preemptive adjustments and learning over time. As supported by participant insights in Chapter 4, AGT is positioned as a novel paradigm that addresses technical and behavioral gaps in current energy optimization approaches.

6.4 Research Contributions

This thesis makes several contributions to the fields of building energy management, digital twin technologies, and human-centered artificial intelligence:

- **Conceptual Innovation:** The study proposes the AGT framework as a novel extension of digital twin theory, embedding behavioral feedback and AI-based decision support within a real-time, adaptive control architecture.
- **Methodological Advancement:** By incorporating expert interviews and AI-generated responses, the study adopts a unique comparative approach to analyzing domain-specific knowledge, enriching our understanding of how AI models perform in highly technical, context-driven tasks.
- **Theoretical Expansion:** The research bridges engineering and social science paradigms, particularly in its emphasis on human-in-the-loop systems and explainable AI (XAI) within the built environment.
- **Practical Guidance:** Insights into deployment challenges, stakeholder engagement, and policy readiness provide a roadmap for practitioners seeking to adopt AGT solutions in office buildings and beyond.

6.5 Potential Benefits of AGT Implementation

AGT implementation offers a range of transformative benefits. Most notably, it can enhance energy efficiency through continuous monitoring, real-time data integration, and dynamic operational adjustments. According to Fathy et al. (2022), digital twin systems can yield up to a 20% reduction in energy consumption.

AGT also improves occupant comfort by incorporating feedback on thermal, lighting, and air quality preferences, resulting in higher satisfaction and performance (Winkler et al., 2016). Predictive maintenance is another critical benefit, allowing facility managers to identify and address issues before they escalate, thereby reducing downtime and long-term costs (Mahalle et al., 2023).

Furthermore, AGT can support cost savings by extending equipment lifespan, optimizing energy loads, and enabling renewable energy integration, such as solar and battery storage, contributing to sustainability goals (Javadi et al., 2022).

6.6 Research Gaps, Limitations, and Future Directions

While this study provides a solid foundation for understanding AGT, several limitations must be acknowledged:

- **Expert Subjectivity:** The findings reflect individual expert perspectives, which may vary across contexts.
- **Limited Sample Size:** Although in-depth, the sample of 5 experts may not fully capture all sectoral or geographic variations.
- **Evolving Technology Landscape:** As AGT is an emerging concept, future developments may shift feasibility or best practices.

Critical research gaps include:

- **Scalability:** Most digital twin systems are building-specific; future research should explore AGT models applicable to building clusters or cities (Wu & Guan, 2024).

- **Data Security and Privacy:** Transparent data governance is essential for public trust and ethical deployment (El-Annan & Hassoun, 2024).
- **User Acceptance:** Research must address usability, engagement strategies, and how AGT interfaces can promote active occupant participation (Bresa et al., 2024).
- **Retrofitting Legacy Infrastructure:** Innovative approaches are needed to ensure compatibility with older building systems (Mohankar, 2024).

6.7 Future Research Directions

While this study offers a foundational exploration of AGT, several avenues for future research remain. First, empirical validation through pilot implementations in different building typologies would provide insight into real-world performance, cost-benefit trade-offs, and user acceptance. Second, longitudinal studies could examine the learning behavior of AGT systems over time, assessing how predictive models evolve and adapt to operational feedback.

Third, interdisciplinary research is needed to refine the integration of human-computer interaction (HCI) principles into AGT interfaces. This includes studying how users interpret AI-generated recommendations and what design features most effectively drive engagement. Finally, developing policy and regulatory frameworks to guide AGT deployment - including standards for data privacy, cybersecurity, and performance benchmarking - remains an urgent research and policy task.

The AGT framework represents a groundbreaking shift in building energy optimization. By combining digital twin systems, AI-driven intelligence, and human-centered design, AGT transcends the constraints of traditional energy management systems. It offers a dynamic, holistic model for operational excellence that balances technological sophistication with occupant needs.

Future work must address implementation feasibility, enhance scalability, and reinforce ethical and regulatory safeguards to realize AGT's transformative potential fully. This study's findings demonstrate that AGT is not just a technological tool but a socio-technical system that promotes sustainability, efficiency, and human empowerment in the built environment.

In an era of accelerating climate challenges, energy demand, and digital disruption, the AGT model is a critical innovation in creating smarter, more sustainable, and more responsive building systems.

6.8 Future Implementation Pathways and Vision for AGT

While this thesis proposes and conceptualizes the AGT framework as a novel integration of Digital Twin technology, augmented intelligence, and human-in-the-loop mechanisms, its implementation remains at a developmental stage. Current efforts focus on defining the architecture, validating the framework conceptually through expert interviews and LLM comparative analysis, and mapping the technological components required for future deployment.

Looking ahead, future implementation of AGT would involve iterative prototyping in real-world building environments. Pilot projects in office buildings, especially within retrofitted or net-zero renovation initiatives, could serve as early testbeds. These pilots would demonstrate how AGT interacts with live sensor data, user interfaces, predictive algorithms, and behavior feedback loops to optimize energy use in real-time.

In the long term, AGT could be embedded into municipal smart-building platforms, linked with utility data, climate forecasting systems, and automated demand response infrastructures. As LLMs and real-time AI continue to evolve, their integration into AGT could enable natural language interfaces, adaptive energy narratives, and continuous co-learning between occupants and systems.

This future vision positions AGT not merely as a technical tool but as a socio-technical infrastructure, designed to evolve in response to user needs, environmental constraints, and digital capabilities. Its success will depend on collaborative design with stakeholders, sustained data governance, and alignment with regulatory frameworks for energy and sustainability.

Ultimately, AGT offers a pathway toward buildings that are not only energy-efficient but also intelligent, participatory, and resilient.

REFERENCES

1. Afram, A., & Janabi-Sharifi, F. (2014). Theory and applications of HVAC control systems—A review of model predictive control (MPC). *Building and Environment*, 72, 343–355.
2. Agostinelli, S., & Cumo, F. (2022). Machine learning approach for predictive maintenance in an advanced building management system. *WIT Transactions on Ecology and the Environment*, 255, 131–138. <https://doi.org/10.2495/EID220121>
3. Agostinelli, S., Cumo, F., Guidi, G., & Tomazzoli, C. (2021). Cyber-physical systems improving building energy management: Digital twin and artificial intelligence. *Energy and Buildings*, 250, 111257. <https://doi.org/10.1016/j.enbuild.2021.111257>
4. Ahmad, M. W., Mourshed, M., & Rezgui, Y. (2021). Computational intelligence techniques for HVAC systems: A review. *Building Simulation*, 14(1), 3–30. <https://doi.org/10.1007/s12273-020-0713-0>
5. Ahmad, T., Chen, H., Guo, Y., & Wang, J. (2021). A comprehensive review of Building Energy Management Systems (BEMS) for improved efficiency. *Energy and Buildings*, 239, 110838. <https://doi.org/10.1016/j.enbuild.2021.110838>
6. Babbie, E. (2020). *The practice of social research* (15th ed.). Cengage Learning.
7. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610–623). ACM. <https://doi.org/10.1145/3442188.3445922>
8. Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. In S. A. Friedler & C. Wilson (Eds.), *Proceedings of the 1st Conference on Fairness, Accountability and Transparency* (pp. 149–159). PMLR.
9. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
10. Bresa, A., Žakula, T., & Ajduković, D. (2024). Occupant-centric control in buildings: Investigating occupant intentions and preferences for indoor environment and grid flexibility interactions. *Energy and Buildings*, 317, 114393. <https://doi.org/10.1016/j.enbuild.2024.114393>
11. Burrell, G., & Morgan, G. (1979). *Sociological paradigms and organizational analysis: Elements of the sociology of corporate life*. Heinemann.
12. Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
13. Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE Publications.
14. Denzin, N. K., & Lincoln, Y. S. (Eds.). (2018). *The SAGE handbook of qualitative research* (5th ed.). SAGE Publications.

15. DiCicco-Bloom, B., & Crabtree, B. F. (2006). The qualitative research interview. *Medical Education*, 40(4), 314–321. <https://doi.org/10.1111/j.1365-2929.2006.02418.x>
16. El-Annan, S. H., & Hassoun, R. (2024). Enhancing Consumer Trust Through Transparent Data Practices and Ethical Data Management in Business. *Advances in Logistics, Operations, and Management Science Book Series*, 105–148. <https://doi.org/10.4018/979-8-3693-8357-5.ch005>
17. Fathy, Y., Jaber, M., & Nadeem, Z. (2021). Digital Twin-Driven Decision Making and Planning for Energy Consumption. *Journal of Sensor and Actuator Networks*, 10(2), 37. <https://doi.org/10.3390/JSAN10020037>
18. Federal Ministry for Economic Affairs and Climate Action (BMWK). (2022). *The Energy Transition – Germany’s Energiewende*. <https://www.bmwk.de/Redaktion/EN/Dossier/energy-transition.html>
19. Francisco, A., Mohammadi, N., & Taylor, J. E. (2020). Smart city digital twin framework for real-time multi-modal data analytics. *Automation in Construction*, 118, 103334. <https://doi.org/10.1016/j.autcon.2020.103334>
20. Grieves, M. (2022). *Intelligent digital twins and the development and management of complex systems*. *Digital Twin*, 3, 8. <https://doi.org/10.12688/digitaltwin.17574.1>
21. International Energy Agency. (2022). Buildings. IEA. <https://www.iea.org/topics/buildings>
22. Javadi, M., Liang, X., Gong, Y., & Chung, C. Y. (2022). Battery Energy Storage Technology in Renewable Energy Integration: a Review. *Canadian Conference on Electrical and Computer Engineering*, 435–440. <https://doi.org/10.1109/CCECE49351.2022.9918504>
23. Kallio, H., Pietilä, A. M., Johnson, M., & Kangasniemi, M. (2016). Semi-structured interviewing in social research: A critical review. *Qualitative Research*, 16(2), 122–139. <https://doi.org/10.1177/1468794114550439>
24. Li, W., He, Y., & Wang, S. (2020). A review of building digital twins to improve energy efficiency in the built environment. *Energy Informatics*, 3(1), 1–19. <https://doi.org/10.1186/s42162-020-00109-2>
25. Li, X., Wen, J., & Bai, E. W. (2020). Developing a dynamic model for co-simulation of building energy and control systems. *Journal of Building Performance Simulation*, 13(3), 251–270. <https://doi.org/10.1080/19401493.2020.1713517>
26. Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. SAGE Publications.
27. Mahalle, P. N., Hujare, P. P., & Shinde, G. R. (2023). *Predictive Maintenance* (pp. 51–60). Springer Nature. https://doi.org/10.1007/978-981-99-4850-5_4

28. Mahdavi, A., et al. (2008). Simulation-assisted building systems control. *Automation in Construction*, 17(5), 634–640.
29. Maxwell, J. A. (2013). *Qualitative research design: An interactive approach* (3rd ed.). SAGE Publications.
30. Merriam, S. B., & Tisdell, E. J. (2015). *Qualitative research: A guide to design and implementation* (4th ed.). John Wiley & Sons.
31. Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook* (2nd ed.). SAGE Publications.
32. Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook* (3rd ed.). SAGE Publications.
33. Mohankar, R. H. (2024). Retrofitting Techniques: A Comprehensive Review. *Indian Scientific Journal Of Research In Engineering And Management*.
<https://doi.org/10.55041/ijrsrem38081>
34. Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G.; PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLOS Medicine*, 6(7), e1000097. <https://doi.org/10.1371/journal.pmed.1000097>
35. Moser, A., & Korstjens, I. (2018). Series: Practical guidance to qualitative research. Part 3: Sampling, data collection and analysis. *European Journal of General Practice*, 24(1), 9–18. <https://doi.org/10.1080/13814788.2017.1375091>
36. Nassif, N. (2012). Modeling and optimization of HVAC systems using artificial intelligence techniques. *Building Simulation*, 5(4), 363–377.
37. Natural Resources Canada. (2021). *Smart Grid Program – Building a cleaner, more resilient electricity system*. Government of Canada. <https://natural-resources.canada.ca>
38. Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods*, 16(1), 1–13. <https://doi.org/10.1177/1609406917733847>
39. Opoku, D. G. J., Perera, S., & Osei-Kyei, R. (2021). Digital twin application in the construction industry: A literature review. *Journal of Building Engineering*, 40, 102726. <https://doi.org/10.1016/j.jobe.2021.102726>
40. Patton, M. Q. (2015). *Qualitative research & evaluation methods: Integrating theory and practice* (4th ed.). SAGE Publications.
41. Ritchie, J., Lewis, J., Nicholls, C. M., & Ormston, R. (Eds.). (2013). *Qualitative research practice: A guide for social science students and researchers* (2nd ed.). SAGE Publications.
42. Rubin, H. J., & Rubin, I. S. (2012). *Qualitative interviewing: The art of hearing data* (3rd ed.). SAGE Publications.
43. Sartori, I., Napolitano, A., & Voss, K. (2016). Net zero energy buildings: A consistent definition framework. *Energy and Buildings*, 48, 220–232

44. Schwandt, T. A. (2015). *The SAGE dictionary of qualitative inquiry* (4th ed.). SAGE Publications.
45. Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction*, 36(6), 495–504. <https://doi.org/10.1080/10447318.2020.1741118>
46. Silverman, D. (2020). *Doing qualitative research* (5th ed.). SAGE Publications.
47. Smart Nation and Digital Government Office. (2021). *Smart Nation: The way forward*. Government of Singapore. <https://www.smartnation.gov.sg>
48. Stebbins, R. A. (2001). *Exploratory research in the social sciences*. SAGE Publications.
49. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2018). Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics*, 15(4), 2405–2415. <https://doi.org/10.1109/TII.2018.2873186>
50. Teisserenc, B., & Sepasgozar, S. M. E. (2021). Risks, barriers and opportunities for the digital twin adoption in the AEC industry. *Journal of Building Engineering*, 40, 102418. <https://doi.org/10.1016/j.jobe.2021.102418>
51. Thomas, D. R. (2006). *A general inductive approach for analyzing qualitative evaluation data*. *American Journal of Evaluation*, 27(2), 237–246. <https://doi.org/10.1177/1098214005283748>
52. Wang, S., Yan, C., & Xiao, F. (2019). Quantitative energy performance assessment methods for existing buildings. *Energy and Buildings*, 198, 532–544.
53. Winkler, D. A., Beltran, A., Esfahani, N. P., Maglio, P. P., & Cerpa, A. E. (2016). FORCES: feedback and control for occupants to refine comfort and energy savings. *Ubiquitous Computing*, 1188–1199. <https://doi.org/10.1145/2971648.2971700>
54. Wu, T., & Guan, C. (2024). Advancing Intra and Inter-City Urban Digital Twins: An Updated Review. *Journal of Planning Education and Research*. <https://doi.org/10.1177/0739456x241260887>
55. Yang, R., Wang, L., & Wang, J. (2017). Intelligent building energy management system for optimal HVAC control. *Energy and Buildings*, 150, 69–79.