A Managerial Perspective on Generative AI's Role in Digital Twin- Enabled Positive Energy Districts

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Abstract

Title: A Managerial Perspective on Generative AI's Role in Digital Twin-Enabled Positive Energy Districts

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As cities worldwide strive toward more sustainable energy systems, Positive Energy Districts (PEDs) have emerged as a promising approach to achieving net-positive annual energy balances. However, the complexity and variability of urban energy supply and demand pose significant challenges for effective energy management. This thesis investigates how the integration of Generative Artificial Intelligence (GenAI) with Digital Twin (DT) technologies can enhance PEDs. Based on a comprehensive literature review, project proposals, and qualitative interviews with industry experts, the research explores how GenAI can strengthen DT capabilities by improving forecasting accuracy, scenario testing and resource allocation. Key findings show that GenAI can fill data gaps, support adaptive modelling and facilitate proactive energy distribution decisions. In addition, the research identifies organisational and regulatory barriers - such as privacy, interoperability standards and the need for capacity building - that must be overcome to realise these benefits. By providing actionable insights into how GenAI can augment DTs, this work contributes to the theoretical and practical knowledge of sustainable urban energy systems. It highlights the importance of strategic planning, stakeholder collaboration and robust governance mechanisms to guide managers and policy makers towards more efficient, equitable and forward-looking energy solutions in DTs.

Keywords: Positive Energy Districts, Digital Twin, Generative AI, Energy Management, Sustainability, Urban Planning, Smart Grids, Smart Cities

Sumário

Título: Uma perspetiva de gestão sobre o papel da IA generativa nos distritos de energia positiva com base na geminação digital

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À medida que cidades globais buscam sistemas energéticos mais sustentáveis, os Distritos de Energia Positiva (PED) surgem como abordagem promissora para obter balanços energéticos líquidos positivos. No entanto, a complexidade e a variabilidade da oferta e da procura de energia urbana impõem desafios à gestão eficaz. Esta tese investiga como a integração da Inteligência Artificial Generativa (GenAI) e das tecnologias de Digital Twin (DT) pode aprimorar os PEDs. Baseando-se em revisão de literatura, projetos e entrevistas com especialistas, explora-se como a GenAI reforça a capacidade dos DT de prever, testar cenários e alocar recursos. As conclusões indicam que a GenAI pode preencher lacunas de dados, apoiar modelagem adaptativa e facilitar decisões proativas de distribuição de energia. Além disso, identificam-se entraves organizacionais e regulatórios — como privacidade, normas de interoperabilidade e desenvolvimento de competências — que devem ser superados. Ao apresentar insights acionáveis sobre a sinergia GenAI-DT, este trabalho contribui para o avanço teórico e prático de sistemas urbanos sustentáveis. Destaca-se a importância do planejamento estratégico, da colaboração entre stakeholders e de mecanismos robustos de governança para orientar gestores e formuladores de políticas rumo a soluções energéticas mais eficientes, equitativas e orientadas ao futuro.

Palavras-chave: Distritos de Energia Positiva, Gémeo Digital, IA generativa, Gestão de Energia, Sustentabilidade, Planeamento Urbano, Redes Inteligentes, Cidades Inteligentes

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1. Introduction

1.1. Background

Energy consumption is a major sustainability challenge, with cities being a major contributor to global energy use and emissions (McCormick et al., 2013). Urban areas around the world face significant challenges in managing energy consumption and achieving sustainability goals. A large number of commercial and residential buildings exhibit inefficient energy use, contributing to increased carbon emissions and perpetuating unstainable practices (Gouveia et al., 2021). Cities are major contributors to global energy consumption, making their role in the sustainability transition critical (McCormick et al., 2013). As projected by the United Nations Population Division (2018), the urban population is expected to continue to grow, with 68.4% of the world's population projected to live in cities by 2050 - an increase from less than 50% in 2000. Looking at Europe, over 80% of population is expected to live in cities by 2050 (United Nations Population Division, 2018). Given their significant impact, cities are key players in the global transition to sustainability (McCormick et al., 2013). ICLEI has developed five pathways for systemic change in urban areas, which serve as a comprehensive guide to sustainable urban development (ICLEI, 2024). One promising approach to achieving sustainability goals for urban areas is the implementation of Positive Energy Districts (PEDs), which aim to create zones with a net-zero or positive energy balance by utilizing renewable energy sources such as solar, geothermal and wind energy (Hinterberger et al., 2020; Zhang, Penaka, et al., 2021).

1.2. Problem Statement

Positive Energy Districts (PEDs) aim to produce more energy than they consume by integrating renewable energy sources, energy storage, and smart grid technologies. However, managing energy within PEDs is complex due to real-time fluctuations in both energy supply and demand. Balancing these dynamics is crucial not only for maintaining the positive energy objectives of PEDs but also for ensuring operational efficiency and cost-effectiveness from a management standpoint. Digital Twins (DTs), virtual replicas of physical systems, have been employed to simulate and analyse energy systems within PEDs. They offer benefits like scenario testing and predictive maintenance, which are valuable tools for decision-makers and managers in planning and optimizing energy resources. Nonetheless, traditional DTs face limitations in processing large volumes of real-time data and rapidly adapting to changes. These shortcomings hamper their effectiveness in managing the dynamic energy landscape of PEDs and pose challenges for strategic energy management. Advancements in Artificial Intelligence (AI), particularly

Generative AI (GenAI), present an opportunity to enhance DT capabilities. GenAI excels at processing extensive datasets, recognizing complex patterns, and generating adaptive predictive models in real time. For business managers and energy operators, integrating GenAI into DTs could significantly improve energy distribution management, enhance the prediction of consumption patterns, and optimize energy flows within PEDs. This integration could lead to better resource allocation and cost savings. Despite this potential, the integration of GenAI and DTs for energy management in PEDs remains underexplored, and their relationship is not well-defined. There is a pressing need to investigate how GenAI can be leveraged to enhance DT systems for better energy management in PEDs. Addressing this gap could lead to innovative solutions that manage the complexities of real-time energy management, contributing to the efficiency, sustainability, and economic viability of PEDs. From a management and business perspective, exploring this integration is both timely and original, with the potential to advance current research and practical applications in sustainable urban energy systems. Such advancements could not only improve operational efficiency but also open new business opportunities in the development and deployment of intelligent energy management solutions for PEDs, fostering sustainable growth and competitive advantage.

1.3. Research Questions

This research aims to explore the integration of Generative Artificial Intelligence (GenAI) with Digital Twin (DT) technologies to enhance energy management in Positive Energy Districts (PEDs) from a management and business perspective. The study seeks to address the complexities of real-time energy supply and demand fluctuations within PEDs by leveraging advanced AI capabilities. To achieve this objective, the main research question was formulated as: "How can generative AI improve digital twin applications for positive energy districts (PEDs)?". In addition, two sub-questions were formulated that focus on the key limitations and barriers to implementing generative AI-assisted DT systems for PEDs: “What are the current limitations of Digital Twin technology in managing energy within PEDs?” and “What are the potential barriers to implementing Generative AI in PEDs from a management and business standpoint?”

The main research question focuses on understanding the ways in which GenAI can augment DT applications to improve operational efficiency, sustainability, and cost-effectiveness in PEDs. This involves analysing how GenAI's capabilities in processing extensive datasets and generating adaptive predictive models can be harnessed to optimize energy flows and distribution.

The first sub-question aims to identify the existing challenges and limitations of current DT technologies used in PEDs. This includes examining their ability to process large volumes of real-time data, adapt to rapid changes in energy dynamics, and provide actionable insights for managers and decision-makers. Understanding these limitations is crucial for pinpointing areas where GenAI can make significant improvements. The second sub-question seeks to uncover the potential barriers to implementing GenAI within PEDs. These barriers may encompass technical challenges, such as integration with existing systems and data security concerns; organizational challenges, like resistance to change or lack of technical expertise; and regulatory or ethical issues, including compliance with data protection laws and ethical considerations in AI deployment. Addressing these barriers is essential for developing effective strategies for the successful integration of GenAI into DT systems.

By investigating these questions, the research intends to provide valuable insights into how GenAI can be leveraged to enhance DT applications in PEDs. The outcomes are expected to contribute to innovative solutions that effectively manage the complexities of real-time energy management. This, in turn, can lead to improved efficiency, sustainability, and economic viability of PEDs, offering significant benefits from a management and business perspective.

1.4. Dissertation Outline

The thesis is divided into six chapters, each of which serves a different purpose in presenting the research. Chapter one introduces the topic by providing essential background information, clearly stating the problem, and outlining the specific research questions that guide this dissertation. Chapter two delves into the theoretical context of the research, providing a literature review that explores key concepts such as digital twin technology, generative AI, and positive energy districts. This enables the foundation for the remaining research. Chapter 3 outlines the methodological approach, detailing the research design, data collection techniques and analysis methods used to address the research questions introduced in chapter two. Chapter 4 presents the primary findings from the interviews and case studies, providing empirical evidence to support the research objectives. Chapter 5 provides a critical interpretation of these findings and discusses their implications for both theoretical understanding and practical application in the field. Finally, Chapter 6 concludes the dissertation by summarising the key findings of the research and suggesting potential paths for future research, thereby contributing to the ongoing academic discourse in this area.

2. Literature Review

2.1. Digital Twin Technology

Digital Twin (DT) Technology has emerged as a tool to manage various complex scenarios. It is a sophisticated, data-driven virtual model of a physical system, continuously synchronized with its real-world counterpart through bi-directional data flows that enable real-time monitoring, simulation, and optimization across the entire lifecycle of the physical assets (VanDerHorn & Mahadevan, 2021).

VanDerHorn & Mahadevan (2021) highlight that a Digital Twin provides a comprehensive, adaptive virtual representation of the physical entity, maintained through ongoing information exchange, which facilitates real-time decision-making and operational improvements. This central characteristic differentiates Digital Twins from other digital technologies such as Cyber-Physical-Systems (CPT) (Semeraro et al., 2021) and Internet of Things (IoT), which provide real-time data but lack the bi-directional integration and analytical depth that define a true Digital Twin (VanDerHorn & Mahadevan, 2021). As highlighted by Kaur et al. (2020), Digital Twins, extend beyond the IoT's conventional data-collection scope by enabling real-time analytics and actionable insights, transforming IoT data into operational intelligence. The origins of Digital Twins trace back to Product Lifecycle Management (PLM), a framework introduced by Michael Grieves, where the DT concept plays a role in supporting assets from design through to end-of-life. As described by Grieves and Vickers (2017), the base of the Digital Twin concept is that each system comprises two parts: the physical system and a new virtual system that contains all the information about the physical one. This lifecycle approach allows Digital Twins to maintain and adapt high-fidelity models across various stages, ensuring that each phase benefits from real-time updated and continuous feedback. Semeraro et al. (2021) emphasize that Digital Twins embody the full lifecycle perspective, mirroring physical systems dynamically to support continuous optimization and data-driven decision-making across all phases.

Further expanding on this, Deng et al. (2021) describe Digital Twins as systems that facilitate a deep convergence between the physical and digital dimensions. This convergence is not only a one-way data flow but a dynamic, closed-loop feedback system, where real-time data updates allow the digital model to adaptively respond to changing conditions in the physical environment. Qi et al. (2021) further illustrate, that a Digital Twin’s capability to serve as a bridge between the physical and virtual worlds involves the integration of the 3C functionalities: computing, communication, and control. This integration enables Digital Twins to process vast amounts of data in real-time, linking the digital model to its physical counterpart. Through the application of IoT, machine learning, and simulation technologies, Digital Twins can predict and prescribe actions based on the evolving conditions of the physical system. This predictive and prescriptive capacity is what differentiates Digital Twins from conventional IoT applications, as DTs are capable of adapting and learning from data, to drive ongoing improvements and proactive responses to potential challenges (Qi et al., 2021).

Additionally, Sharma et al. (2022) note that Digital Twins are designed to replicate not only the physical attributes of an asset but also its behavioural characteristics, enabling scenario analysis, risk assessment and optimized decision-making. This capability allows Digital Twins to go beyond simply monitoring, supporting predictive maintenance and operational planning based on data-driven insights. Tao et al. (2019) emphasize the DT's role in supporting the entire value chain by merging data from various staged of a product's lifecycle. This comprehensive data integration is crucial for achieving operational efficiencies and sustainability goals.

In conclusion, a Digital Twin can be defined as a high-fidelity virtual representation of a physical system, continually synchronized through real-time data exchange to mirror, adapt, and predictively model the physical entity's state and behaviour. By integrating IoT, machine learning, and simulation capabilities, Digital Twins enable data-driven decision-making, predictive maintenance, and optimized operations across the asset's lifecycle, distinguishing them from simpler digital models or CPS systems. This unique combination of real-time feedback, lifecycle integration, and predictive modelling capabilities positions Digital Twins as a transformative technology for enhancing operational efficiency and sustainability in diverse applications, from manufacturing to urban energy management (Deng et al., 2021; Qi et al., 2021; Semeraro et al., 2021; Sharma et al., 2022; Tao et al., 2019; VanDerHorn & Mahadevan, 2021).

Type of Digital Twin	*Application Domain*	*Key Technologies*	*Data Sources*	*Benefits and Advantages*	*Challenges/Limitations/ Barriers*
Product Twin	Manufacturing	IoT, Machine Learning, Simulation Models	Sensor data, real-time data, historical data	Real-time monitoring and optimization across the product lifecycle; predictive maintenance; operational improvements; data-driven decision-making	Integration complexity; need for continuous synchronization; handling vast amounts of data; maintaining high-fidelity models
Asset Twin	Complex Physical Systems	Bi-directional Data Flows, Machine Learning, Simulation Technologies	Real-time data, sensor data	Real-time decision-making; continuous optimization; scenario analysis; risk assessment; optimized decision-making based on data-driven insights	ensuring ongoing synchronization; challenges in merging data from various lifecycle stages; regulatory and ethical considerations
System Twin	Urban Energy Management	IoT, 3C functionalities, Simulation technologies	Real-time data, sensor data	Enhancing operational efficiency, achieving sustainability goals; predictive modelling; proactive responses to challenges; lifecycle integration	Technical and operational barriers; need for dynamic closed-loop feedback systems; data security and privacy consideration
Process Twin	Industrial Processes	IoT, Machine Learning, Simulation Technologies	Real-time data, sensor data	improved process efficiency; predictive maintenance; quality control; streamlined workflow; reduced downtime; data-driven decision-making	Integration complexity across stages; need for robust data processing; challenges in real-time adaptation for varying conditions

Table 1: Types of Digital Twins

2.2. Generative AI

Artificial intelligence (AI) is transforming industries by offering capabilities for reasoning based on inputs and learnings from differences between expected and actual outcomes (Dwivedi et al., 2023). It enhances decision-making processes and allows organizations to derive actionable insights from vast amounts of data. As Dwivedi et al. (2023) explain, new AI algorithms now are capable of processing unstructured data, such as raw text and images, which were traditionally out of reach for conventional algorithms (Lecun et al., 2015). Machine Learning (ML) lays the groundwork for more advanced AI techniques. ML enables machines to learn from data patterns without explicit programming, allowing for more autonomous system behaviours as highlighted by LeCun et al. (2015). It plays a role in various fields ranging from predictive analytics to the automation of routine tasks, setting the foundation for deep learning techniques. Deep learning, introduces representation-learning methods that utilize multi-layered neural networks (Lecun et al., 2015). These networks transform inputs into increasingly abstract representations, making it possible to handle complex tasks such as natural language understanding and image recognition (Collobert et al., 2011; Lecun et al., 2015). Unlike traditional ML, deep learning architectures like convolutional neural networks (CNNs) and recurrent natural networks (RNNs) are specifically designed to model high-dimensional data, making them extremely effective for big data applications (Lecun et al., 2015; Schmidhuber, 2015).

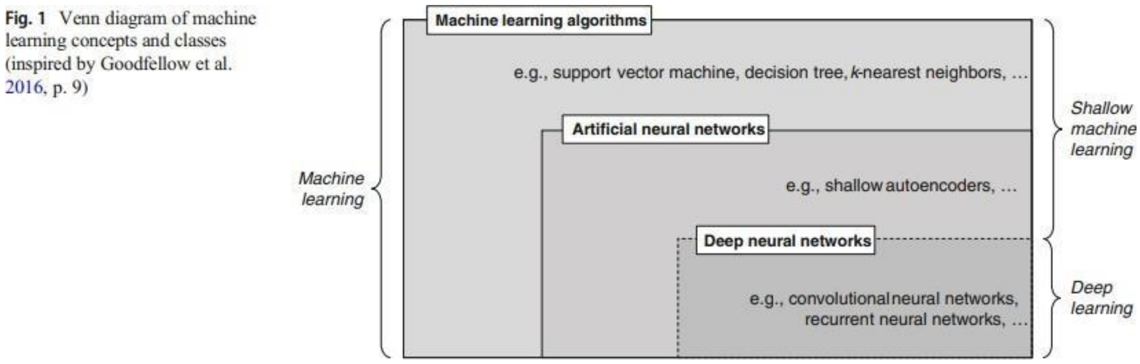


Figure 1: Venn Diagram of machine learning concepts and classes (from Janiesch et al., 2021)

Building upon the foundations of machine learning and deep learning, generative AI adds the capability of creating new content. As Susarla et al. (2023) describe, generative AI models are capable of producing novel data in forms such as text, images and even audio. The models generate synthetic data realistic enough to mimic real-world data and human creativity (Bandi et al., 2023; Toews, 2023). Highlighted by Garon (2023) generative AI models are able to evaluate and combine data, synthesizing known information to provide unique answers. As explained by Susarla et al. (2023), the functionality of models like ChatGPT or Dall-E can be extended by providing precise prompts, adapting them to new task requires little to no coding.

By creating human-like content, generative AI is applicable across all organizational levels, on strategic, functional, and operational, reshaping how businesses function. At the strategic level, generative AI can assist with data collection, perception, and analysis, leading to improved decision-making based on using more data (Korzynski et al., 2023). Additionally, as Korzynski et al. (2023) highlight, generative AI also plays a vital role in knowledge management and will challenge existing theories. On a functional level, generative AI improves customer service and internal functions such as Human resource management or human resource development (Korzynski et al., 2023), thereby enhancing overall organizational efficiency. Operationally, generative AI facilitates task scheduling and work management, however, this might introduce unwanted control mechanisms (Korzynski et al., 2023). Additionally, it facilitates predictive maintenance and automating routine tasks.

There are several types of generative AI models, varying in the way they are programmed, trained and used. Generative Adversarial Networks (GANs), which consist of two neural networks—a generator and a discriminator—that work in opposition to create new data samples, excel in creating realistic images, video content, and audio data (Bengesi et al., 2024). This makes them particularly useful for visual and multimedia industries. Their unsupervised learning capacity also makes them suitable for tasks where labelled data is scarce, they excel at generating realistic and diverse data (Bandi et al., 2023). Variational Autoencoders (VAEs), composed of encoder and decoder layers, transform input data into a latent space and reconstruct it, producing new data similar to the original input (Bandi et al., 2023; Kar et al., 2023). VAEs are commonly used for tasks such as anomaly detection, data denoising, and semi-supervised learning, the also offer generative and estimation capabilities (Kar et al., 2023).

As described by Bandi et al. (2023), transformer-based models that use, self-attention mechanisms to process sequences of data, capture global dependencies between input and output tokens. These models are the backbone of popular generative AI tools like GPT-4, known for generating human-like text through pre-training on vast datasets. Additionally, diffusion models generate high-quality samples by iteratively refining noisy inputs and have recently shown promise in generating photorealistic images and complex data structures by learning the dynamics of data noise and denoising processes (Bandi et al., 2023). Lastly, hybrid models combine different architectures and training methods, levering the respective strengths of the other models, offering flexibility and tailored generative capabilities (Bandi et al., 2023).

Generative AI promises to shape the future of technology, creativity, and various industries, with applications that include text and image generation, music composition, and human-like conversations (Kar et al., 2023). One of the latest developments is OpenAI's latest chatbot model, which represents a significant improvement in AI's usefulness for science. AS described by Jones (2024), this model uses chain-of-thought logic, allowing it to reason through complex problems and perform self-correction. Generative AI is revolutionizing how organizations operate by automating creative tasks, enhancing efficiency, and providing strategic advantages. For example, digital twins in energy districts can leverage generative AI for scenario analysis, synthetic data generation, and predictive maintenance, thereby improving overall sustainability and operational performance.

Type of GenAI model	*Programming*	*Training*	*Application*	*Challenges/Limitations/Barriers*
Generative Adversarial Networks (GANs)	two neural networks - generator and discriminator, work in opposition to create new data samples	unsupervised learning; the generator creates to fool discriminator which tries to distinguish real from generated data	creating realistic images, video content and audio data; visual and multimedia industries	training can be unstable; issues like mode collapse; require careful balancing between generator and discriminator, computationally intensive
Variational Autoencoders (VAEs)	decoder and encoder layers; transform input data into latent space and reconstruct it	semi-supervised learning	anomaly detection, data denoising; generative and estimation capabilities	generated outputs might be less sharp pd realistic compared to GANy; may struggle with complex data distributions; require tuning to achieve desired output quality
Transformer-based models	self-attention mechanisms to process sequences of data; capture global dependencies between input and output tokens.	pre-trained on vast datasets to learn language models; finetuned for specific tasks	generation of human-like text; language translation; summarization; GPT-4	require large amounts of data and computational resources; may generate biased or inappropriate content if not properly managed; challenges in interpretability
Diffusion Models	generate high-quality samples by iteratively refining noisy inputs, learn dynamics of data noise and denoising processes	learn to reverse process pf adding noise to data; iterative refinement during training	generating photorealistic images; complex data structures	computationally intensive; training can be slow; require careful tuning of noise schedules; less mature compared to other models; potential for high resource consumption
Hybrid Models	combine different architectures and training methods; leverage strengths of various models	tailored training methods combining elements from multiple model types; adaptable to specific needs	offer flexibility and tailored generative capabilities; can be adapted for specialized applications	complexity in design and implementation; may inherit limitations from constituent models; increased computational requirements difficulty in balancing combined methodologies

Table 2: Types of Generative AI models

2.3. Positive Energy Districts

The concept of the circular economy represents a shift from the traditional linear “take-make-waste” economic model to one that is regenerative, restorative, and renewable (Alizadeh et al., 2023). Unlike conventional systems that lead to excessive resource consumption and waste, CE focuses on principles such as recycling, reusing, reducing, and recovering. The goal is to minimize environmental impacts while fostering sustainable production and consumption models that support global sustainability as highlighted by Sánchez Levoso et al. (2020). Given the substantial environmental footprint of cities - which account for up to 80% of global energy consumption, 70% of greenhouse gas emissions, and 75% of natural resource use (IUCN, International Union for Conservation of Nature and Natural Resources, 2023) - transitioning cities toward circular practices is essential. Cities, therefore, play a critical role in global sustainability efforts (McCormick et al., 2013), and effective governance is necessary to ensure this transformation (Nevens et al., 2013). In the broader context of sustainable urban development, circular cities emphasize minimizing energy consumption, reducing waste, and fostering self-sufficient systems. At the heart of this transformation is the development of sustainable buildings and districts that contribute positively to the environment. Zero-Energy Buildings (ZEBs), for instance, aim to achieve energy neutrality at the individual building level, meaning they produce as much energy as they consume annually as explained by Lindholm et al. (2021). These buildings are typically equipped with renewable energy systems like solar panels and are designed to maximize energy efficiency (Lindholm et al., 2021). However, as the name suggests, ZEBs only focus on single structures, which limits their impact on broader urban systems.

Expanding the scope from single buildings to neighbourhoods, as highlighted by Brozovsky et al. (2021) and Derkenbaeva et al. (2022) there a numerous concepts for climate friendly neighbourhoods. Zero Emission Neighbourhoods (ZENs) focus reducing on both direct and indirect greenhouse gas emissions to zero over their lifecycle (Woods & Berker, 2019). This model incorporates energy-efficient designs, smart energy management, and sustainable infrastructure, making ZENs a step forwards in achieving neighbourhood-wide sustainability. Further advancing this concept, Salom et al. (2022) describe Sustainable Plus Energy Neighbourhoods (SPENs) as interconnected groups of buildings that generate more renewable energy than they consume annually. These neighbourhoods prioritize local renewable energy generation and storage, incorporating technologies like smart grids to manage energy flows between buildings (Brozovsky et al., 2021).

As part of the European Union's IRIS research project, Near Zero Energy Retrofit Districts (nZERDs) focus on retrofitting existing buildings to achieve nearly zero energy use. This models is particularly useful in older urban areas where a significant portion of the infrastructure is outdated but still functional (Woods & Berker, 2019). The emphasis is on improving energy efficiency and integrating renewable energy into older buildings. Unlike models aiming for complete energy neutrality or surplus, Low Energy Districts (LEDs) focus on reducing energy consumption across a district without necessarily achieving net zero energy (Brozovsky et al., 2021). They implement advanced energy efficient measures but may still rely on external energy sources to meet part of their energy demand. At the community level, Zero

Energy Communities (ZECs) strive to balance their total annual energy consumption with renewable energy consumption (Carlisle et al., 2009). Similar to ZEBs but on a larger scale, ZECs aim for net-zero energy consumption across a community by integrating renewable energy source and managing energy use collectively as described by (Carlisle et al., 2009). Building on these sustainable neighbourhood models, Positive Energy Districts (PEDs) represent a more advanced approach to energy management, with the goal of achieving an annual net surplus of renewable energy, as defined by SET-Plan ACTION n°3.2 Implementation Plan (2018). PEDS are characterized by their ability to produce more energy than they consume on a district-wide scale, making them a key component in the decarbonization of urban areas. Unlike other models that focus primarily on reducing energy consumption or achieving net-zero emissions, PEDs emphasize energy-positive outcomes – where districts not only meet their own energy needs but also contribute excess energy back to the grid (Hinterberger et al., 2020).

PEDs operate on four key pillars: infrastructure, buildings, mobility, and connectivity. Infrastructure includes renewable energy sources like solar panels, wind turbines, and waste heat recovery systems. PEDs are often equipped with smart grids that optimize energy distribution and storage, ensuring energy resilience and reducing reliance on external energy sources. The building component focuses on using sustainable materials, implementing energy-efficient designs, and retrofitting existing structures to improve insulation, reduce energy consumption, and increase compatibility with renewable energy systems.

Mobility in PEDs encourages the adoption of electric vehicles (EVs), such as e-cars and e-bikes, along with shared mobility services that reduce the need for individual car ownership. By promoting emission-free transport, PEDs contribute to cleaner urban mobility solutions. Connectivity relies on digital technologies, such as the Internet of Things (IoT), to monitor and control energy flows in real time. Additionally, Brozovsky et al. (2021) note that digital twin technology provides virtual models of PEDs' energy systems, offering insights into optimal energy flows, forecasting demand, and enabling better management of resources. PEDs can be classified into several categories. PED Autonomous districts are completely self-sufficient, generating all the energy they need within their geographic boundaries while exporting any excess to external networks as explained by (Lindholm et al., 2021). PED Dynamic districts interact with external energy networks and neighbouring districts, contributing surplus energy while also importing energy when necessary to balance supply and demand (Wyckmans et al., 2019). PED Virtual districts extend beyond their physical boundaries by incorporating renewable energy sources and storage systems located remotely. This model allows cities with limited space or resources to optimize energy generation and storage through external systems (Wyckmans et al., 2019).

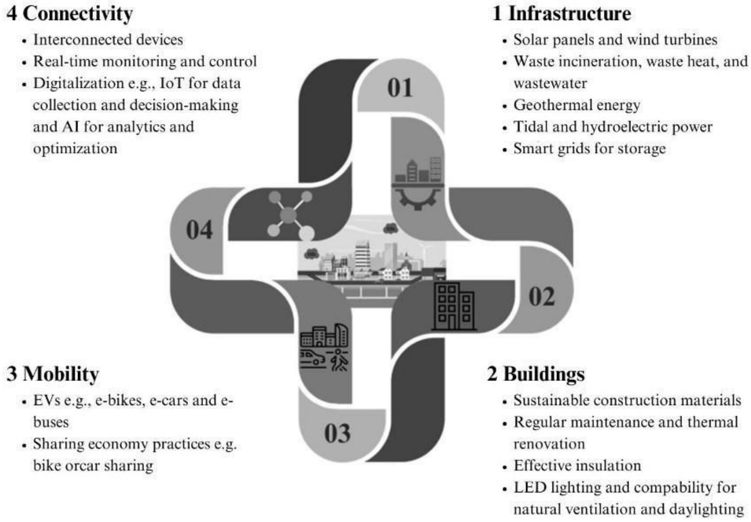


Figure 2: A Positive Energy District and its four main pillars (adapted from Brozovsky et al., 2021)

Candidate Positive Energy Districts (PEDs) are areas that have not yet achieved net-positive energy production but are actively working toward this goal (Lindholm et al., 2021; Wyckmans et al., 2019). These districts often rely on importing certified green energy to meet part of their demand, serving as transitional zones on the path to full PED status according to Lindholm et al. (2021) and Wyckmans et al. (2019). This classification underscores the flexibility of PEDs and highlights the different approaches cities can adopt to scale renewable energy integration (Lindholm et al., 2021; Wyckmans et al., 2019).

Positive Energy Districts aim for net zero CO_2 emissions by representing mixed-use, energy-efficient districts where annual local renewable energy production exceeds consumption (Wyckmans et al., 2019). Achieving this requires active management of energy distribution and balance involving buildings, residents, and integration with regional energy, mobility, and ICT systems as described by Wyckmans et al. (2019). Additionally, PEDs focus on fostering social, economic, and environmental sustainability for current and future generations, necessitating adaptation to specific regional and local contexts due to variations in climate, resources, and policy frameworks as explained by Zhang et al. (2021).

Furthermore, PEDs must account for emerging trends like increased demand for electric vehicle (EV) charging and emission-free transport, emphasizing that integration is essential for maximizing positive impacts on urban energy systems and supporting the transition to sustainable cities (Wyckmans et al., 2019). PEDs are central to the future of sustainable cities. They offer a flexible, scalable model for integrating renewable energy at the district level, supporting the shift toward resilient urban energy systems. By adopting PEDs, cities can significantly reduce their carbon footprint, foster energy independence, and promote sustainable growth tailored to local resources and needs (Lindholm et al., 2021).

Type of PED	*Description*	*Key characteristics*
PED Autonomous	Self-sufficient districts, generating all energy needed within boundaries	Complete energy self-sufficient; local energy generation meets all consumption; surplus energy is exported; minimal reliance on external sources
PED Dynamic	Annual energy generation higher than demand, interact with external energy networks and neighbouring PEDs	Flexible energy exchange; import and export energy as required; dynamic balancing of supply and demand; integration with external grids and neighbours
PED Virtual	Extend beyond physical boundaries by incorporating remote renewable energy sources and storage systems	Use of remote energy resources; integration of external renewable sources and storage; energy infrastructure extends beyond physical limits
Candidate PEDs	Areas actively working toward achieving net-positive energy production but not yet meeting the full criteria, often importing certified green energy during the transition phase	Transitioning to full PED status; import certified green energy; implementing measures to increase local renewable production; active development toward net-positive energy

Table 3: Different Types of PEDs

2.4. Potential and Challenges of PEDs

As mentioned earlier in Chapter 2.3, PEDs play a crucial role in transforming cities towards a more sustainable future. By emphasizing renewable energy generation, they help lower urban carbon footprints and support national and international climate targets. Additionally, PEDs facilitate the development of resilient energy systems that can withstand fluctuations in supply and demand, ensuring stability for local and regional energy networks.

However, realizing the full potential of PEDs requires advanced energy management systems that can effectively balance energy generation and consumption in real time. These systems must integrate a range of renewable energy sources with varying technical characteristics. For example, solar energy generation varies with weather conditions, necessitating complementary storage solutions or additional renewable sources like wind or geothermal energy to maintain grid stability (Derkenbaeva et al., 2022). Digital Twins (DTs) and Generative AI (GenAI) are key technologies that can optimize energy flows and predict energy consumption patterns, further enhancing the efficiency of PEDs. One significant barrier to PED adoption is the challenge of achieving interoperability among various technologies. PEDs must coordinate multiple energy systems—each with distinct technical requirements and operational standards—while also integrating with existing energy infrastructures, which may still be heavily reliant on fossil fuels. This technical complexity is compounded by the need for regulatory frameworks that support the adoption of renewable energy solutions (Brozovsky et al., 2021).

2.5. Digital Twin Technology in PEDs

Digital Twin (DT) technology is essential for managing the complex, data-intensive environments of PEDs. DTs create virtual models that mirror the behaviour of physical energy systems, enabling real-time monitoring, simulation, and optimization of energy generation, consumption, and distribution. This capability is vital for PEDs, which require dynamic management due to the variable nature of renewable energy sources (VanDerHorn & Mahadevan, 2021). By using DTs, PEDs can optimize energy flows, predict demand, and make informed decisions based on real-time data, ensuring efficient energy management. DTs enable bi-directional information flow, allowing for the continuous simulation of operational scenarios. This capability is invaluable for tasks such as predictive maintenance, resource allocation, and risk management. By simulating different energy production and consumption scenarios, DTs can help operators anticipate and respond to changes in energy demand or supply, improving the reliability of PED energy systems. Additionally, (Sharma et al., 2022) note that Digital Twins are designed to replicate not only the physical attributes of an asset but also its behavioural characteristics, enabling scenario analysis, risk assessment, and optimized decision-making. Despite their potential, DTs face several limitations when applied to PEDs.

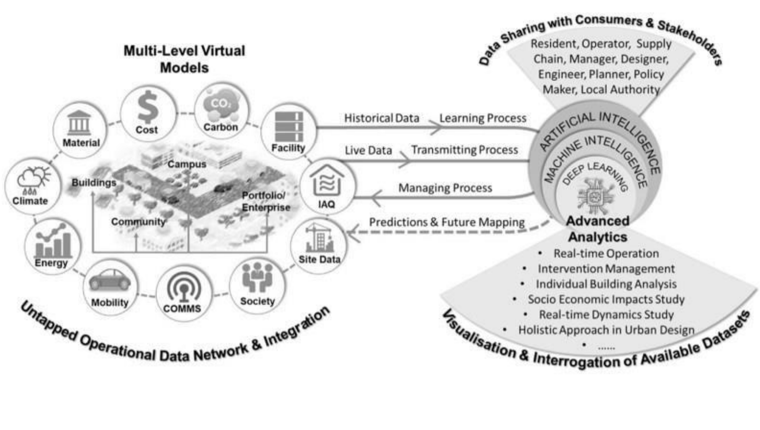


Figure 3: Schematic design of key components in a digital PED twin (from Zhang et al., 2021)

The complexity of urban energy systems - characterized by fluctuating demand and variable renewable energy supply - makes it challenging for DTs to provide accurate predictions and optimizations. Scaling DTs to cover entire districts requires significant computational resources, which may limit their practical application (Qi et al., 2021). The lack of standardization across DT platforms also hampers interoperability between different energy systems, further complicating their integration into PEDs (Semeraro et al., 2021).

2.6. Integrative Potential of Generative AI and Digital Twins in PEDs

Generative AI (GenAI) offers significant opportunities to enhance Digital Twin technology in Positive Energy Districts. By combining GenAI's predictive analytics with DTs' real-time monitoring capabilities, PEDs can rapidly conduct scenario analysis and respond proactively to energy supply and demand fluctuations. This integration improves the overall adaptability and resilience of PED energy systems, enabling more effective management of renewable energy resources (Bilgram & Laarmann, 2023). GenAI can augment the predictive capabilities of DTs by generating hypothetical scenarios, forecasting energy demand, and suggesting optimal adjustments based on projected trends. This capability is particularly valuable in PEDs, where energy supply and demand are subject to frequent fluctuations due to weather patterns and consumption changes (Bilgram & Laarmann, 2023). Several GenAI models can be applied to enhance the functionality of DTs in PEDs. For instance, Generative Adversarial Networks (GANs) can generate high-fidelity simulations of energy demand and supply scenarios, helping operators optimize energy distribution and storage strategies as described by (Bandi et al., 2023). Variational Autoencoders (VAEs) and Diffusion Models refine predictive capabilities by producing more accurate forecasts under uncertain conditions, effectively managing energy supply variability (Bandi et al., 2023).). Additionally, Transformer-Based Models can optimize communication flows within smart grids, improving the efficiency of energy distribution across PEDs (Kar et al., 2023).

The combined use of GenAI and DTs maximizes the efficiency of PED energy systems by enabling dynamic, data-driven adjustments to energy distribution strategies. This synergy supports PEDs in achieving sustainability goals by optimizing the use of renewable energy, reducing waste, and minimizing reliance on external energy sources (Peres et al., 2023). Furthermore, PEDs must account for emerging trends like increased demand for electric vehicle (EV) charging and emission-free transport. Wyckmans et al. (2019) emphasize that integration is essential for maximizing positive impact on urban energy systems and supporting the transition to sustainable cities. By leveraging GenAI and DTs, PEDs can better manage these trends, ensuring efficient energy distribution and meeting the evolving needs of urban mobility.

Despite the considerable benefits, the application of AI-augmented DTs in PEDs presents several challenges. The computational demands of real-time data processing and predictive modelling can be resource-intensive, limiting scalability in large districts. Additionally, concerns about data privacy and security arise from the use of real-time data from smart devices and IoT networks in PEDs. Korzynski et al. (2023) note that data privacy and ethical concerns are particularly relevant in the context of real-time data collection, which may expose sensitive information. Addressing these concerns will require robust regulatory frameworks and safeguards to ensure the ethical use of AI technologies (Kshetri et al., 2024). Risks associated with algorithmic bias and the robustness of predictive models under varying conditions also need to be addressed to ensure reliable and equitable energy management (Sareen et al., 2022). To overcome these challenges, careful planning and cross-disciplinary collaboration are essential. Developing scalable, secure, and efficient systems for PEDs requires not only technological innovation but also regulatory frameworks that support the ethical deployment of AI-driven technologies. Addressing these challenges will be crucial for realizing the full potential of GenAI and DT integration in PEDs.

2.7. Summary of Literature Review

The literature demonstrates that Digital Twin and Generative AI technologies can significantly advance the goals of Positive Energy Districts. DTs provide a robust infrastructure for real-time monitoring and analysis, while GenAI offers the predictive capabilities necessary to optimize energy flows and enhance system efficiency. The integration of DTs and GenAI enables PEDs to achieve net-positive energy production by dynamically adjusting energy distribution based on real-time conditions. This combined approach contributes to broader urban sustainability goals by reducing energy waste and optimizing renewable energy use.

However, several challenges must be addressed to fully implement these technologies in PEDs. Scalability, interoperability between different systems, and data privacy are key concerns that require further attention. Additionally, robust regulatory frameworks are needed to ensure the safe and ethical use of AI technologies in urban environments.

The literature reveals gaps in practical strategies for integrating DT and GenAI technologies into PEDs. Specifically, there is a lack of studies addressing regulatory and ethical considerations associated with the integration. Also, the need for cross-disciplinary collaboration to overcome technical and operational barriers is not sufficiently explored. Addressing these gaps, will enable cities to fully leverage these technologies to achieve sustainable energy systems and reduce their carbon footprint.

3. Methodology

This chapter outlines the methodological approach used in this study, including the research design, data collection methods, sampling strategy, and analytical approach. A qualitative methodology was chosen to explore the role of Generative AI in enhancing Digital Twin applications for Positive Energy District. This approach enables a detailed and nuanced understanding for participants' perspectives, which is essential in examining an emerging and complex intersection of technologies.

3.1. Research Design

Qualitative research was conducted, which is suited for exploring complex and context-dependent phenomena. Silverman (2017) highlights that qualitative research is most effective for addressing "what" and "how" questions, as it focuses on understanding processes and experiences rather than quantifying variables. By emphasizing the meaning and interpretation of participant experiences, qualitative research hallows for a deeper exploration of the research questions (Silverman, 2017). A semi-structured interview guide (Appendix 1) was developed based on the preliminary theoretical analysis to conduct the interviews properly. This type of interview is best suited to the research objectives and inductive research design of this study, as it is relatively flexible in its design, thereby facilitating the emergence of new knowledge contingent on the course of the conversation (Saunders et al., 2018). Following the Gioia approach (Gioia et al., 2013), the interview guide was not standardized but was continuously developed and adapted based on the flow of conversations with interviewees and the emerging findings. To incorporate additional information, further questions were posed in response to initial answers. In total, the interview guide consisted of 6 areas of interest, with 11 main questions and additional sub-questions to delve deeper into specific topics as needed.

3.2. Data Collection

The data for this study was collected through semi-structured interviews and secondary data from the EXPEDITE project. The seme-structured interviews were chosen for their flexibility and depth, while the secondary data provided contextual information that enriched the analysis. The interview guide was developed following the five-phase framework proposed by Kallio et al. (2016). The process began by identifying the prerequisites for using semi-structured interviews, based on the exploratory nature of the research. Prior knowledge was retrieved by reviewing existing literature on Digital Twin technology, Generative AI, and PEDs to identify key themes and gaps, as well as by examining the relevant outputs and documentation from the

EXPEDITE project. An interview guide was then formulated, focusing on questions that aligned with the dissertations research questions. The interviews were conducted using Microsoft Teams to accommodate participants from diverse geographical locations. Each interview lasted approximately 30 minutes, providing sufficient time for interviewees to elaborate on their experiences while maintaining focus on the kay themes. With participants' consent, the interviews were recorded and subsequently transcribed using Microsoft Teams. For the interviews held in any other language than English, DeepL was used to translate them. By triangulating insights from both primary and secondary sources, the study achieved a more robust and well-rounded perspective on the evolving field of Digital Twins and their potential impact on PEDs.

3.3. Sampling Method

A purposeful sampling strategy was used to select participants who could provide rich and relevant insights into the research questions. Suri (2011) defines purposive sampling as a method for identifying information-rich cases that can provide an in-depth understanding of the phenomenon under study. This approach is well suited to qualitative studies where the aim is to gain in-depth knowledge rather than statistical generalisability. Interview candidates were selected based on three criteria. First, they were required to have expertise in the areas of Generative AI, Digital Twin technology, or PEDs. Additionally, experts in the field of sustainable energy were also considered. Second, practical experience with implementing or researching these technologies was a key consideration to ensure that participants could offer insights grounded in real-world applications. Finally, efforts were made to include participants from diverse professional and geographical backgrounds to capture a range of perspectives and experiences. The description of the sample used in this research for primary data is presented in the table below (Table 4). Furthermore, ease of contact and potential willingness to participate were additional criteria for selection.

Interview Partner	Position	Background	Experience
1	Technical Manager	Business/Technology	30+
2	Head of Integrated Infrastructure Planning Unit	Business/Technology	15+
3	Digital Delivery Lead	Digital transformation/Digital project management	5+
4	IT Services and IT Consulting	Engineering/AI solutions in energy, finance, security and health	N/A

Table 4: Sample Profile

3.4. Data Analysis

The Gioia approach guided the data analysis process, providing a structured approach to coding and thematic exploration. As noted by Gioia et al. (2013), the approach emphasizes first-order coding, which captures interviewees' language and perspectives, and second-order coding, which enables the researcher to develop theoretical interpretations. Those themes are synthesized into aggregated dimensions that address the study's overarching research questions (Gioia et al., 2013). This ensures a flexible pathway for deriving theoretical insights. To structure and visualize the emerging insights, a data structure was constructed in with the recommendations (Gioia et al., 2013). This structure represents the progression from First order-concepts to Second-order themes and aggregate dimensions, providing a clear and systematic overview of the findings and the analytical process. To ensure transparency and traceability, each statement used was assigned a code (Appendix 2). To enhance rigor and credibility, the study applied triangulation by incorporating diverse perspectives from participants, ensuring that findings were not biased by a single viewpoint.

4. Findings

This section presents the results of the study, which are organised according to the research areas explored in the literature and investigated through both primary and secondary data collection. The results of the interviews are analysed using the Gioia method of analysing qualitative data, whereby the results are combined with secondary data and categorised. A complete overview of the Gioia structure can be found in Appendix 3. To ensure a comprehensive overview, the findings were summarised in five different dimensions: *Positive Energy Districts, Digital, Twins, Generative AI, Organizational Transformation, Barriers and Challenges*.

4.1. Positive Energy Districts

The adoption of Positive Energy Districts (PEDs) is driven by a number of factors, with the urgent need to address high energy consumption in buildings being a primary motivator. As interviewee 3 commented, "The whole thing started from the consumption of high energy in buildings" (PED1). Another key driver is the need to reduce dependence on fossil fuels, emphasising the importance of sustainable alternatives with reduced environmental impact. This is reflected in interviewee 3's comment: "Don't consume as much oil and gas [...] and make things greener" (PED2). PEDs aim to optimise energy use by facilitating the sharing of surplus energy, as highlighted by interviewee 3: "Share the excess energy [...] distribute that to the rest of the grid" (PED3). In addition, PEDs make use of local renewable resources, which interviewee 4 identified as "crucial for a sustainable future and utilising local renewable resources" (PED14).

The benefits of Positive Energy Districts go beyond environmental benefits, providing economic opportunities and promoting alternative forms of energy. Interviewee 3 highlighted these benefits, stating that they include "a better environment, alternative forms of economy, and economic benefits" (PED4). PEDs also drive innovation by incorporating advanced materials and technologies, particularly in the development of smart solutions, as interviewee 3 noted: "Innovating in materials [...] creating smart materials for sustainability" (PED5). Furthermore, the alignment of energy consumption and production within the PEDs enhances grid efficiency and energy optimisation, as interviewee 1 explained: "To bring energy and consumption together [...] fundamental for optimizing grid efficiency" (PED9). Community engagement is another essential factor in ensuring long-term energy transformation, as highlighted by Interviewee 2: “Community engagement is crucial for long-term energy goals” (PED12).

Despite these benefits, the implementation of Positive Energy Districts faces significant challenges. A recurring theme is the difficulty of retrofitting existing neighbourhoods to meet PED standards, as interviewee 3 explained: “The biggest challenge comes [...] how you convert [existing districts] to positive energy districts” (PED6). Socio-economic factors influencing adoption and comfort levels also require attention, as interviewee 3 also pointed out: “The existing literature doesn’t address socio-economic factors” (PED7). In addition, local conditions such as climate and environment need to be considered during implementation, as noted by interviewee 3: “You need to consider local factors [...] climate, environment” (PED8). Regulatory challenges further complicate the development of PEDs, as interviewees 1 and 2 noted: “Legislative complexity in Germany makes PED development difficult” (PED10) and “Municipal laws vary widely, making PED implementation complex” (PED11). Finally, a clear distinction between retrofitting existing neighbourhoods and creating new PEDs is crucial, as each presents unique challenges. Interviewee 4 observed: “Distinguishing between retrofitting existing districts and creating new PEDs is important” (PED13).

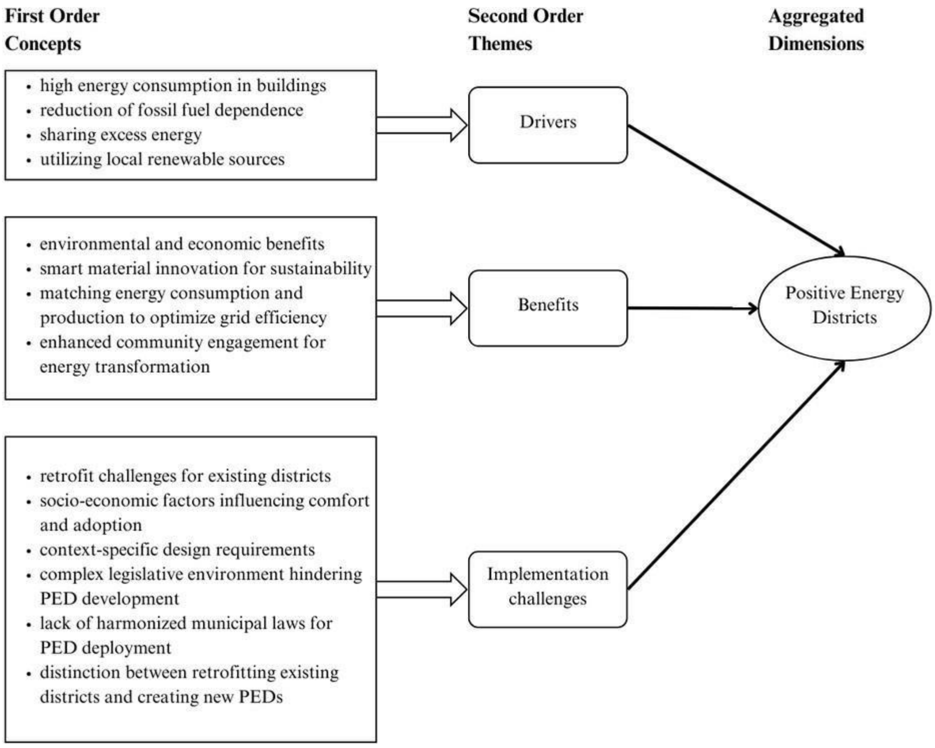


Figure 4: PEDs data structure

4.2. Digital Twins

The implementation of Digital Twins (DTs) for Positive Energy Districts (PEDs) presents several data-related challenges. A key issue, as noted by interviewee 3, is the lack of standardisation and interoperability between data systems, which requires careful consideration of data integration: "You need to consider a lot of other factors […] data interoperability" (DT1). Concerns about data security and ethical considerations regarding its use were highlighted by interviewee 3, who stated: "Data safety, data security, ethical approaches..." (DT2). Gaps in the consideration of socio-economic factors in current research were also identified by respondent 3: "The existing literature [...] doesn't account for socio-economic factors" (DT3). Coordination with end users, such as urban planners, is crucial to align data collection and analysis with practical needs, as interviewee 2 pointed out: "You need to discuss with city planners [...] what kind of information they need" (DT4). In addition, challenges related to the collection of real-time and historical data were noted, with interviewee 1 commenting: "We always have a database [...] it is never 100% accurate" (DT9). The difficulty of maintaining detailed maps of energy infrastructure was also highlighted by Interviewee 2, who stated: "Many energy grids lack detailed infrastructure mapping" (DT11).

Digital Twins have important applications for Positive Energy Districts, particularly in supporting energy simulation and optimisation. Interviewee 3 highlighted their role in real-time monitoring and visualisation tools, stating: “Digital technologies can support [...] the creation of a Positive Energy District” (DT5). This is further reinforced by the Expedite project, who described their use in managing energy flows: “EXPEDITE enables us to [...] real-time monitoring, visualization, and management of district-level energy flows” (DT13). This is illustrated by Interviewee 2's observation: “Digital twins can help virtually test pathways without investing in them physically” (DT14).

The data also highlight several practices for effective design and implementation of Digital Twins. Structured data environments are fundamental to enabling information sharing and management, as highlighted by respondent 3: “BIM provides a framework for sharing [...] handling information” (DT7). Integration with Building Information Modelling (BIM) processes is identified as a beneficial approach to improving design and operational efficiency. Interviewee 3 noted: “BIM assists in sharing this information for enhanced planning and operations” (DT8). In addition, the use of Digital Twins to manage automated network interventions and perform predictive scenario analysis supports improved decision making. As interviewee 1 and 2 remarked: “We need Digital Twins fed with real-time data to automate grid interventions” (DT10) and “Integrate predictive scenario modules into decision making” (DT12).

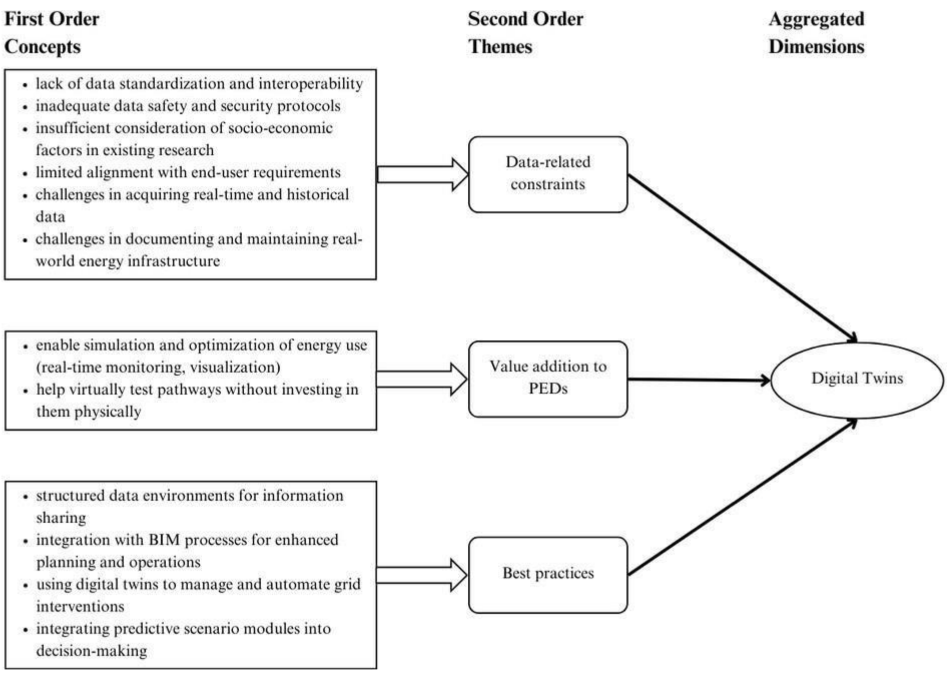


Figure 5: Digital Twins data structure

4.3. Generative AI

Generative AI (GenAI) demonstrates strong capabilities in optimising the use of data and filling gaps in Positive Energy District (PED) monitoring systems. As interviewee 3 noted, Generative AI can fill in missing data points in real-time systems by using trained models: "When...you've got 200,000 sensors...AI can fill in the gaps based on historical data" (GenAI1). It also enables predictive modelling to address sustainability and disaster management challenges, as highlighted by interviewee 3: "You can perform predictive modelling [...] for disasters and sustainability" (GenAI3). In addition, GenAI supports efficient energy planning by predicting the energy generation and consumption patterns of prosumers, as noted by interviewee 4: "[...] have been applied to predict the energy generation and consumption patterns of prosumers" (GenAI10).

Generative AI also offers contributions to urban planning by automating repetitive tasks. For example, it can generate layout solutions for urban planning processes, as interviewee 3 explained: "Generative AI can assist in urban planning [...] by generating solutions for layout" (GenAI4). Additionally, it assists in the development of urban planning strategies using Geographic Information System (GIS) data, providing innovative ways to design and optimise infrastructure. Interviewee 3 noted: "If you load GIS information [...] it can give you different options" (GenAI2). Generative AI can also tailor solutions to specific user environments, improving overall efficiency, as interviewee 4 pointed out: “Generative AI could tailor solutions to specific user environments and improve efficiency” (GenAI9).

In the area of energy management, GenAI automates processes to improve efficiency. Interviewee 1 noted its ability to identify optimal charging times for electric vehicles, ensuring alignment with energy availability: “It would make sense to charge electric cars when energy is abundant” (GenAI5). Generative AI is also used to balance solar energy production and grid flows through automation, as highlighted by the same Interviewee: “Matching solar production and grid consumption through automation” (GenAI6). It also optimises the integration of renewables by identifying the most effective mix of energy configurations, as described by Interviewee 2: “AI can help identify the best mix of renewable energy sources” (GenAI7). Finally, GenAI supports scenario testing for future energy configurations, allowing the simulation of multiple setups. As interviewee 2 also noted: “Simulations allow testing multiple future energy configurations” (GenAI8).

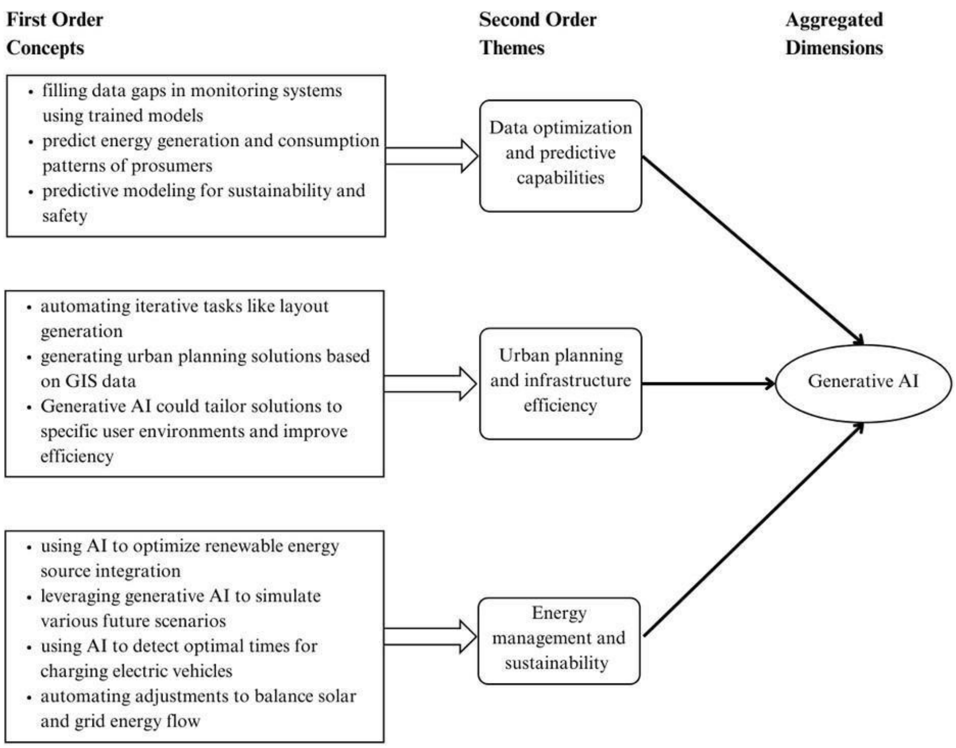


Figure 6: Generative AI data structure

4.4. Organizational Transformation

Implementing Generative AI (GenAI) for Digital Twins in Positive Energy Districts (PEDs) requires significant capacity building within organisations. Cross-disciplinary expertise is essential, as developing and managing GenAI models for Digital Twins requires skills in AI, data science, and urban energy systems. As interviewee 3 explained, “You need proper expertise [...] to train those AI models” (Org1). In addition, upskilling employees in IT and cybersecurity is critical to ensure the safe operation of generative AI in real-time energy monitoring systems. This was emphasised by interviewee 1, who stated, “We need many more IT specialists to handle data and cybersecurity” (Org5). For technical teams working on digital twins, training in advanced data analytics and AI integration is also needed to optimise functionality, as noted by interviewee 2: “Technical teams need training in modern tools for effective use” (Org6). Resistance to adoption is another key challenge in implementing Generative AI for Digital Twins. Misconceptions about the capabilities and uses of AI can create fear and hinder adoption, as interviewee 3 points out: “People hear AI and think of Skynet or Terminator” (Org3). Educational initiatives are crucial to address this issue. Interviewee 3 pointed out that educating stakeholders about how AI works and its benefits in optimising energy systems and urban planning can help reduce resistance: "You need to educate people [...] about how AI works" (Org4). The integration of GenAI for Digital Twins into PEDs is highly dependent on stakeholder collaboration. Collaboration between municipalities, local councils, energy providers, and citizens is crucial to align technical and societal goals, as noted by interviewee 3. Joint efforts between technologists and policymakers are also essential to ensure compliance with regulatory frameworks and alignment with policy objectives, as emphasised by interviewee 2: “Joint efforts between technologists and policymakers are important to ensure compliance” (Org7). Furthermore, innovative strategies such as gamification and co-creation can improve public engagement and foster collaboration, as highlighted by the Expedite Project: “The project incorporates gamification and co-creation to improve public engagement” (Org8).

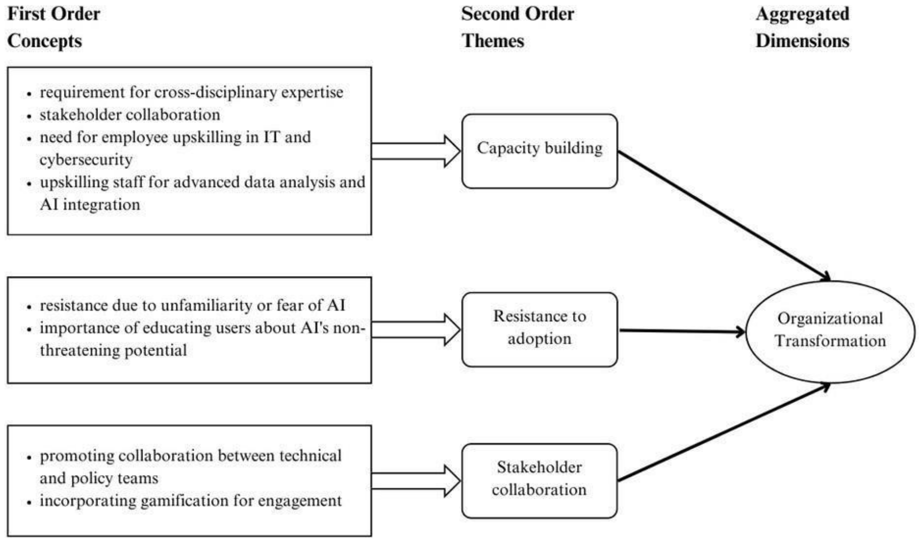


Figure 7: Organisational Transformation data structure

4.5. Barriers and Challenges

The implementation of Generative AI for Digital Twins in PEDs involves a range of technical and regulatory challenges. These barriers, as identified by multiple interviewees, highlight both infrastructural and ethical considerations. Interviewee 3 highlighted the difficulty of sourcing the clean and interoperable data needed to train AI systems, stating "You need the correct information and clean data to train AI models" (Barrier1). Another issue, noted by the same interviewee, is the reluctance of organisations to share proprietary data, which limits collaboration and data integration (Barrier 2). The high cost of retrofitting old infrastructure, such as equipping buildings with sensors and other technologies, was highlighted by interviewee 3. In addition, the issue of grid capacity was raised by interviewee 1, who pointed out that "grids lack sufficient capacity for peak loads" (Barrier 6). Finally, interviewee 2 highlighted the operational risks associated with the use of AI in different sectors, noting that "risk management is essential for AI applications in practice" (Barrier8).

Compliance with data protection regulations, such as GDPR, was highlighted by interviewee 3, who stated, "You need to consider GDPR regulations and ethical barriers" (Barrier3). Similarly, the limited availability of historical and contextual data for training AI models was noted by interviewee 3, who remarked, "You need access to historical data […] and contextual data for effective training" (Barrier4). Legal ambiguity around data governance in AI projects was also raised as a challenge by interviewee 2, who observed, "Legal ambiguity around data governance is a challenge for AI" (Barrier9). Finally, interviewee 4 highlighted the importance of adhering to regulatory frameworks, noting, "Regulation and GDPR compliance are essential for data privacy and ethical AI use" (Barrier10).

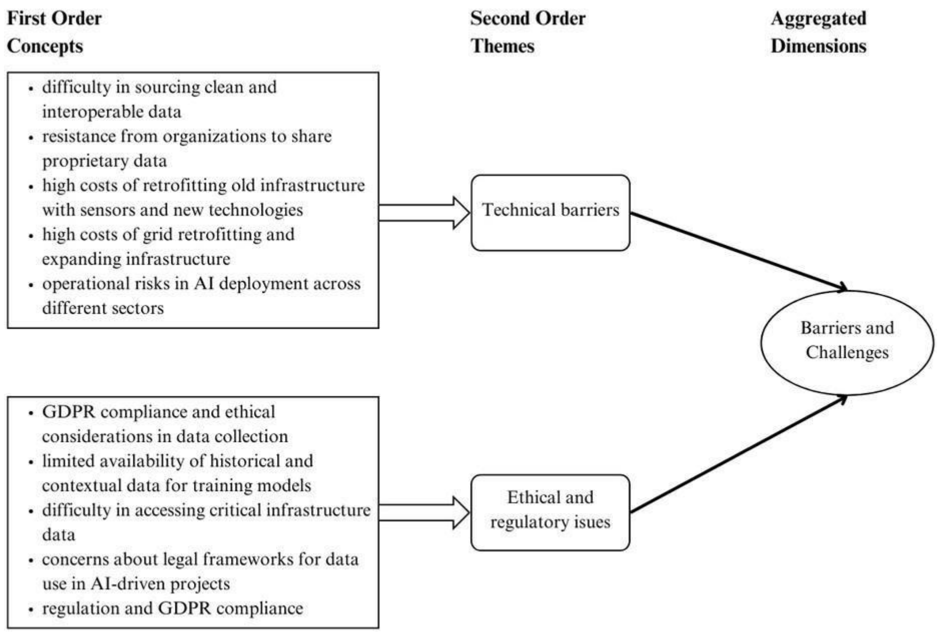


Figure 8: Barriers and Challenges data structure

5. Discussion

5.1. Discussion of Findings

This chapter analyses how Generative AI can enhance Digital Twin applications in Positive Energy Districts, addressing the primary research question: *How can Generative AI enhance Digital Twin applications for Positive Energy Districts (PEDs)?* and its sub-questions. Through a synthesis of findings from interviews, the EXPEDITE project and the literature review, the discussion demonstrates how the two technologies complement each other and explores the challenges in their integration.

Digital Twins have emerged as a tool for managing the complexities of energy flows in PEDs. With their ability to provide real-time data-driven insights, simulate scenarios. And optimize energy use, DTs significant opportunities to advance sustainability objectives. Nevertheless, the current implementation of these technologies is constrained by a number of limitations that limit their capacity to achieve the ambitious goals of the PEDs in generating more energy than they consume. These limitations, including those associated with data interoperability, scalability, predictive accuracy, and stakeholder engagement, have been highlighted by both primary data and the existing body of research. A significant obstacle to the comprehensive realization of DT capabilities is the issue of data interoperability and standardisation. The operation of Positive Energy Districts is contingent upon the deployment of a diverse array of energy systems, including photovoltaic panels, wind turbines, energy storage units, and electric vehicle charging networks. These systems generate data in varying formats and adhere to a range of technical standards. This diversity presents a considerable challenge in integrating data across platforms. The third interviewee emphasised the critical significance of "data harmonisation," indicating that an absence of standardised protocols hinders the optimisation of energy flow and disrupts the decision-making process. This finding is consistent with those of Semeraro et al. (2021), who argue that the absence of standardised interfaces undermines the scalability and operational efficiency of DTs in complex systems like PEDs. Similarly, Deng et al. (2021) argue that seamless data exchange is a fundamental requirement for the effective functioning of smart urban energy systems, and that interoperability is a key enabler of PED efficiency. The issue of scalability represents a further significant challenge. PEDs are designed to operate on a district-wide scale, encompassing numerous interconnected components that must be monitored and managed in real time. This generates a considerable amount of data, which far exceeds the computational capacity of many current DT implementations. Interviewee 1 highlighted that achieving "real-time accuracy" on a large-scale PED is a significant challenge given the computational demands of high-fidelity modelling. These limitations are reflected in the work of Qi et al. (2021), who highlight that digital twins require substantial computational resources to process large volumes of sensor data while maintaining synchronisation with physical systems. Such resource demands not only constrain the scalability of DTs but also introduce financial obstacles that may impede broader adoption. Although digital twins are designed to provide predictive insights, their capacity to anticipate and adapt to rapidly evolving circumstances remains constrained. The variable nature of renewable energy sources, such as solar and wind power, presents a significant challenge to the precise forecasting of energy production. Interviewee 3 observed that DTs frequently fail to provide "reliable predictions under uncertain conditions," which limits their applicability in dynamic environments. Deng et al. (2021) reinforce this observation, arguing that conventional DT architectures lack the advanced adaptive learning mechanisms required to handle the complexity of supply and demand fluctuations in real time. In addition to the technical challenges already discussed, concerns surrounding data security and ethical considerations present significant barriers to the broader implementation of DTs in PEDs. Urban energy systems are dependent on the collection of real-time data from IoT devices, which creates vulnerabilities in relation to data privacy and misuse. Interviewee 3 underscored the necessity of addressing "data safety and ethical concerns" to establish trust among stakeholders, particularly in urban contexts where public approval is vital. (Sharma et al., 2022) reiterate these concerns, emphasising that unresolved issues of data governance and privacy represent a significant barrier to the widespread adoption of DT technologies in smart cities. Furthermore, there is a discrepancy between the technical solutions proposed by DTs and the practical requirements of urban planners and policymakers, as highlighted by Interviewee 2.

Generative AI emerges as a powerful solution to these limitations, with its predictive capabilities, adaptive algorithms, and ability to process diverse data formats. By integrating GenAI into Digital Twin systems, PEDs can achieve a higher level of efficiency, scalability, and adaptability. For example, Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) can generate highly accurate forecasts of energy demand and supply, enabling PED operators to proactively anticipate and mitigate fluctuations. Interviewee 3 emphasised that GenAI's ability to provide "accurate predictions under uncertainty" positions it as a critical enabler of real-time decision making. Bandi et al. (2023) similarly highlight the potential of GANs to generate realistic energy demand scenarios, while VAEs refine these predictions by learning from historical data and dynamically adapting to new information. This capability is particularly relevant for PEDs, where unpredictable variables such as weather conditions and consumption patterns require responsive and flexible energy management strategies.

In addressing data interoperability challenges, Generative AI provides algorithms that can harmonise data from disparate sources, effectively bridging the gaps between incompatible systems. Interviewee 3 noted that GenAI's ability to "synthesise and standardise data inputs" significantly improves the coherence of energy operations within PEDs. This is consistent with the findings of Deng et al. (2021) who argue that seamless data integration is a prerequisite for the successful implementation of smart city technologies. By enabling consistent data exchange, GenAI reduces the complexity of integrating renewable energy systems, storage units and mobility solutions, ensuring that PEDs operate as cohesive and efficient entities. Generative AI also facilitates the automation of resource allocation, further enhancing the operational capabilities of PEDs. By simulating different energy configurations and analysing their outcomes, GenAI models can identify the most efficient strategies for energy generation, storage and distribution. Respondent 2 highlighted that 'automated scenario testing' enables operators to make informed decisions quickly, optimising resource use while minimising waste. Sharma et al. (2022) similarly emphasise that AI-enhanced DTs can dynamically adjust energy flows to match real-time demand, advancing the sustainability goals of PEDs by reducing reliance on external energy sources and minimising carbon footprints.

Another key contribution of GenAI is its ability to address data gaps, which often undermine the accuracy of digital twin simulations. By leveraging historical and contextual data, GenAI can fill in missing information in real-time systems, ensuring that decision-making processes remain robust even when data is incomplete. Interviewee 3 noted that AI models excel at “compensating for missing data points” , a capability that is particularly valuable in urban environments where infrastructure inconsistencies are common. Sharma et al. (2022) further emphasise that AI-driven systems can mitigate the impact of data gaps, enabling PEDs to maintain operational continuity under challenging conditions. Despite these benefits, the integration of Generative AI in Digital Twins is not without challenges. Technical barriers, such as the high computational demands of GenAI models, pose significant obstacles, particularly for real-time applications in large PEDs. Interviewee 1 highlighted that existing infrastructure often lacks the capacity to support the “resource-intensive operations” required by GenAI enhanced DTs. Additionally, access to high-quality training data is often limited by proprietary restrictions, as noted by interviewee 3. (Sharma et al., 2022) argue that without adequate data availability, the performance of AI models can be severely compromised, limiting their utility in practice. Regulatory and ethical challenges further complicate the use of GenAi in PEDs. The use of real time data raises concerns about privacy, governance and compliance with frameworks such as GDPR. Interviewee 3 emphasised that "privacy and ethical considerations" need to be addressed to ensure responsible implementation.

Finally, resistance within the organisation is a significant barrier to the adoption of GenAI. Misconceptions about the capabilities and risks of GenAi can lead to hesitation among stakeholders, as noted by interviewee 3. To integrate GenAI effectively, educational initiatives and capacity building efforts are important, as well as building the technical expertise of staff. These efforts need to be complemented by cross-sector collaboration to align technical innovation with regulatory frameworks and public expectations.

In conclusion, GenAI offers transformative opportunities to overcome limitations of Digital Twin technology and enhance their application in Positive Energy Districts. By providing predictive modelling, data interoperability, and resource optimization, GenAI enables PEDs to achieve their sustainability objectives while addressing the complexities of dynamic energy systems. However, realizing this potential requires addressing technical, regulatory, and organizational barriers through strategic planning and collaborative efforts. By leveraging the synergies between the technologies, PEDs can invent new models of sustainable urban energy management, contributing to the global transition toward resilient and energy-efficient cities.

5.2. Theoretical Contributions

This research advances the theoretical understanding of how the integration of Generative Artificial Intelligence (GenAI) with Digital Twin (DT) technologies can improve energy management within Positive Energy Districts (PEDs). It extends the existing literature on urban energy management systems by addressing critical gaps in the integration of AI technologies with PED frameworks. Previous research has recognised the value of DTs in real-time monitoring and predictive maintenance. This study theorises how GenAI extends these capabilities, moving DTs beyond traditional simulation and control functions into adaptive, data-driven predictive modelling. Existing PED and DT theories have underplayed organizational and governance dimensions, focusing mainly on technology adoption. By incorporating the role of stakeholder collaboration, regulatory compliance, and knowledge building, the study introduces a theoretical view that aligns the technological integration of GenAI and DTs with socio-technical transformation. Overall, this research shifts the theoretical conversation from the feasibility of DTs and PEDs in isolation to a more integrated perspective. It highlights GenAI as a catalyst for overcoming the scalability, interoperability and predictive limitations that have limited the theoretical understanding and real-world implementation of sustainable urban energy systems.

5.3. Managerial Implications

From a managerial and practical perspective, the findings of this research provide insights for energy managers, urban planners and organisational leaders. Integrating GenAI algorithms into DT frameworks enables managers to make more informed, data-driven decisions. The integration can help managers to optimise grid operations, reduce costs and improve the overall sustainability of the PED. However, managers should establish clear protocols and standards for data exchange to ensure that the GenAI-driven insights are both ethically derived and reliable. Alongside these technical considerations, capacity building emerges as a management priority. Equipping teams with new skills in (Generative) AI, data science and cybersecurity promotes organisational resilience and reduces reliance on external experts. Beyond the technical and operational spheres, this research highlights the importance of collaboration with stakeholders. Effective communication with policymakers, regulators and community members can build trust and acceptance for AI-enabled energy solutions. By embracing these managerial implications, integrating advanced AI capabilities, improving data governance, investing in human capital, and engaging stakeholders, organisations can translate theoretical insights into practical strategies. In doing so, managers can position their PED-related initiatives not just as technological upgrades, but as forward-looking, socially responsible efforts that shape more efficient, sustainable and human-centred urban energy landscapes. A framework for the implementation of GenAI into Digital Twin enabled PEDs is provided in the appendix (Appendix 3).

5.4. Research Limitations

While the study provides valuable insights, several limitations must be acknowledged. First, the small number of respondents limits the generalisability of the findings. Although over 80 experts in relevant fields were contacted, only four participants were willing to be interviewed. This may be due to the short timeframe of the study and its timing at the end of the year. Although the interviews provided qualitative data, a larger sample might have strengthened the findings and provided a wider range of perspectives. Technical limitations are also a constraint. The computational demands of integrating GenAI with DT systems, particularly in real-time applications, were highlighted as significant barriers. However, the research did not quantitatively assess these demands, leaving the scalability challenge to be explored in future studies. Finally, regulatory and ethical challenges surrounding the deployment of AI, such as data privacy and governance, were identified but not explored in depth. Further research into specific legal and cultural contexts is needed to comprehensively address these barriers.

5.5. Future Research Directions

Recommendations for future research directions aim to address the identified research gaps and limitations. There is a need for further theoretical development, particularly regarding the regulatory and ethical frameworks for the integration of GenAI and DTs in PEDs. This includes exploring the socioeconomic and behavioural dimensions of energy management, refining, predictive models to improve accuracy under uncertain conditions, and ensuring privacy, and security rights. In addition, the development of scalable computational architectures capable of handling complex, real-time data streams - while maintaining sustainability objectives - deserves further attention. Furthermore, it would be valuable to gather more qualitative data to obtain more robust empirical evidence and gather broader perspectives.

6. Conclusion

This thesis has shown that the integration of Generative AI into Digital Twins can improve the management of Positive Energy Districts. Addressing the main research question "How can Generative AI enhance Digital Twin applications for Positive Energy Districts?", the results indicate that GenAI-driven DTs can go beyond traditional simulation and monitoring functions to provide dynamic, predictive modelling capabilities. By processing large, real-time data sets and adapting to sudden changes in supply and demand, GenAI enables DTs to optimise energy flows, improve scenario planning and anticipate maintenance needs. This can lead to more efficient resource allocation, reduced operating costs and greater resilience to the uncertainties in energy management, supporting the overarching goal of achieving net positive energy balances within PEDs.

Regarding the first sub-question What are the current limitations of digital twin technology in managing energy within PEDs?", the research identifies several constraints. Existing DTs often lack the computational scalability to handle the complexity at the district level and rely on static assumptions that make them less effective at handling the variability of renewable energy sources. Additionally, they often overlook the social, economic and behavioural dimensions that influence energy demand. These limitations create gaps in accuracy, adaptability and stakeholder engagement. The second sub-question "What are the potential barriers to implementing Generative AI in PEDs from a management and business perspective?", is addressed by highlighting that the adoption of GenAI raises concerns beyond the technical sphere. Although GenAI can enhance DT capabilities, its successful implementation depends on organizational readiness, data governance frameworks, ethical standards and regulatory compliance. Data privacy laws, intellectual property rights, and limited access to proprietary datasets can hinder the adoption of GenAI, while resistance to change, misconceptions about AI, and a shortage of skilled employees can slow adoption. Overcoming these barriers will require concerted efforts to invest in training and upskilling, foster transparent communication between stakeholders, and ensure that policy and regulatory guidelines keep pace with technological innovation.

In summary, this thesis demonstrates that the integration of GenAI and DTs can transform he management of PEDs, but success recognising and addressing both technological and non-technological challenges. By improving predictive analytics and operational responsiveness, GenAI enables PEDs to meet ambitious sustainability goals. However, organisations must simultaneously navigate the complexities of data sharing, align AI solutions with existing regulations, and engage with local communities to ensure buy-in. While the study's limited sample size and evolving regulatory landscape provide avenues for further research, these findings lay the groundwork for more holistic, adaptive and ethically guided approaches to energy management within PEDs.

List of References

Alizadeh, M., Kashef, A., Wang, Y., Wang, J., Okudan Kremer, G. E., & Ma, J. (2023). Circular economy conceptualization using text mining analysis. *Sustainable Production and Consumption*, *35*, 643–654. https://doi.org/10.1016/j.spc.2022.12.016

Bandi, A., Adapa, P. V. S. R., & Kuchi, Y. E. V. P. K. (2023). The Power of Generative AI: A Review of Requirements, Models, Input–Output Formats, Evaluation Metrics, and Challenges. *Future Internet*, *15*(8), Article 8. https://doi.org/10.3390/fi15080260

Bengesi, S., El-Sayed, H., Sarker, M. K., Houkpati, Y., Irungu, J., & Oladunni, T. (2024). Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers. *IEEE Access*, *12*, 69812–69837. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3397775

Bilgram, V., & Laarmann, F. (2023). Accelerating Innovation With Generative AI: AI-Augmented Digital Prototyping and Innovation Methods. *IEEE Engineering Management Review*, *51*(2), 18–25. https://doi.org/10.1109/EMR.2023.3272799

Brozovsky, J., Gustavsen, A., & Gaitani, N. (2021). Zero emission neighbourhoods and positive energy districts – A state-of-the-art review. *Sustainable Cities and Society*, *72*, 103013. https://doi.org/10.1016/j.scs.2021.103013

Carlisle, N., Geet, O., & Pless, S. (2009). Definition of a 'Zero Net Energy' Community. *National Renewable Energy Laboratory*. https://doi.org/10.2172/969716

Collobert, R., Com, C., Weston, J., Bottou, L., Org, B., Karlen, M., Karlen, M., Kavukcuoglu, K., & Kuksa, P. (2011). Natural Language Processing (Almost) from Scratch. *Journal of Machine Learning Research*, *12*, 2493–2537.

Deng, T., Zhang, K., & Shen, Z.-J. (Max). (2021). A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. *Journal of Management Science and Engineering*, *6*(2), Article 2. https://doi.org/10.1016/j.jmse.2021.03.003

Derkenbaeva, E., Halleck Vega, S., Hofstede, G. J., & Van Leeuwen, E. (2022). Positive energy districts: Mainstreaming energy transition in urban areas. *Renewable and Sustainable Energy Reviews*, *153*, 111782. https://doi.org/10.1016/j.rser.2021.111782

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Garon, J. (2023). *A Practical Introduction to Generative AI, Synthetic Media, and the Messages Found in the Latest Medium* (SSRN Scholarly Paper No. 4388437; Issue 4388437). https://doi.org/10.2139/ssrn.4388437

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, *16*(1), 15–31. https://doi.org/10.1177/1094428112452151

Gouveia, J. P., Seixas, J., Palma, P., Duarte, H., Luz, H., & Cavadini, G. B. (2021). Positive Energy District: A Model for Historic Districts to Address Energy Poverty. *Frontiers in Sustainable Cities*, *3*. https://doi.org/10.3389/frsc.2021.648473

Grieves, M., & Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches* (pp. 85–113). Springer International Publishing. https://doi.org/10.1007/978-3-319-38756-7_4

Hinterberger, R., Gollner, C., Noll, M., Meyer, S., & Schwarz, H.-G. (2020, March 23). *Positive Energy Districts (PED)*. JPI Urban Europe. https://jpi-urbaneurope.eu/ped/

ICLEI. (2024). *Our approach*. ICLEI. https://iclei.org/our_approach/

IUCN, International Union for Conservation of Nature and Natural Resources. (2023, October). *Cities and nature* [Resource]. https://iucn.org/resources/issues-brief/cities-and-nature

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685–695. https://doi.org/10.1007/s12525-021-00475-2

Jones, N. (2024). 'In awe': Scientists impressed by latest ChatGPT model o1. *Nature*, *634*(8033), 275–276. https://doi.org/10.1038/d41586-024-03169-9

Kallio, H., Pietilä, A., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: Developing a framework for a qualitative semi-structured interview guide. *Journal of Advanced Nursing*, *72*(12), 2954–2965. https://doi.org/10.1111/jan.13031

Kar, S., Roy, C., Das, M., Soumita Mullick, & Saha, R. (2023). AI Horizons: Unveiling the Future of Generative Intelligence. *International Journal of Advanced Research in Science, Communication and Technology*, 387–391. https://doi.org/10.48175/IJARSCT-12969

Kaur, M. J., Mishra, V. P., & Maheshwari, P. (2020). The Convergence of Digital Twin, IoT, and Machine Learning: Transforming Data into Action. In M. Farsi, A. Daneshkhah, A. Hosseinian-Far, & H. Jahankhani (Eds.), *Digital Twin Technologies and Smart Cities* (pp. 3–17). Springer International Publishing. https://doi.org/10.1007/978-3-030-18732-3_1

Korzynski, P., Mazurek, G., Altmann, A., Ejdys, J., Kazlauskaite, R., Paliszkiewicz, J., Wach, K., & Ziemba, E. (2023). Generative artificial intelligence as a new context for management theories: Analysis of ChatGPT Analysis of ChatGPT. *Central European Management Journal*, *31*. https://doi.org/10.1108/CEMJ-02-2023-0091

Kshetri, N., Dwivedi, Y. K., Davenport, T. H., & Panteli, N. (2024). Generative artificial intelligence in marketing: Applications, opportunities, challenges, and research agenda. *International Journal of Information Management*, *75*, 102716. https://doi.org/10.1016/j.ijinfomgt.2023.102716

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lindholm, O., Rehman, H., & Reda, F. (2021). Positioning Positive Energy Districts in European Cities. *Buildings*, *11*(1), Article 1. https://doi.org/10.3390/buildings11010019

McCormick, K., Anderberg, S., Coenen, L., & Neij, L. (2013). Advancing sustainable urban transformation. *Journal of Cleaner Production*, *50*, 1–11. https://doi.org/10.1016/j.jclepro.2013.01.003

Nevens, F., Frantzeskaki, N., Gorissen, L., & Loorbach, D. (2013). Urban Transition Labs: Co-creating transformative action for sustainable cities. *Journal of Cleaner Production*, *50*, 111–122. https://doi.org/10.1016/j.jclepro.2012.12.001

Peres, R., Schreier, M., Schweidel, D., & Sorescu, A. (2023). On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice. *International Journal of Research in Marketing*, *40*(2), 269–275. https://doi.org/10.1016/j.ijresmar.2023.03.001

Qi, Q., Tao, F., Hu, T., Anwer, N., Liu, A., Wei, Y., Wang, L., & Nee, A. (2021). Enabling technologies and tools for digital twin. *Journal of Manufacturing Systems*, *58*, 3–21. https://doi.org/10.1016/j.jmsy.2019.10.001

Salom, J., Tamm, M., Andresen, I., Cali, D., Magyari, Á., Bukovszki, V., Balázs, R., Dorizas, P., Toth, Z., Zuhaib, S., Mafé, C., Cheng, C., Reith, A., Civiero, P., Pascual, J., & Gaitani, N. (2022). Correction: Salom et al. An Evaluation Framework for Sustainable Plus Energy Neighbourhoods: Moving beyond the Traditional Building Energy Assessment. Energies 2021, 14, 4314. *Energies*, *15*(15), 5646. https://doi.org/10.3390/en15155646

Sánchez Levoso, A., Gasol, C. M., Martínez-Blanco, J., Durany, X. G., Lehmann, M., & Gaya, R. F. (2020). Methodological framework for the implementation of circular economy in urban systems. *Journal of Cleaner Production*, *248*, 119227. https://doi.org/10.1016/j.jclepro.2019.119227

Sareen, S., Albert-Seifried, V., Aelenei, L., Reda, F., Etminan, G., Andreucci, M.-B., Kuzmic, M., Maas, N., Seco, O., Civiero, P., Gohari, S., Hukkalainen, M., & Neumann, H.-M. (2022). Ten questions concerning positive energy districts. *Building and Environment*, *216*, 109017. https://doi.org/10.1016/j.buildenv.2022.109017

Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks, C. (2018). Saturation in qualitative research: Exploring its conceptualization and operationalization. *Quality & Quantity*, *52*(4), 1893–1907. https://doi.org/10.1007/s11135-017-0574-8

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, *61*, 85–117. https://doi.org/10.1016/j.neunet.2014.09.003

Semeraro, C., Lezoche, M., Panetto, H., & Dassisti, M. (2021). Digital twin paradigm: A systematic literature review. *Computers in Industry*, *130*, 103469. https://doi.org/10.1016/j.compind.2021.103469

SET-Plan ACTION n°3.2 Implementation Plan. (2018). *Europe to Become a Global Role Model in Integrated, Innovative Solutions for the Planning, Deployment, and Replication of Positive Energy Districts*. https://setis.ec.europa.eu/system/files/2021-04/setplan_smartcities_implementationplan.pdf

Sharma, A., Kosasih, E., Zhang, J., Brintrup, A., & Calinescu, A. (2022). Digital Twins: State of the art theory and practice, challenges, and open research questions. *Journal of Industrial Information Integration*, *30*, 100383. https://doi.org/10.1016/j.jii.2022.100383

Silverman, D. (2017). *Doing qualitative research* (5th edition). Sage.

Suri, H. (2011). Purposeful Sampling in Qualitative Research Synthesis. *Qualitative Research Journal*, *11*(2), 63–75. https://doi.org/10.3316/QRJ1102063

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus Effect of Generative AI: Charting the Path for Responsible Conduct of Scholarly Activities in Information Systems. *Information Systems Research*, *34*(2), 399–408. https://doi.org/10.1287/isre.2023.ed.v34.n2

Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., Guo, Z., Lu, S. C.-Y., & Nee, A. Y. C. (2019). Digital twin-driven product design framework. *International Journal of Production Research*, *57*(12), 3935–3953. https://doi.org/10.1080/00207543.2018.1443229

Toews, R. (2023, February 9). *The Next Generation Of Large Language Models*. Forbes. https://www.forbes.com/sites/robtoews/2023/02/07/the-next-generation-of-large-language-models/

United Nations Population Division. (2018). *World Urbanization Prospects—Population Division—United Nations*. https://population.un.org/wup/DataQuery/

VanDerHorn, E., & Mahadevan, S. (2021). Digital Twin: Generalization, characterization and implementation. *Decision Support Systems*, *145*, 113524. https://doi.org/10.1016/j.dss.2021.113524

Woods, R., & Berker, T. (2019). Living labs in a zero emission neighbourhood context. *IOP Conference Series: Earth and Environmental Science*, *352*(1), 012004. https://doi.org/10.1088/1755-1315/352/1/012004

Wyckmans, A., Karatzoudi, K., Brigg, D., & Ahlers, D. (2019, October 31). *D9.5: Report on Attendance at events held by other SCC-01 co-ordinators 2*. https://cityxchange.eu/wp-content/uploads/2019/11/D9.5_Report-on-Attendance-at-events-held-by-other-SCC-01-co-ordinators2.pdf

Zhang, X., Penaka, S. R., Giriraj, S., Sánchez, M. N., Civiero, P., & Vandevyvere, H. (2021). Characterizing Positive Energy District (PED) through a Preliminary Review of 60 Existing Projects in Europe. *Buildings*, *11*(8), Article 8. https://doi.org/10.3390/buildings11080318

Zhang, X., Shen, J., Saini, P. K., Lovati, M., Han, M., Huang, P., & Huang, Z. (2021). Digital Twin for Accelerating Sustainability in Positive Energy District: A Review of Simulation Tools and Applications. *Frontiers in Sustainable Cities*, *3*. https://doi.org/10.3389/frsc.2021.663269

Appendix

Appendix 1

Interview Questionnaire: The role of Generative Ai in Digital Twin-enabled Positive Energy Districts

1. Background and Expertise

- **Experience Overview**
    - Could you please describe your background and experience in the energy sector or in digital technologies that support sustainable energy solutions? Please mention any specific roles or projects you've been involved in.
- **Organizational Engagement**
    - How does your organization currently engage with or prioritize sustainable energy and digital innovation? Could you provide examples of initiatives or strategies your organization is implementing?

2. Role and Applications of Digital Technologies in Sustainable Energy Management

- **Technology's Role**
    - In your opinion, what role can digital technologies—such as digital twins, and generative AI—play in enhancing energy efficiency and sustainability at the neighbourhood or community level? Are there specific technologies you believe are most impactful?

      OR
    - How can digital technologies like digital twins and AI improve energy efficiency and sustainability in a neighbourhood?
- **Effectiveness of Digital Tools**
    - How effective do you think AI and Digital Twins are for managing complex energy systems, especially those aiming to generate more energy than they consume?

3. Potential Benefits of Specific Technologies

- **Digital Twin Technology**
    - How do you think Digital Twins can contribute to sustainable energy management in a neighbourhood?
- **Generative AI**
    - Generative AI is used for tasks like predictive analysis, scenario simulation, and synthetic data generation. How do you think these capabilities could support sustainable energy solutions? Are there any concerns or limitations

you foresee? In which areas do you believe it could be applied most effectively?

4. Challenges and Barriers to Adoption

- What do you see as the major barriers to using advanced AI technologies like generative AI and Digital Twins in sustainable energy management?

5. Strategic Value and Business Perspective

- **Organizational Adaptation**
  - How can energy companies best adapt to DT and GenAI? What should they do?

    For further probing: Could you discuss areas such as workforce training, change management, or infrastructure upgrades?

- **Metrics for Success**
  - Are there specific metrics or outcomes—such as energy efficiency gains, cost reductions, or customer satisfaction—that would be most valuable for assessing the success of these technologies? Which metrics do you prioritize, and why?

6. General Feedback and Insights

- Are there any other insights or recommendations you'd like to share about the potential role of AI and digital technologies in supporting sustainable energy management?
- Are there other colleagues or contacts you would recommend who might offer additional insights on this subject?

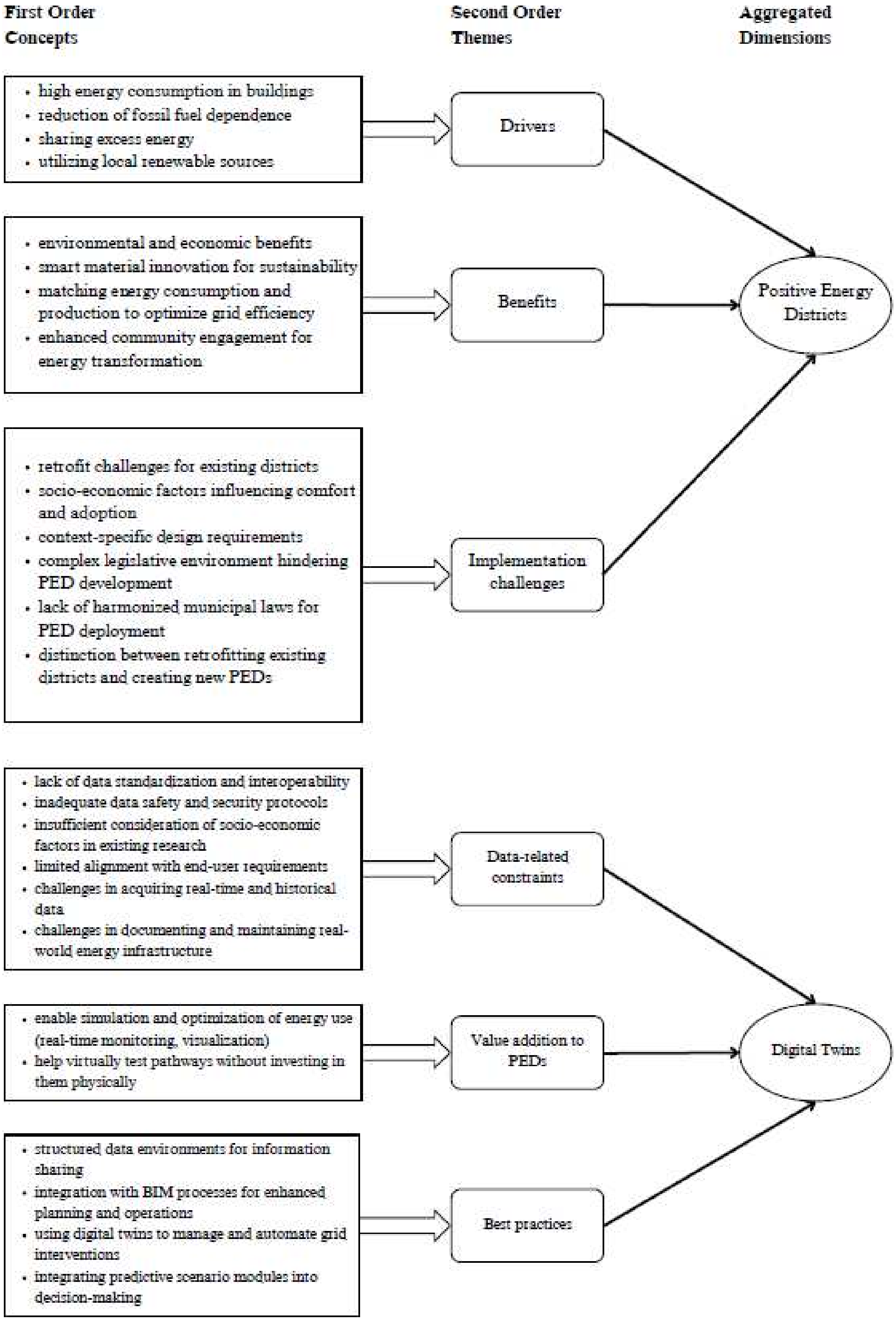
Appendix 2

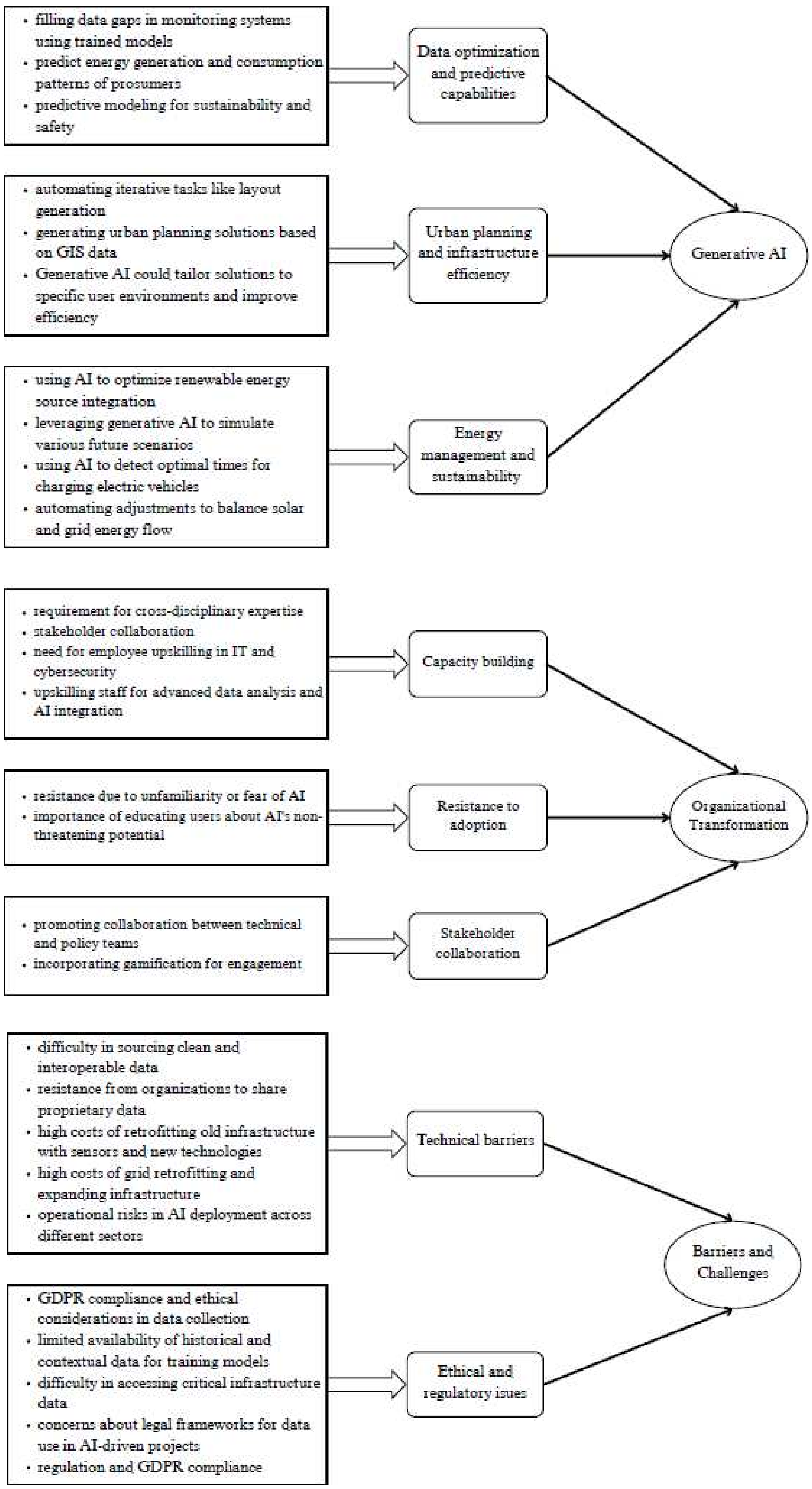
Interviewee	Citation	Code
3	"The whole thing started from the consumption of buildings."	PED1
3	"Don't consume as much oil and gas and... make things greener."	PED2
3	"Share the excess energy...distribute that to the rest of the grid."	PED3
4	"Positive energy districts are crucial for sustainable futures and utilizing local renewable resources."	PED14
3	"The benefits are...a better environment, alternative forms of economy, and innovating."	PED4
3	"Innovating in materials...creating smart districts."	PED5
1	"To bring energy and consumption together...fundamental challenge."	PED9
2	"Community engagement is crucial for long-term energy goals."	PED12
3	"The biggest challenge comes...how you convert [existing districts] to positive energy districts."	PED6
3	"The existing literature doesn't look into socio-economic factors."	PED7
3	"You need to consider local factors...climate, environment."	PED8

1	"Legislative complexity in Germany makes PED development difficult."	PED10
2	"Municipal laws vary significantly, making PED implementation complex."	PED11
4	"Distinction between retrofitting existing districts and creating new PEDs is important."	PED13
3	"You need to consider a lot of other factors...data interoperability."	DT1
3	"Data safety, data security, ethical approaches."	DT2
3	"The existing literature...doesn't account for socio-economic factors."	DT3
2	"You need to discuss with city planners...what kind of information they need."	DT4
1	"We always have a database...it is never 100% accurate."	DT9
2	"Many energy grids lack detailed infrastructure mapping."	DT11
3	"Digital technologies can assist...creation of a positive energy district."	DT5
EXPEDITE project	EXPEDITE aims to … for real-time monitoring, visualization, and management of district level energy flows.	DT13
2	Digital twins can help virtually test pathways without investing in them physically.	DT14
3	"BIM provides a framework for sharing...handling information."	DT7
3	"BIM assists in sharing this information...and running simulations."	DT8
1	"We need digital twins fed with live data to manage networks."	DT10
2	"Adding scenario analysis modules aids energy planning precision."	DT12
3	"When...you've got 200,000 sensors...AI can fill in the gaps based on historical data."	GenAI1
4	"… have been applied to predict the energy generation and consumption patterns of prosumers."	GenAI10
3	"You can perform predictive modelling...for disasters and sustainability."	GenAI3
3	"Generative AI can assist in urban planning...by generating solutions for layout."	GenAI4
3	"If you load GIS information...it can give you different options."	GenAI2
4	"Generative AI could tailor solutions to specific user environments and improve efficiency."	GenAI9
2	"AI can help identify the best mix of renewable energy sources."	GenAI7
2	"Simulations allow testing multiple future energy configurations."	GenAI8
1	"It would make sense to charge electric cars when energy is abundant."	GenAI5
1	"Matching solar production and grid consumption through automation."	GenAI6
3	"You need proper expertise...to train those AI models."	Org1
3	"You will need municipalities, local councils, and citizens to collaborate."	Org2
1	"We need many more IT specialists to handle data and cybersecurity."	Org5
2	"Technical teams need training in modern tools for effective use."	Org6
3	"People hear AI and... think of Skynet or Terminator."	Org3
3	"You need to educate people...on how AI works."	Org4
2	"Joint efforts between technologists and policymakers are essential."	Org7

EXPEDITE project	"The project incorporates gamification and co-creation to improve public engagement."	Org8
3	"You need the correct information and clean data to train AI models.	Barrier1
3	"Organizations are not willing to share their data...faultlessly."	Barrier2
3	"Old buildings...need investment in new equipment or sensors to transmit data."	Barrier5
1	"Networks lack sufficient capacity for peak loads...a huge problem."	Barrier6
2	"Risk management is vital for AI operations in practical applications."	Barrier8
3	"You need to consider GDPR regulations and ethical barriers."	Barrier3
3	"You need access to historical data...and contextual data for effective training."	Barrier4
1	"We are operators of critical infrastructure...access to data is difficult."	Barrier7
2	"Legal ambiguities around data ownership pose challenges for AI."	Barrier9
4	"Regulation and GDPR compliance are essential for data privacy and ethical AI use."	Barrier10

Appendix 3


First Order Concepts
Second Order Themes
Aggregated Dimensions
• high energy consumption in buildings
• reduction of fossil fuel dependence
• sharing excess energy
• utilizing local renewable sources
Drivers
• environmental and economic benefits
• smart material innovation for sustainability
• matching energy consumption and production to optimize grid efficiency
• enhanced community engagement for energy transformation
Benefits
Positive Energy Districts
• retrofit challenges for existing districts
• socio-economic factors influencing comfort and adoption
• context-specific design requirements
• complex legislative environment hindering PED development
• lack of harmonized municipal laws for PED deployment
• distinction between retrofitting existing districts and creating new PEDs
Implementation challenges
• lack of data standardization and interoperability
• inadequate data safety and security protocols
• insufficient consideration of socio-economic factors in existing research
• limited alignment with end-user requirements
• challenges in acquiring real-time and historical data
• challenges in documenting and maintaining real-world energy infrastructure
Data-related constraints
• enable simulation and optimization of energy use (real-time monitoring, visualization)
• help virtually test pathways without investing in them physically
Value addition to PEDs
Digital Twins
• structured data environments for information sharing
• integration with BIM processes for enhanced planning and operations
• using digital twins to manage and automate grid interventions
• integrating predictive scenario modules into decision-making
Best practices



filling data gaps in monitoring systems using trained models
predict energy generation and consumption patterns of prosumers
predictive modeling for sustainability and safety
Data optimization and predictive capabilities
automating iterative tasks like layout generation
generating urban planning solutions based on GIS data
Generative AI could tailor solutions to specific user environments and improve efficiency
Urban planning and infrastructure efficiency
Generative AI
using AI to optimize renewable energy source integration
leveraging generative AI to simulate various future scenarios
using AI to detect optimal times for charging electric vehicles
automating adjustments to balance solar and grid energy flow
Energy management and sustainability
requirement for cross-disciplinary expertise
stakeholder collaboration
need for employee upskilling in IT and cybersecurity
upskilling staff for advanced data analysis and AI integration
Capacity building
resistance due to unfamiliarity or fear of AI
importance of educating users about AI's non-threatening potential
Resistance to adoption
Organizational Transformation
promoting collaboration between technical and policy teams
incorporating gamification for engagement
Stakeholder collaboration
difficulty in sourcing clean and interoperable data
resistance from organizations to share proprietary data
high costs of retrofitting old infrastructure with sensors and new technologies
high costs of grid retrofitting and expanding infrastructure
operational risks in AI deployment across different sectors
Technical barriers
Barriers and Challenges
GDPR compliance and ethical considerations in data collection
limited availability of historical and contextual data for training models
difficulty in accessing critical infrastructure data
concerns about legal frameworks for data use in AI-driven projects
regulation and GDPR compliance
Ethical and regulatory isues

Appendix 4

Managerial Framework for Generative AI integration in Digital Twin-enabled PEDs

Key Managerial Challenges	**Strategic Managerial Actions**	**Sustainability and Business Outcomes**
Establishing clear protocols and standards for data exchange to ensure ethical and reliable AI-driven insights	Define and implement robust data governance frameworks to maintain data quality and ethical AI practices	Enhanced trust in AI-generated insights and improved reliability in decision-making
Addressing skill gaps in Generative AI, data science, and cybersecurity within managerial teams	Invest in capacity-building initiatives to upskill teams in AI-related competencies, fostering organisational resilience	Reduced reliance on external expertise and increased operational self-sufficiency
Securing stakeholder trust and acceptance for AI-enabled energy solutions	Develop communication strategies to engage policymakers, regulators, and community members effectively	Strengthened stakeholder relationships and community support for PED initiatives
Translating theoretical insights into actionable strategies for PED implementation	Integrate Generative AI algorithms into Digital Twin frameworks to enable data-driven decision-making and operational optimization	Optimized grid operations, reduced costs, and improved overall PED sustainability
Balancing technical priorities with the need for socially responsible energy management	Position PED initiatives as human-centered and socially responsible efforts through transparent, collaborative approaches	More efficient, sustainable, and human-centered urban energy landscapes