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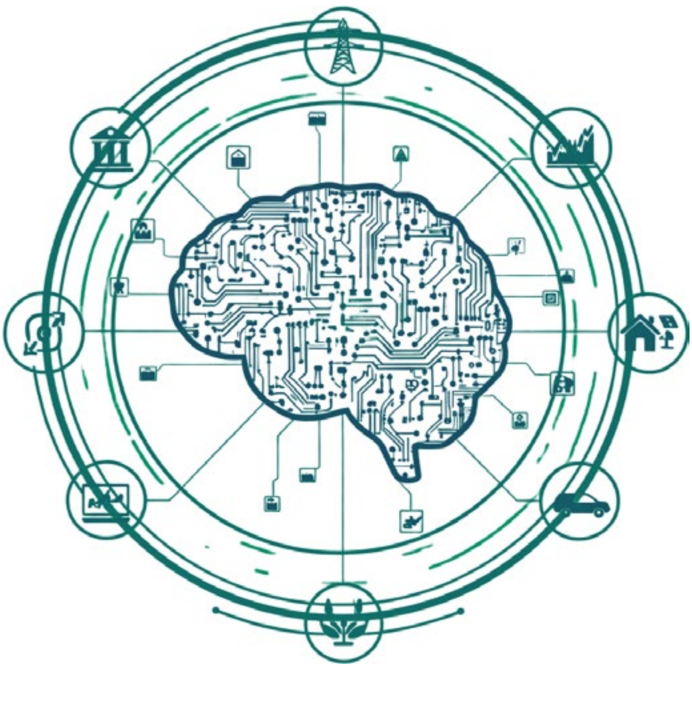
Predictive Analytics in Smart Grids:

Examining the Interplay Between Expectations and Thoughts on Adoption

Theodore Kindong



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Abstract

The transition toward smart and more resilient energy systems has become increasingly urgent as electricity grids confront climate change, rapid industrialization, and rising demand. This transition has seen a significant increase in the integration of renewable energy and an increase in the complexity of managing the grid. Thus, predictive analytics is widely promoted as a digital innovation to address this complexity by generating rich insights, providing real-time visibility, and enabling monitoring in smart grids. Yet its adoption remains shaped by stakeholders' thoughts on its role and value in smart grid operations. This thesis examines the interplay between stakeholder expectations and thoughts on the adoption of predictive analytics in smart grids, focusing on how such expectations are constructed, aligned, and enacted across organizational and institutional contexts. Drawing on Organizing Vision Theory as its primary theoretical lens, the study conceptualizes predictive analytics not only as a technical capability but as a socially embedded innovation whose adoption depends on shared interpretations, legitimacy, and coordinated action. This thesis investigates how policymakers, grid operators, market actors, and energy users interpret the value and role of predictive analytics in the smart grid, and how their expectations of what predictive analytics is shapes thoughts on adoption. Based on an embedded single-case study conducted within the Swedish smart grid context, the findings show that predictive analytics often diffuses through compelling visions that align managerial aspirations, vendor narratives, and policy priorities, amid divergent expectations and institutional logics. By foregrounding expectations as a central analytical object, this thesis contributes to research on digital innovation in complex socio-technical systems and offers insights into how predictive analytics can be adopted and operationalized in the smart grid. At the same time, it highlights how unresolved tensions among stakeholder expectations continue to shape thoughts on adoption, underscoring the importance of collective sensemaking and institutional alignment in the evolution of smart grids.

Keywords: Smart grid, predictive analytics, Artificial intelligence, Expectations, Adoption, and Organizing Vision

Sammanfattning

En förändring mot smartare och ett mer motståndskraftigt elnät har blivit alltmer angeläget i takt med klimatförändringar, ökad industrialisering och ökad efterfrågan på elektricitet. Förändringen innebär en betydande ökning av integration av olika källor av el (förnybar el) samt en ökad komplexitet i styrning och användning av elnätet. Mot denna bakgrund lyfts prediktiv analys i stor utsträckning fram som en digital innovation för att hantera denna komplexitet genom att generera insikter, tillhandahålla realtidsöversikt och möjliggöra övervakning i smarta elnät. Trots uttryckta fördelar formas dess införande i hög grad av intressenters uppfattningar om dess roll och värde i smarta elnät. Avhandlingen undersöker samspelet mellan intressenters förväntningar och uppfattningar kring införandet av prediktiv analys i smarta elnät, med fokus på hur sådana förväntningar konstrueras, samordnas och omsätts inom organisatoriska och institutionella kontexter. Med Organizing Vision Theory som huvudsakligt teoretiskt ramverk kontextualiserar studien prediktiv analys inte enbart som en teknisk förmåga, utan som en socialt inbäddad innovation vars införande är beroende av delade tolkningar, legitimitet och samordnat handlande. Avhandlingen undersöker hur beslutsfattare, nätoperatörer, marknadsaktörer och energianvändare tolkar värdet och rollen av prediktiv analys i det smarta elnätet, samt hur deras förväntningar på vad prediktiv analys är formar tankegångar om införande. Baserat på en fallstudie genomförd inom den svenska smarta elnätsmarknaden visar resultaten att prediktiv analys ofta sprids genom övertygande visioner som samordnar ledningsambitioner, leverantörsnarrativ och politiska prioriteringar, trots divergerande förväntningar och institutionella logiker. Genom att lyfta förväntningar bidrar denna avhandling till kunskap om prediktiv analys som digital innovation i komplexa sociotekniska system och erbjuder insikter i hur prediktiv analys kan införas och operationaliseras i det smarta elnätet.

Nyckelord: Smarta elnät, prediktiv analys, artificiell intelligens, förväntningar, införande samt Organizing Vision Theory

Foreword

Information Systems (IS) is a research discipline within the Faculty of Arts and Sciences at Linköping University (LiU) in Linköping, Sweden. IS studies human work and the development and evolution of various types of IT systems in organizational and societal settings. The research discipline encompasses theories, strategies and policies, models, methods, co-working principles, and artifacts related to information systems development. Development and change situations can be examined through planning, analysis, specification, design, implementation, maintenance, evaluation, and redesign of information systems. The discipline also focuses on interplay with other forms of organizational development and on processes of digitalization and innovation. It further examines the prerequisites for and results of information systems development, including institutional settings and studies of usage and the consequences of information systems at the individual, group, organizational, and societal levels.

The IS research at LiU is conducted in collaboration with private and public organizations. Collaboration also includes national and international research partners in the information systems research field. The research has a clear ambition to give distinct theoretical contributions within the information systems research field and relevant focus areas. Simultaneously, the research aims to contribute with practically needed and useful knowledge.

This work, Predictive Analytics in Smart Grids: Examining the Interplay Between Expectations and Thoughts on Adoption, is written by Theodore Kindong, Linköping University. He presents this work as his Licentiate thesis in Information Systems, Division of Information Systems and Digitalization, Department of Management and Engineering, Linköping University, Sweden.

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Linköping, June 2026

Björn Johansson
Senior Associate Professor

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List of papers

I. Kindong, T., Johansson, B., & Paulsson, V. (2025). AI-Enabled Predictive Analytics in Smart Grids: The Case of Sweden. Complex Systems Informatics and Modeling Quarterly, (42), 43-62.
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II. Kindong, T., Johansson, B., & Paulsson, V. (2025). From Control to Co-Creation: Predictive Analytics in Resilient Distributed Energy Resources, ACIS 2025 Proceedings. 94, AIS eLibrary.
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III. Kindong, T., Johansson, B., & Paulsson, V. (2026). Predictive Analytics in Smart Grids: Examining the trade-off between Accuracy and Transparency, *Submitted to The Forty-Seventh International Conference on Information Systems, Lisbon, Portugal 2026.*

Related articles not included in the thesis.

I. Kindong, T., Johansson, B., & Paulsson, V. (2024). A systematic literature review of AI-enabled predictive analytics in smart grids. In BIR Workshops (pp. 16-30).
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II. Kindong, T. (2024), AI applications in SG for reliability, security, and stability. In BIR Workshops (pp. 267-278). *Published open access under the CC BY license*.

III. Kindong, T., & Iqbal, S. (2025). Edge-based Machine Learning Models in IoT Devices for Improved Anomaly and Intrusion Detection. In 2025, the 9th International Conference on Cryptography, Security and Privacy (CSP) (pp. 127-131). IEEE.

IV. Kindong, T., Gianluigi, V & Johansson, B. (2026). Balancing Openness and Security in Digital Energy Ecosystems, *accepted to be presented at DESRIST2026 and will be published in Springer proceedings.*

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Chapter One

1 Introduction

This chapter introduces a study of predictive analytics in smart grids by outlining the background, defining the research problem, and justifying the research gap and the topic's relevance. It then presents the aims and research questions that guide the investigation, clarifies the study's scope and limitations, and concludes with an overview of the thesis's organization.

1.1 Background and Research Problem

The ongoing transformation of global energy systems (Singh et al., 2025) is not merely a matter of technological advancement but a fundamental structural requirement for modern economies. As electricity networks grow more complex, demand patterns become more unpredictable due to the rise of weather-dependent renewable energy and the evolving challenges posed by distributed energy resources. Smart grids have emerged as a critical innovation, integrating digital technologies with physical infrastructure to enable bidirectional electricity flow and to create more responsive, adaptive, and efficient energy systems. This paradigm shift is captured in the following quote.

"A 21st-century economy cannot be run on a 20th-century grid; it needs an intelligent grid that can predict, adapt, and learn."

(An excerpt from U.S. Department of Energy Report, (U.S. Department of Energy, 2009, p. 3).

This quote underscores the importance of moving toward intelligent, data-driven energy systems that can predict, adapt, and learn. At the heart of this transition lies predictive analytics, which has the potential to equip smart grids with anticipatory capabilities to forecast electricity demand, align demand with current supply, and learn from historical and real-time data to improve grid management and enable a shift from reactive to proactive and adaptive grid management. The relevance of these capabilities has become increasingly evident in light of recent extreme weather events, which have exposed critical vulnerabilities in modern electricity systems. For instance, severe heatwaves across Southern Europe between May and July 2022 led to record electricity demand while simultaneously reducing wind power output by more than 30%

in some regions due to stagnant atmospheric conditions (Molina et al., 2023; Xu et al., 2025). Similar climate-driven vulnerabilities are evident in the Nordic context, where Storm Johanna caused widespread power outages in Sweden, leaving thousands of households without electricity (TT News Agency, 2025). Thus, highlighting the limitations of traditional electricity grids in anticipating cascading failures and coordinating timely responses (You et al., 2025), underscoring the need for predictive analytics in smart grids to leverage insights from historical and real-time data to forecast future electricity demand and supply.

In addition, climate-related stressors, such as surging demand and declining renewable energy output, have become defining challenges for power systems, particularly during prolonged heatwaves (Bromberger et al., 2026). Thus, traditional grids, designed for predictable demand and centralized generation, struggle to cope with increased electrification, decentralized renewables, and climate-driven volatility, resulting in inefficiencies and reliability risks (Arnold, 2011; Dhara et al., 2022; Zohuri, 2023). Thus, predictive analytics has the potential to enhance the smart grid by enabling real-time monitoring, adaptive control, and data-driven decision-making (Babayomi et al., 2023; Syed et al., 2020). In smart grids, predictive analytics serves as an input to a downstream human decision-making process, enabling the system to sense, predict, learn, and adapt to deliver reliable, resilient, and sustainable energy (Babayomi et al., 2023; Syed et al., 2020; Yan et al., 2019; Zhongtuo et al., 2020).

The increasing digitalization of the electricity grid, combined with the growing potential of predictive analytics, has prompted significant research interest in predictive analytics in smart grids, with a focus on understanding the conditions under which predictive analytics can effectively support resilient smart grids (Lopez et al., 2018). However, research remains heavily dominated by technical and engineering perspectives. Most studies focus on algorithms, optimization, and computational performance (Bhattarai et al., 2019; Zhang et al., 2018), treating predictive analytics primarily as a technical artifact rather than as an information system embedded within organizational and institutional decision-making. Consequently, a critical socio-technical dimension remains underexplored. Considering that predictive analytics output (e.g., predictions and forecasting) serves as input to downstream decision-making processes in smart grids. Thus, it is important to understand what stakeholders expect from predictive analytics, and how such expectations shape their views on adopting predictive analytics in practice, and how expectations related to transparency, reliability, and interpretability shape adoption decisions, especially given the growing interest in using AI techniques such as machine learning techniques for predictive analytics (Kampars et al., 2024; Pandya, 2021). Similarly, while technical integration challenges are well-documented, research rarely examines organizational readiness, data governance, institutional routines, or sense-making processes that influence whether predictive analytics delivers its anticipated value (Bhattarai et al., 2019; Syed et al., 2020).

Also, smart grids are inherently socio-technical systems that combine digital infrastructures, organizational processes, and human judgment (Lakemond et al., 2025). Therefore, predictive analytics in smart grids constitutes a form of digital innovation as defined by Nambisan et al. (2020) and is characterized by the ongoing recombination of digital technologies with physical infrastructure to reconfigure how future grid states are imagined, governed, and enacted. Rather than representing a bounded technical upgrade, predictive analytics unfolds as a generative and indeterminate innovation process in which value, roles, and outcomes emerge over time through use and organizational adaptation (Nambisan et al., 2020). Thus, in the context of predictive analytics in smart grids, agency becomes increasingly distributed across humans, algorithms, and material infrastructures, while initial expectations remain provisional and subject to continual revision. From this perspective, predictive analytics in smart grids is sustained through a dynamic interplay between technological capabilities and actors' evolving interpretations, assumptions, and expectations regarding what predictive analytics is, what it can become, and how it should be integrated into existing practices. Consequently, adoption and scaling, particularly involving AI, depend less on technical capability alone (Haefner et al., 2023; Yu et al., 2024) and more on collective sensemaking, governance arrangements, and the ability of organizations and ecosystems to align and recalibrate expectations as the innovation evolves.

1.2 Research Gap and Topic Justification

Smart grids, like many contemporary socio-technical systems, are characterized by increasing complexity arising from the interdependence of digital infrastructures, physical assets, organizational processes, and human expertise (Lakemond et al., 2025). Within this context, predictive analytics in smart grids is a prominent form of digital innovation, offering capabilities such as demand forecasting and renewable generation prediction, and supporting proactive and adaptive grid management (Babayomi et al., 2023; Yan et al., 2019). These capabilities are particularly critical for addressing uncertainties arising from increasing electricity demand, distributed renewables, and climate-driven variability. Consequently, predictive analytics in smart grids has attracted significant attention from both academic researchers and industry practitioners due to its perceived potential strategic importance. Despite the rapidly growing interest in predictive analytics across both academia and industry, a clear gap remains between its demonstrated potential and its practical deployment in real-world smart grid environments. A substantial portion of prior research has relied on experimental designs and simulated datasets (Idima et al., 2023; Kampars et al., 2024; Pandya, 2021), with findings largely derived from controlled or idealized settings rather than operational contexts. Within these studies, simulated results are frequently used to prioritize model optimization, focusing on improving predictive accuracy and computational performance under laboratory conditions (Babayomi et al., 2023; Bhattarai et al., 2019; Pandya, 2021). While such work has produced significant experimental success and reinforced claims about the high potential of advanced techniques, including machine learning and AI-driven approaches (Boopathy et al., 2024; Bose, 2017; Olawumi & Oladapo, 2025; Zhongtuo et al., 2020), these outcomes have not translated into widespread adoption in real-world settings.

In practice, many grid operators continue to rely on Supervisory Control and Data Acquisition systems for control and monitoring (Pinzón et al., 2020), with relatively low-to-medium levels of analytics, indicating a persistent disconnect between technological advancement and operational uptake. This misalignment suggests that technical performance alone is insufficient to drive adoption. Indeed, existing research remains heavily skewed toward technical dimensions, such as algorithms, data architectures, and optimization (Barth et al., 2022; Boopathy et al., 2024; Ferreira et al., 2019; Zhang et al., 2026), while offering limited insight into how predictive analytics is understood, evaluated, and implemented by stakeholders in real-world settings. As a result, there is insufficient understanding of how expectations regarding value, reliability, associated risks, cost, and usability are formed and how they influence thoughts about adoption and adoption decisions.

Empirical evidence further highlights that real-world implementations are often constrained by organizational challenges, including issues of trust, transparency, and data governance (Bhattarai et al., 2019; Yu et al., 2015; Zhang et al., 2018). These barriers contribute to a gap between innovation maturity and institutional readiness (Benson, 2019; Webster & Gardner, 2019), underscoring the fact that digital innovation adoption is not solely a function of innovation maturity but also of institutional readiness. Thus, unlike prior research that predominantly emphasizes technical performance and model optimization (Bhattarai et al., 2019; Diamantoulakis et al., 2015; Idima et al., 2023; Meyer et al., 2024; Pandya, 2021), this study addresses the critical need to examine predictive analytics within its real-world context. Specifically, it examines how stakeholders' expectations regarding the real-world adoption of demonstrated advanced predictive analytics techniques in smart grids are formed, negotiated, and revised as predictive analytics transitions from experimental promise to operational reality. This perspective is essential because the successful adoption and sustained use of predictive analytics in smart grids ultimately depend on aligning perceived technological value with stakeholders' evolving readiness to integrate these solutions into practice.

1.3 Aims and Research Questions

Building on the identified gap between the experimentally demonstrated potential of predictive analytics and its limited real-world adoption in smart grids, this thesis positions predictive analytics in smart grids as a digital innovation whose value is not inherent in technical performance alone, but is socially constructed, interpreted, and enacted in practice. While prior research has largely emphasized model optimization and performance improvements in simulated environments, this study shifts attention toward how such innovations are understood, legitimized, and integrated within organizational and institutional contexts.

Accordingly, the aim of this thesis is to examine how stakeholders construct, interpret, and revise organizing visions for predictive analytics in smart grids, and how these visions evolve as the technology moves from experimental promise to operational reality. To achieve this, the thesis adopts Organizing Vision Theory (Swanson & Ramiller, 1997) as its primary analytical lens (Cf. section 3.6). This perspective enables exploration of how diverse actors, including policymakers, grid operators, market participants, and energy users, collectively interpret predictive analytics within the broader digital innovation of energy systems. In doing so, the thesis moves away from the overly technical dimension to investigate how expectations of the anticipated benefits from predictive analytics shape their views on adoption. To support this shift, the thesis adopts a sociotechnical perspective, conceptualizing predictive analytics not merely as a computational tool but as a technical subsystem (technology) in which outputs serve as inputs to a downstream decision-making process for the social subsystem (people) to interpret system needs, articulate strategic priorities (Chen et al., 2023). From this standpoint, the study explores how smart grid stakeholders' expectations are formed, what underlying assumptions shape them, and how they evolve as stakeholders engage with predictive analytics in real-world contexts. Furthermore, it examines how different interpretations of the digital innovation coalesce into a collective organizing vision and how discrepancies between envisioned benefits and operational realities influence adoption trajectories and innovation outcomes.

In this way, the thesis contributes to research by advancing understanding of how digital innovations, such as predictive analytics, are shaped not only by technological capabilities but also by the interplay of expectations and stakeholders' views on adoption. It specifically addresses the gap between empirically grounded demonstrated potential and limited real-world implementation by examining the innovation and institutional readiness (Benson, 2019; Webster & Gardner, 2019) of predictive analytics in smart grids as a digital innovation.

Beyond its academic contribution, this research is motivated by the urgent societal need to ensure secure, resilient, and sustainable energy systems amid increasing climate-related disruptions and accelerating electrification. This need is particularly acute in Sweden, where electricity demand is projected to increase by more than 60% due to industrial transformation and the electrification of transport (Le Coq et al., 2025). At the same time, Sweden's leadership in fossil-free steel, electro-fuels, and green hydrogen intensifies the need for advanced, data-driven capabilities to manage system uncertainty and infrastructure planning. In this context, understanding how predictive analytics is envisioned, interpreted, and adopted is critical to realizing the potential of smart grids as resilient digital infrastructures. The aim of this thesis is achieved by answering the following research questions (RQ):

- RQ1: How do smart grid stakeholders understand and envision the role of predictive analytics in the smart grid context?
- RQ2: What is the interplay between stakeholders' expectations and thoughts on the adoption of predictive analytics in smart grids?

1.4 Scope and Limitations

The scope of this thesis is defined as follows. The thesis examines how stakeholders' expectations regarding predictive analytics in smart grids form, evolve, and shape perceptions of adoption. Adopting an interpretive tradition as an underlying assumption, the study focuses on how predictive analytics is envisioned, legitimized, and enacted across organizational and institutional contexts, rather than on its technical performance, predictive accuracy, or optimization efficiency. This scope reflects an Information Systems tradition that conceptualizes digital technologies as socially embedded and meaning-laden rather than as value-neutral artifacts (Orlikowski & Iacono, 2001; Orlikowski & Robey, 1991). In addition, guided by Organizing Vision Theory as its primary analytical lens, the analysis foregrounds collective sensemaking, coordination, and institutional alignment as central mechanisms shaping adoption trajectories (Swanson & Ramiller, 1997; Swanson & Ramiller, 2004). Thus, the scope of his thesis is as follows.

First, on the methodology front, the study adopts a qualitative, interpretive embedded case study design to prioritize contextual depth and analytical insight over statistical generalization (Stake, 1978; Walsham, 2006).

Second, on the empirical front, this study is confined to the Swedish smart grid context, selected for its advanced digital infrastructure and active engagement in digital innovation and energy transition initiatives. The analysis focuses on purposively selected embedded units of observation, including an energy management system provider, grid operators, vehicle-to-grid stakeholders, and policymakers. The study does not pursue cross-national comparison, nor does it aim to represent all possible stakeholder groups within the smart grid ecosystem (Yin, 2018). Furthermore, data collection is limited to a combination of literature review, document analysis, and semi-structured interviews to support triangulation and interpretive depth (Merriam & Tisdell, 2016; Walsham, 2006). Thus, the study excludes survey-based methods, experimental evaluations, and quantitative performance assessments, consistent with its focus on expectations, meanings, and institutional dynamics rather than technical optimization outcomes.

Moreover, the following limitations are acknowledged in this thesis to clarify its scope and position within qualitative information systems research.

i) Research perspective.

This study adopts an interpretive, social constructivist perspective that foregrounds stakeholders' meanings, expectations, and sensemaking processes. Consistent with interpretive research, the researcher is understood as an active participant in knowledge construction, and the findings reflect both participants' accounts and the researcher's analytical interpretations (Orlikowski & Robey, 1991; Walsham, 1995; Walsham, 2006). Moreover, although triangulation across interviews, documents, and prior literature enhances credibility (Merriam & Tisdell, 2016), this thesis acknowledges that alternative interpretations may emerge if different actors, contexts, or theoretical lenses were applied. The study does not assess the technical performance, predictive accuracy, or optimization efficiency of analytics models, reflecting the established IS distinction between evaluating technical artifacts and examining how technologies are socially embedded and enacted in practice (Hirschheim, 1985; Orlikowski & Iacono, 2001). Consequently, claims regarding quantitative improvements in grid resilience fall outside the scope of this thesis.

ii) Research method.

The thesis employs an embedded single-case study design focused on the Swedish smart grid context, prioritizing depth and contextual understanding over statistical generalization (Merriam & Tisdell, 2016; Stake, 1978). Accordingly, the findings are intended to support analytical depth rather than empirical generalization by contributing to theory on expectations and adoption in complex digital infrastructures (Yin, 2018). In addition, the empirical material captures stakeholder expectations during a specific phase of smart grid transformation; as interpretive case studies often provide temporal snapshots rather than fully longitudinal accounts, the study cannot fully assess long-term stabilization or large-scale diffusion of predictive analytics (Walsham, 1995; Walsham, 2006). Finally, the selection of embedded units, including energy management system providers, vehicle-to-grid stakeholders, and grid operator actors and policymakers, necessarily excludes other perspectives, such as residential consumers not engaged in flexibility initiatives, thereby constraining the range of expectations represented (Parmar et al., 2010). The strong contextual embeddedness of the case further limits transferability, as knowledge is shaped by institutional and societal conventions that vary across settings (Becker & Niehaves, 2007).

Taken together, these limitations reflect recognized trade-offs in qualitative, interpretive, and case-based research rather than deficiencies in empirical richness (Merriam & Tisdell, 2016; Stake, 1978; Walsham, 1995), and point to opportunities for future comparative, longitudinal, or mixed-method studies.

1.5 Thesis organization

The overall organization outlines the chapters' logical and chronological flow. The structure shows how the study's components are interrelated and build on one another. It begins with Chapter 1 (Introduction), which establishes the research background, motivation, scope, limitations, and research questions. This is followed by Chapter 2 (Background), which introduces the empirical context, and Chapter 3 (Theoretical background), which situates the study within existing research and informs the development of the theoretical framework that guides the analysis. Chapter 4 (Methodology) outlines the research design and methods used in the study. The empirical insights are presented in Chapter 5 (Summary of Included Papers), which feeds into Chapter 6 (Synthesis of Findings), where results are integrated and interpreted, and into Chapter 7 (Discussion), where the analysis of findings is discussed in relation to the research questions and theory. Finally, Chapter 8 (Conclusions and future research direction) summarizes the contributions, discusses implications, and outlines directions for future research. The chapters are interconnected, with earlier theoretical and methodological choices shaping later analysis and conclusions.

Chapter 2

2 Background

This chapter provides the empirical context for the study by describing the technological and organizational environment in which predictive analytics is deployed in smart grids. It outlines the power grid's evolution toward increasingly digital and data-driven infrastructure and positions predictive analytics as a key capability in this transformation. The chapter then introduces the main stakeholder groups in smart grids and examines their roles and interdependencies. Finally, it highlights stakeholders' expectations for predictive analytics, focusing on how differing views on performance, transparency, and operational value shape adoption decisions. Together, these sections establish the contextual foundation for the analytical framework and research design developed in subsequent chapters.

2.1 Evolution and Development of the Power Grid

The modern power grid represents a significant transformation from traditional, centralized electricity systems to intelligent, decentralized infrastructure capable of managing complex, dynamic energy flows. This transition has been driven by rising energy demand, climate change, and the growing integration of renewable energy sources. Since the nineteenth century, electricity networks have evolved from unidirectional systems, delivering power from large-scale generation plants to passive consumers, into smart grids that integrate digital technologies and distributed energy resources to enable bidirectional electricity flow, real-time coordination, and system optimization (Babayomi et al., 2023; Dhara et al., 2022; Idima et al., 2023; Lopez et al., 2018) as seen in Figure 1. Thus, traditional grids are being transformed into smart grids: modern electricity networks that use digital technologies, sensors, and automation to monitor, manage, and optimize the generation, distribution, and consumption of electricity in real time (Dhara et al., 2022). Smart grids enhance system reliability and efficiency by enabling demand forecasting, load balancing, and cybersecurity (Idima et al., 2023; Lopez et al., 2018). At the same time, the integration of distributed energy resources (DERs) has enabled the emergence of prosumers, who both produce and consume electricity through technologies such as solar panels and battery storage (Bessa et al., 2018). As a result, electricity systems have shifted toward more flexible, data-driven, and interconnected infrastructures (Bayindir et al., 2016; Dhara et al., 2022; Sifat et al., 2023). This increasing decentralization has expanded the range of actors involved in grid operations, including grid operators (transmission system operators (TSOs) and distribution system operators (DSOs)), market actors (energy retailers, technology providers, utilities), policymakers and regulators, and energy users (prosumers, energy communities) (Bhattarai et al., 2019; Cajsa & Perna, 2014). Such developments reflect broader digital transformation processes in complex systems, where digital technologies reshape coordination mechanisms, innovation processes, and organizational roles (Lakemond et al., 2025; Nambisan et al., 2017; Svahn et al., 2017). Consequently, smart grids generate large volumes of heterogeneous data from infrastructure, users, and environmental conditions. While this creates challenges for data management and processing, it also enables improved forecasting, situational awareness, and system resilience (Syed et al., 2020). In this context, advanced predictive analytics in smart grids has emerged as an essential component for managing complexity and uncertainty, positioning it as a core enabler of modern smart grid innovation (Babayomi et al., 2023; Bhattarai et al., 2019; Syed et al., 2020).

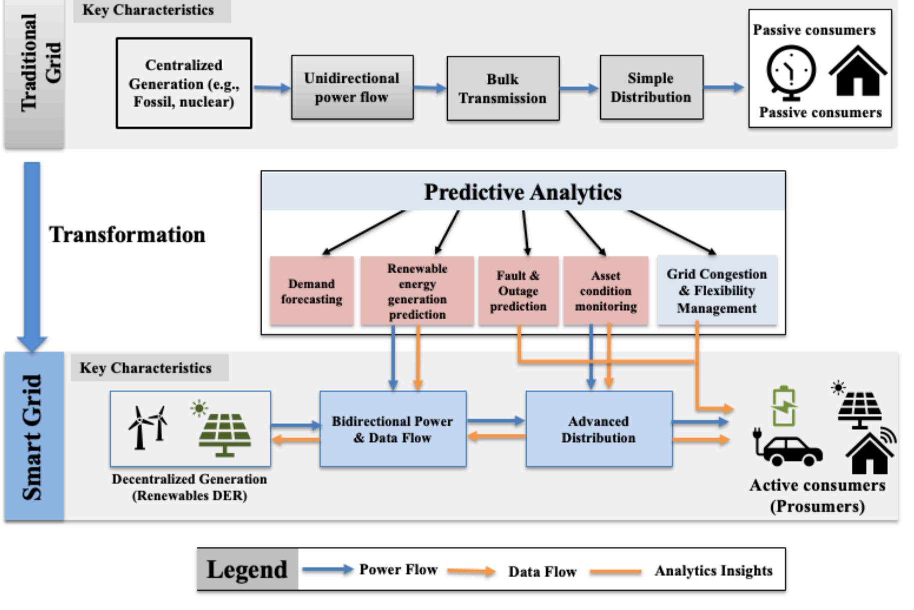

Figure 1. Conceptual illustration of the transition from traditional to smart grids

2.2 Predictive analytics in smart grids

In smart grids, predictive analytics has emerged as an enabler, allowing stakeholders to use statistical models and artificial intelligence techniques to generate insights from historical and real-time data, anticipate future system states, and support operational and strategic decisions (Babayomi et al., 2023; Bhattarai et al., 2019). By leveraging data from diverse sources, including grid infrastructure, DERs, environmental conditions, and user behavior, predictive analytics enhances situational awareness and enables more efficient coordination of complex energy flows, allowing electricity systems to anticipate, respond to, and adapt to increasingly dynamic and uncertain energy environments. Advances in AI and large-scale data infrastructure have the potential to further strengthen predictive analytics capabilities. Hence, predictive analytics in smart grids has the potential to enhance grid efficiency, reliability, and resilience, support the integration of renewable energy sources, and address the constraints of aging infrastructure (Bhattarai et al., 2019; El-Hawary, 2016; Faheem et al., 2018; Idima et al., 2023; Meyer et al., 2024). As illustrated in Figure 1, the transition from traditional to smart grids is accompanied by greater integration of digital technologies, such as predictive analytics, positioned between decentralized energy generation and advanced grid operations to support key functions, including demand forecasting, renewable energy prediction, fault detection, asset monitoring, and congestion management. In doing so, it enables a shift from reactive grid management to more proactive, data-driven grid management.

However, the transition from the traditional grid to the smart grid has also enabled many stakeholders to become actively involved in managing and operating the grid, thereby broadening the stakeholder base.

2.3 Stakeholders in smart grids

Smart grids integrate physical infrastructure, digital technologies, and human decision-making (Bhattarai et al., 2019; Dhara et al., 2022; El-Hawary, 2016). This is similar to socio-technical systems (Erlinghagen & Markard, 2012; Lakemond et al., 2025), and their functioning depends on continuous data exchange, digital communication, and predictive decision support, as well as on how stakeholders interpret and use these technologies (Dhara et al., 2022; El-Hawary, 2016; Faheem et al., 2018).

Drawing on stakeholder theory (Parmar et al., 2010), this thesis conceptualizes smart grid operations as a network of interdependent actors whose roles, responsibilities, and expectations shape system performance and resilience (Lopez et al., 2018). As shown in Figure 2, key actors in smart grids include policymakers and regulators, grid operators (transmission and distribution system operators), energy users, and market actors, each with distinct roles and responsibilities. Policymakers and regulators (e.g., government bodies and regulatory authorities) establish the rules and regulatory frameworks governing smart grid operations. Grid operators, namely transmission system operators (TSOs) and distribution system operators (DSOs), operate and manage the electricity network, ensuring a secure, environmentally sustainable, and cost-effective power system and providing access to the grid. Energy users, including households, industrial consumers, and energy communities, consume electricity and may also produce electricity as prosumers. Market actors include electricity trading companies (e.g., Bixia), energy trading platforms (e.g., Nord Pool and EPEX Spot), and energy management systems that provide flexibility services.

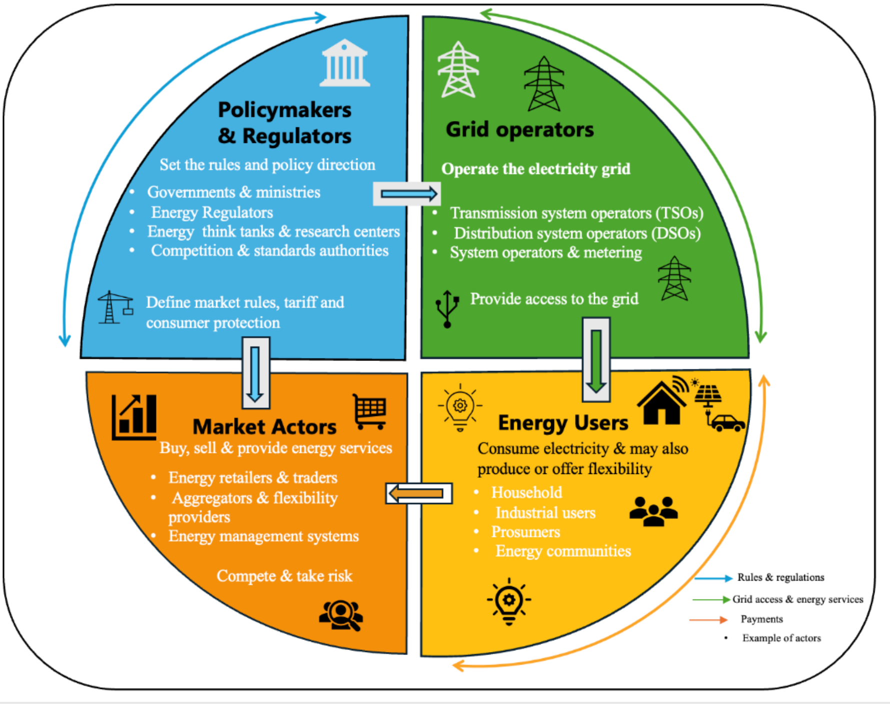

Figure 2 : Overview of Smart Grid context and category of actors

Table 1: Summary of Stakeholder groups according to Mitchell et al. (1997)' s stakeholder salience model

Stakeholder group	**Key Attributes**	**Smart grid context**	**Salience Level**	**Expectations**
Policymakers & regulators (Energimarknadsinspektionen or Ei)	Power, Legitimacy & Urgency	National and local governments, energy regulators, environmental agencies	Very high	Expect predictive analytics to support system security, climate targets, regulatory compliance, data protection, transparency, and long-term resilience
Grid operators e.g TSOs, DSOs,	Power, Legitimacy, & Urgency	Transmission and distribution system operators,	High	Expect predictive analytics to improve reliability, forecast demand and faults, optimize assets, support operational decision-making, and justify infrastructure investments
Market actors	Legitimacy, Limited power, & Situational urgency	Energy retailers, aggregators, energy & flexibility service providers, utilities, technology providers	Moderate	Expect predictive analytics to enhance market efficiency, price forecasting, flexibility trading, risk management, and profitability
Energy users/ prosumers	Legitimacy, & (Sometimes) urgency	Households, residential consumers, businesses, prosumers, community energy groups	Low to moderate	Expect predictive analytics to enable affordable, reliable, and sustainable energy, protect privacy, improve outage response, and support participation in flexibility schemes

The government, through regulatory agencies, defines the institutional and legal framework for grid operations, while consumers and prosumers provide consumption and generation data and increasingly participate in demand response and flexibility markets (Svenska kraftnät, 2024). Thus, the functioning of a smart grid depends not only on coordination among these actors but also on how they expect digital technologies, particularly predictive analytics, to support their roles and decision-making.

Also, in smart grids, stakeholders possess different levels of power and legitimacy, according to Mitchell et al. (1997)'s stakeholder salience level (cf. Table 1). As seen in Figure 2, policymakers/regulators, who typically possess high power, legitimacy, and urgency, shape regulatory requirements for grid operation and the electricity market and set the rules, while grid operators (TSOs/DSOs), with high power and legitimacy, operationalize these roles through infrastructure investments and system design. Market actors buy, sell, trade, and offer flexible services, while energy users contribute legitimacy and urgency through participation, data provision, and pay for the different services. Thus, predictive analytics in smart grids is not merely a technical optimization but a subsystem of a complex socio-technical system whose adoption depends on how different stakeholders envision its role, trust its outputs, and adapt their practices, accordingly, as shown in Table 1. Also, different stakeholders have diverse expectations about the value of predictive analytics, how it should be implemented, and how its value is interpreted and sustained over time.

2.4 Stakeholders' Expectations on Predictive Analytics

Smart grid stakeholders have distinct roles and responsibilities and are subject to different institutional norms. Thus, predictive analytics in smart grids extend beyond technical efficiency and raise broader concerns related to governance, market design, data governance, and social equity, and are shaped by diverse stakeholder expectations. As depicted in Figure 3, predictive analytics is positioned at the core of the smart grid ecosystem and is shaped by the expectations of multiple stakeholder groups. Policymakers and regulators expect predictive analytics to enhance system security, sustainability, and regulatory compliance, thereby supporting policy objectives related to decarbonization and system resilience (European Commission, 2022). Grid operators anticipate improved operational transparency, reliability, and decision-support capabilities for managing transmission and distribution networks. Market actors, including energy retailers, trading platforms, and energy service providers, expect predictive analytics to improve market efficiency, price forecasting, and flexibility services. Energy users, including households, industrial consumers, and energy communities, expect enhanced reliability, affordability, and transparency, as well as opportunities for active participation in demand response and flexibility markets. These heterogeneous expectations reflect socio-technical tensions similar to those observed during electricity market liberalization, where decision-makers faced cognitive and political constraints in balancing economic, environmental, and societal objectives (Midttun, 1996). The integration of predictive analytics in smart grids similarly requires aligning technological innovation with institutional legitimacy, market structures, and societal values.

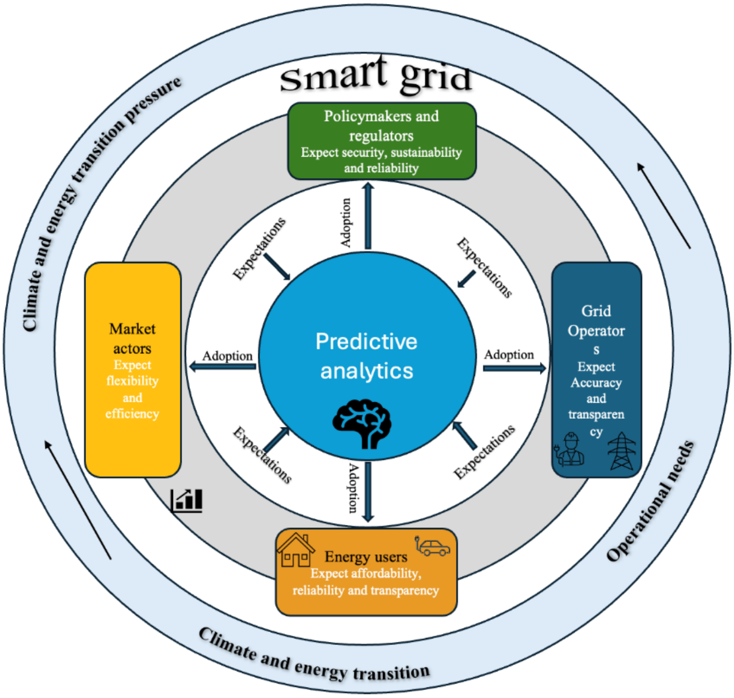

Figure 3 : Stakeholder Expectations of Predictive Analytics in Smart Grids

Chapter 3

3 Theoretical Background and Framework

This chapter develops the thesis's theoretical foundation by synthesizing literature on predictive analytics in smart grids. It adopts a sociotechnical perspective, positioning predictive analytics not merely as a technical capability but as an innovation shaped by organizational, institutional, and societal contexts. The chapter proceeds in three steps. First, it conceptualizes predictive analytics and its theoretical underpinnings. Second, it situates predictive analytics within the smart grid domain, tracing its evolution and growing reliance on artificial intelligence (AI). Third, it introduces the theoretical framework, grounded in Organizing Vision Theory (OVT) and complemented by sensemaking theory, to explain how stakeholder expectations shape thinking about the adoption of predictive analytics.

3.1 Predictive Analytics in Sociotechnical Systems

Predictive analytics in sociotechnical systems involves using statistical modeling, machine learning, and data mining to generate insights from historical and real-time data, enabling organizations to anticipate future outcomes. It is embedded within and shaped by human, organizational, and social contexts. As defined by IBM (2025), predictive analytics is a branch of advanced analytics that transforms diverse datasets into actionable forecasts and predicts future outcomes using methods such as classification, regression, clustering, and time-series modeling. Its growth is closely tied to the rise of big data and machine learning, which have expanded the scale and complexity of data that organizations can analyze (Zhang et al., 2021). However, predictive analytics does not operate in isolation; it is embedded within organizational and social contexts, and its value and impact depend on how people design models, interpret predictions, make decisions based on them, and govern their use within social, ethical, and institutional structures.

Moreover, predictive analytics has a distinct theoretical foundation that sets it apart from exploratory modeling in information systems. Shmueli and Koppius (2011) emphasize this distinction by arguing that explanatory models aim to test causal hypotheses, whereas predictive models prioritize forecasting accuracy, focusing on out-of-sample performance, robustness, and the availability of variables at prediction time. This differentiation carries important methodological and practical implications, as predictive analytics requires processes centered on validation, generalizability, and proactive decision support in organizations. Hence, predictive analytics extends far beyond its technical capabilities; it is embedded within organizational contexts and shaped by strategic, cultural, and process-related factors. Importantly, predictive analytics is not solely a technical artifact but is embedded within organizational structures and practices. Mikalef and Krogstie (2020) demonstrate that big data analytics capabilities drive innovation only when aligned with organizational structures, resources, and decision-making practices. Thus, realizing the benefits of predictive analytics depends on organizational readiness, data governance, and process integration, not just algorithmic sophistication.

At a broader societal level, predictive analytics in sociotechnical systems raises important governance and ethical considerations. Chen et al. (2023) argues that predictive systems contribute to the broader decision-making and operations of the organization through anticipation, precaution, and preemption, raising concerns about transparency, fairness, bias, and accountability. Thus, as predictive analytics becomes embedded across public and private decision-making, it increasingly functions as a boundary infrastructure (Carlile, 2002; Gal et al., 2005) through which technical models, organizational practices, and institutional logics (Berente et al., 2019) become tightly interwoven and difficult to disentangle. Hence, this thesis frames predictive analytics as a component of broader socio-technical systems encompassing technical modeling methods, organizational capabilities, and governance. This sociotechnical framing is relevant to this thesis, which positions predictive analytics as a foundational forecasting and analytical tool that supports decision-making within the smart grid ecosystem. Building on this general understanding, it becomes essential to consider what stakeholders expect from predictive analytics and how such expectations shape thoughts on adoption. The smart grid is characterized by multiple actors, a high-volume sensor network, real-time system dynamics, complex operational requirements, and the generation of huge amounts of data. Thus, predictive analytics within the smart grid is essential and presents very domain-specific challenges, opportunities, and modeling requirements that distinguish it from other applications, as presented in the preceding section.

3.2 Predictive analytics in smart grids

Predictive analytics has emerged in the literature as a digital innovation in modern smart grids, with foundational capabilities that can enable electricity systems to anticipate, respond to, and adapt to increasingly dynamic and uncertain energy environments. This role has been further strengthened by advances in AI and large-scale data infrastructures. Previous studies position predictive analytics as an enabler that enhances grid efficiency, reliability, and resilience, supports the integration of renewable energy sources, and addresses the constraints of aging infrastructure (Bhattarai et al., 2019; El-Hawary, 2016; Faheem et al., 2018; Meyer et al., 2024). As smart grids evolve into complex, data-intensive socio-technical systems, predictive analytics is increasingly seen as essential for managing DERs, balancing supply and demand, and maintaining overall grid stability. Thus, a growing body of research reflects both academic and industrial interest in predictive analytics in smart grids, an interest further amplified by rapid advancements in AI and its demonstrated impact across other sectors (Khalid, 2024; Kindong et al., 2024; Olufemi A. & Haoran, 2021; You et al., 2020; Yu et al., 2024).

Recent studies on predictive analytics in smart grids can be broadly grouped into three interrelated research streams. The first focuses on integrating AI into smart grid planning, management, and operations, emphasizing improvements in system efficiency, reliability, and automated control (Arévalo & Jurado, 2024; Bose, 2017; Kindong et al., 2024; Li et al., 2024; Marques & Oliveira, 2024; Olufemi A. & Haoran, 2021). The second examines forecasting and risk prediction, such as forecasting energy demand, predicting outages, and addressing cybersecurity risks, including the integration of blockchain-based distributed ledger technologies to support energy automation and trust (Cao et al., 2023; Idima et al., 2023; Kehkashan et al., 2024; Li et al., 2024; Pandya, 2021; Zhongtuo et al., 2020). The last addresses system-level optimization, such as grid stability and peak load management, with increasing attention to deep learning and reinforcement learning approaches for real-time optimization and adaptive control (Barth et al., 2022; Boopathy et al., 2024; Ferreira et al., 2019; José R. & Zoltán, 2019; Khan et al., 2022; Shi et al., 2018; Zhongtuo et al., 2020).

While recent literature on predictive analytics has demonstrated significant potential to enhance smart grid performance, its capabilities have not emerged fully formed but have developed progressively alongside advances in technology, data availability, and organizational readiness. This co-evolution reflects increasing levels of digital innovation maturity and institutional adaptation (Webster & Gardner, 2019), making it essential to examine how predictive analytics has evolved over time to understand its current role and future trajectory within smart grid systems.

3.3 The evolution of predictive Analytics

Previous studies on predictive analytics in smart grids have evolved from early rule-based and statistical models to advanced machine learning and AI techniques capable of handling complex, high-volume data. Predictive models are the algorithms that produce predictions, while predictive analytics is the overarching analytical framework that uses these models to support decisions and optimize system performance in smart grids. This evolution has become increasingly sophisticated, moving from basic statistical methods for load forecasting to advanced techniques capable of addressing the complexities of modern energy systems (Fan & McDonald, 1994; Syed et al., 2020). This shift has moved away from early approaches that primarily employed time series analysis and regression, using historical consumption and weather data. Moreover, this evolution has been driven by the increased accessibility of powerful computing resources, which facilitate broader experimentation of various forecasting methods, and by the rise of non-linear techniques for tackling challenging problems (Fan & McDonald, 1994; Garulli et al., 2014). The integration of intelligent components and the grid's increasing complexity have further accelerated the need for precise demand and generation forecasting. Hernandez et al. (2014) examines the key research in electricity demand prediction spanning the last 40 years, showcasing the evolution of models and projecting future trends. This highlights the evolution of predictive models in smart grids and reflects a transition from fundamental statistical tools to intricate AI-powered solutions driven by data growth, computational progress, and the imperative for a more efficient and resilient energy future (Garulli et al., 2014; Hernandez et al., 2014).

Furthermore, predictive analytics has evolved over the years, and many diverse forecasting models have been employed for electricity and power predictions, because no single model has achieved universal consensus nor capable of meeting future challenges. Thus, it has continued to evolve with different approaches ranging from statistical methods such as multivariate regression, multiple regression, and Support Vector Machines (SVM) (Garulli et al., 2014; Kuster et al., 2017) to time series analysis techniques, such as Auto-regressive Moving Average (ARMA) (Fan & McDonald, 1994), and increasingly, artificial neural networks (ANN) for tasks like short-term load forecasting in microgrids, building-level optimization, and long-term regional consumption prediction (Kuster et al., 2017). This evolution provides a choice of models that often depends on expert preference, since there is no one-size-fits-all model. Thus, research on predictive analytics continues to evolve as different stakeholders have varying preferences and priorities; since some simpler methods can perform as well as, or better than, complex ones, highlighting the importance of identifying the most suitable model for a specific situation based on available data, timeframe, resolution, and scale. This evolution has also been influenced by the rapid development of AI.

3.4 AI and predictive Analytics

Research on integrating Artificial Intelligence (AI) into smart grids has grown in response to the increasing complexity and data volume of modern power systems (Bhattarai et al., 2019; Hu & Vasilakos, 2016). This is because traditional electromechanical grids have struggled to efficiently manage the bidirectional flow of energy and information resulting from distributed generation and demand-side management (El-Hawary, 2016; Faheem et al., 2018; Olufemi A. & Haoran, 2021). Thus, the late 20th and early 21st centuries have seen a rise in foundational research on applying computational intelligence to tasks such as load forecasting and essential grid control. Early research on AI applications in this field has involved expert systems and basic machine learning algorithms to enhance operational efficiency and reliability (Bose, 2017). The rise of digital technologies and the initial deployment of smart meters laid the groundwork for a more data-driven approach, paving the way for deeper AI integration.

Moreover, as smart grid infrastructure matured, the focus shifted to leveraging the vast amounts of collected data for proactive decision-making (Bhattarai et al., 2019; Hu & Vasilakos, 2016). This era marked the rise of predictive analytics as a critical component of smart grid functionality (Hu & Vasilakos, 2016; Kindong et al., 2024; Pandya, 2021). Initially, statistical methods such as time series analysis and regression dominated the forecasting of energy demand and renewable energy generation (Fan & McDonald, 1994; Kuster et al., 2017). However, the increasing availability of computational power and advancements in machine learning prompted the research on more sophisticated techniques, including machine learning, deep learning, artificial neural networks, and reinforcement learning (Barth et al., 2022; Boopathy et al., 2024; Bose, 2017; Cao et al., 2023; Chae et al., 2016). The research on AI-driven predictive models indicates huge potential for utilities to anticipate potential grid issues, optimize energy dispatch, enhance asset management through predictive maintenance, and ultimately strive for a more resilient and efficient energy future (Babayomi et al., 2023; Boopathy et al., 2024; Idima et al., 2023; Pandya, 2021). The ongoing evolution involves exploring deep learning and real-time analytics to refine predictive capabilities within smart grid environments (Boopathy et al., 2024; Zhongtuo et al., 2020). Moreover, this evolution is not limited to technology alone but has also seen an increase in the number of stakeholders, introducing new stakeholders and transforming the roles of existing ones.

Thus, the effectiveness of predictive analytics in smart grids also depends on stakeholders' expectations for how it should perform, how outputs should be interpreted, and how insights should be integrated into operational routines. Similarly, while research shows AI's potential to increase the computational power of predictive analytics, it also raises stakeholders' expectations regarding accuracy, transparency, interpretability, timeliness, and decision support. Furthermore, different stakeholders and organizations within the smart grid have distinct expectations of predictive analytics (cf. section 2.4), which must be aligned to enable adoption and integration into organizational routines. This is because expectations are crucial for legitimizing and guiding the use of digital technologies (Tona & Carlsson, 2013), while institutional structures shape how and whether such technologies are embedded in practice (Currie, 2011). Thus, in line Orlikowski and Scott (2008)'s sociomateriality, trust in predictive analytics within smart grids emerges when technological expectations align with everyday work practices, allowing the technology to be appropriated as a reliable, embedded part of smart grid operations.

Collectively, this literature demonstrates the technical potential of predictive analytics to support key smart grid functions, including demand forecasting, fault detection, predictive maintenance, and DER optimization (Ahmad et al., 2018; Bhattarai et al., 2019; Idima et al., 2023); and to enable proactive decision-making by analyzing historical and real-time data streams to anticipate disruptions, improve operational efficiency, and enhance system resilience (Cao et al., 2023; Kehkashan et al., 2024; Kindong et al., 2024; Li et al., 2024). For example, Cao et al. (2023) show how predictive models can identify potential failure points and maintenance needs, extend asset lifecycles, and reduce downtime in grid operations. These capabilities have positioned predictive analytics as a cornerstone of envisioned smart grid operations, but research has focused more on the technology, creating a sociotechnical gap.

3.5 Sociotechnical Gaps and Stakeholder Expectations

Despite rapid advances in predictive analytics for smart grids as seen in literature, previous studies have largely adopted a technocentric perspective, emphasizing computational efficiency, forecasting accuracy, and scalable algorithms, while paying limited attention to sociotechnical dynamics (Babayomi et al., 2023; Bhattarai et al., 2019; Diamantoulakis et al., 2015). Consequently, critical dimensions such as human factors, organizational practices, and stakeholder expectations remain underexplored, contributing to a persistent gap between theoretical advances and their effective adoption in real-world grid environments. This gap is evident in empirical studies that highlight organizational constraints, implementation challenges, immature integration strategies, and ongoing uncertainty about system performance and value realization (Bhattarai et al., 2019; Diamantoulakis et al., 2015; Zhang et al., 2018). Thus, from a sociotechnical systems perspective, these challenges are not merely technical shortcomings but misalignments between technological capabilities and the organizational and institutional contexts in which they are embedded (Dwyer, 2011). Accordingly, adopting and implementing predictive analytics requires the co-evolution of technical infrastructures, organizational routines, and governance mechanisms, rather than the isolated optimization of analytical models (Chen et al., 2023).

A central yet underdeveloped issue in this context is the role of stakeholder competing expectations (van Lente & Bakker, 2010). Smart grids involve a heterogeneous set of actors, including policymakers, regulators, grid operators, market participants, and end users, each operating under distinct institutional logics and priorities. These actors hold different expectations regarding the immediacy, accuracy, transparency, and operational value of predictive analytics; aligning these expectations is central to its diffusion, as predictive analytics increasingly operates as boundary infrastructure across organizational and institutional domains (Carlile, 2002; Gal et al., 2005). When such expectations diverge or remain uncoordinated, they hinder implementation efforts and exacerbate the mismatch between anticipated benefits and realized outcomes (Hansen et al., 2024). This challenge can be better understood through the dynamics of expectations in emerging technologies, where innovation trajectories are shaped by competing and evolving expectations that influence legitimacy, investment, and development (van Lente & Bakker, 2010). In this sense, expectations not only guide technological development but also shape how predictive analytics is interpreted and valued within the smart grid context. These insights challenge the implicit assumption in the existing literature that the value of predictive analytics is self-evident or technically guaranteed. Instead, its adoption and impact depend on how expectations are constructed, negotiated, and aligned among stakeholders within a complex sociotechnical system. To address this limitation, this thesis adopts Organizing Vision Theory (OVT) as its primary analytical lens. OVT conceptualizes technological innovations as shared interpretive frameworks that reduce uncertainty, legitimize investments, and mobilize collective action (Swanson & Ramiller, 1997; Swanson & Ramiller, 2004). In this study, predictive analytics in smart grids is positioned as a digital innovation, understood as an organizing vision. Its adoption depends on innovation and institutional readiness (Benson, 2019; Webster & Gardner, 2019), which are shaped by stakeholder expectations. It also serves as a focal point for aligning policy objectives, operational practices, market strategies, and user engagement.

By framing predictive analytics in the smart grid as an organizing vision, the analysis shifts from a purely technical focus to the sociotechnical processes by which meaning, legitimacy, and coordinated action are established. This perspective enables examination of how expectations are articulated, legitimized, and enacted across policy, operational, and market domains, thereby shaping the adoption and governance of predictive analytics in the transition toward resilient and sustainable energy systems. In doing so, the study moves beyond dominant narratives that position predictive analytics solely as a technical solution for reducing uncertainty and enhancing grid resilience (Arnold, 2011; Dhara et al., 2022; Lopez et al., 2018; Zhongtuo et al., 2020), advancing instead a sociotechnical framing that emphasizes the role of stakeholder expectations in shaping both adoption and ongoing use.

Thus, these sociotechnical gaps underscore that successful adoption of predictive analytics in smart grids requires more than technical analysis; it demands a framework that explains how expectations are constructed, aligned, and translated into coordinated action. Accordingly, the following section introduces the study's theoretical framework, grounded in OVT (Swanson & Ramiller, 1997) and complemented by sensemaking theory (Weick, 1995), to examine how predictive analytics is socially constructed, legitimized, and enacted within the smart grid ecosystem.

3.6 Theoretical Framework

The transition toward resilient and sustainable energy systems through smart grids is shaped not only by technological innovation but also by how stakeholders make sense of predictive analytics through expectations about the potential benefits of emerging digital capabilities. Prior research suggests that the adoption and effective use of digital innovations depend on perceived utility, novelty, regulatory burden, cost, skill requirements, and associated risks (Benson, 2019; Webster & Gardner, 2019). Consequently, the successful adoption of predictive analytics in the smart grid depends on how stakeholders' expectations regarding these factors are constructed, legitimized, and translated into collective action. Moreover, research shows that advanced analytics, AI, and digital infrastructure are inherently ambiguous innovations, with uncertain value propositions, contested implementation pathways, and benefits that often materialize only through ecosystem-wide coordination rather than isolated organizational decisions (Bharadwaj et al., 2013; Swanson & Ramiller, 1997). Therefore, adoption depends critically on shared interpretations, legitimacy, alignment among heterogeneous stakeholders, and perceived benefits.

Thus, in the smart grid context, predictive analytics is embedded within a complex socio-technical system comprising policymakers and regulators, grid operators (e.g., TSOs, DSOs), market actors, and energy users. These actors operate under differing institutional logics (Berente et al., 2019), regulatory and institutional constraints (Currie, 2011), and technological capabilities, making the alignment of expectations challenging and consequential. Understanding the interplay between expectations and thought on the adoption of predictive analytics in smart grid contexts, therefore, calls for a theoretical lens that captures how multiple expectations are articulated, circulate across fields, acquire legitimacy, and become mobilized among interdependent actors. Rather than reducing adoption to individual acceptance decisions, the OVT lens foregrounds the shared visions that coordinate action across organizational, professional, and institutional boundaries, making it particularly well-suited to settings characterized by heterogeneous stakeholders and distributed agency.

3.6.1 Organizing Vision Theory as an analytical lens

Organizing Vision Theory (OVT) explains how emerging innovations are collectively understood, justified, and implemented within organizational fields. Originally developed by Swanson and Ramiller (1997) OVT, conceptualizes the diffusion of innovations not merely as a technical process, but as a socially constructed phenomenon shaped through discourse among diverse stakeholders. At the core of OVT is the notion of an organizing vision, defined as a shared, evolving interpretation of an innovation that enables coordination across organizations and actors. This vision is constructed and disseminated through what the theory terms community discourse, involving consultants, vendors, industry analysts, and adopting organizations. Through this discourse, the innovation acquires meaning, legitimacy, and practical direction.

Moreover, OVT is anchored in three interrelated processes (Interpretation, legitimation, and mobilization) necessary for the organization of vision to mature. Interpretation refers to developing a shared understanding of the innovation, clarifying what it is and how it should be perceived. Due to the inherent ambiguity of new technologies, interpretation allows multiple actors to project their own interests and expectations onto the innovation. This is preceded by legitimation, the process by which the innovation is justified and gains acceptance. This is often achieved through success stories, benchmarking, and appeals to institutional norms, which position adoption as both rational and necessary. This lays the necessary groundwork for mobilization, which involves activating the resources and actions required for implementation, including investments, organizational restructuring, and stakeholder alignment. These three concepts highlight OVT's emphasis on ambiguity as a productive feature rather than a limitation. The lack of a fixed meaning enables broader participation and adaptation across contexts, thereby facilitating diffusion. At the same time, the organizing vision evolves, typically following a lifecycle from emergence and expansion to eventual stabilization or decline as competing visions arise.

Thus, this study adopts OVT as an analytical lens, situating predictive analytics in the smart grid within a broader socio-institutional context and highlighting how its adoption is shaped by multiple sensemaking processes rather than purely technical considerations. This perspective is particularly useful for understanding contemporary innovations marked by high uncertainty and strong external influences. Hence, this thesis adopts OVT as its primary theoretical lens to examine how stakeholders involved in smart grids make sense of predictive analytics, and how expectations, experiences, and considerations surrounding adoption are socially constructed and institutionalized. OVT explains how shared narratives and interpretations about a technology influence how organizations interpret, legitimize, and adopt it (Swanson et al., 2025; Swanson & Ramiller, 1997). Rather than focusing solely on technical characteristics or rational decision-making, OVT emphasizes the collective discourse created by vendors, consultants, media, academics, and practitioners, which shapes perceptions of what a technology is, why it is significant, and how it should be implemented (Swanson & Ramiller, 2004; Tona & Carlsson, 2013). These shared visions help organizations interpret innovation, justify investment decisions, and coordinate actions across organizational fields. Consequently, organizing visions highlight the social and institutional processes through which technologies acquire meaning and drive organizational change, framing information technology innovations as accompanied by evolving narratives that define their purpose, relevance, and implementation pathways (Swanson & Ramiller, 1997; Swanson & Ramiller, 2004). Through processes of interpretation, legitimation, and mobilization, organizing visions reduce uncertainty and enable diverse actors to coordinate expectations and actions amid technological and institutional ambiguity. This perspective allows predictive analytics to be examined not only for their technical capabilities but also as a socio-organizational construct that shapes and is shaped by collective sensemaking within the smart grid ecosystem.

Moreover, OVT is particularly well-suited to addressing the first research question, which examines how smart grid stakeholders understand and envision the role of predictive analytics in enhancing grid resilience. The contribution of predictive analytics to resilience, through capabilities such as anticipatory maintenance, demand forecasting, and adaptive control, is rarely self-evident and must instead be articulated through interpretive narratives. Furthermore, organizing visions provides a shared frame (Orlikowski & Gash, 1994) through which stakeholders link analytics capabilities to broader goals of reliability, sustainability, and intelligent energy management. Moreover, IS research shows that analytics and digital innovations often diffuse through compelling visions that align managerial aspirations, vendor narratives, and institutional priorities, even when empirical evidence of realized benefits remains limited or contested (Tona & Carlsson, 2013). Such visions operate as shared sensemaking devices that help actors interpret technological ambiguity and coordinate action.

3.6.2 Sensemaking Theory as a Complementary Analytical Lens

Building on OVT as the primary analytical lens, this study also draws on Sensemaking Theory, primarily associated with Weick (1995), to further explain how individuals and organizations interpret and act upon predictive analytics in smart grids. Sensemaking is the process by which actors construct meaning in situations characterized by ambiguity and uncertainty. Rather than passively receiving information, individuals actively interpret cues from their environment and retrospectively create coherent narratives that guide action. Key characteristics of sensemaking include its retrospective nature (understanding emerges after action), its social embeddedness (meanings are shaped through interaction), and its reliance on plausibility rather than accuracy. In organizational contexts, this implies that adoption decisions are driven less by objective evaluations and more by shared interpretations that appear reasonable and credible. In relation to OVT, sensemaking operates at the micro-level, complementing the macro-level discourse of organizing visions. While OVT explains how a shared narrative around an innovation is formed across a field, sensemaking explains how actors within organizations interpret, negotiate, and enact that narrative in practice. Hence, sensemaking theory provides a complementary theoretical foundation for understanding how actors interpret ambiguous technologies and translate these interpretations into practice. Moreover, sensemaking theory emphasizes that meaning is constructed retrospectively through ongoing interactions, which is grounded in actors' identities, experiences, and situated contexts (Weick, 1995, 2012). In research, sensemaking is central to post-adoptive use and value realization, as organizational actors continuously interpret how technologies afford actions and outcomes (Hsieh et al., 2011; Sen et al., 2022). During complex implementations, such as enterprise systems or sustainability-oriented technologies, sensemaking processes shape how users reconcile competing interpretations, negotiate affordances, and stabilize patterns of use over time (Mesgari & Okoli, 2019; Tan et al., 2020). Thus, technological value does not emerge automatically from adoption but is enacted through distributed sensemaking processes.

While sensemaking theory provides a strong foundation for understanding how technological value emerges, OVT shifts the analytical focus from intra-organizational meaning construction to collective sensemaking among heterogeneous actors. Beyond explaining how individuals and organizations interpret and enact technologies in situated contexts, OVT clarifies how shared interpretations are constructed, legitimized, and mobilized through public discourse, industry narratives, and institutional framing (Swanson et al., 2025; Swanson & Ramiller, 1997). In this sense, organizing visions can be understood as field-level sensemaking structures that stabilize meaning, coordinate expectations, and guide action across organizational boundaries. By integrating sensemaking theory with OVT, this thesis captures both the micro-processes through which stakeholders interpret predictive analytics and the macro-level visions that align those interpretations into a coherent, actionable understanding of analytics-driven resilience in smart grids. This integration provides a more comprehensive explanation of how predictive analytics moves from technological possibility to collectively enacted infrastructure within a complex socio-technical system.

3.6.3 Diverse Visions as Micro-Level Institutional Logics

While institutional theory offers valuable insights into IT adoption by emphasizing legitimacy, isomorphic pressures, and compliance with established regulatory, normative, and cognitive structures (Currie, 2011; Thorén et al., 2018), this thesis selects OVT as its primary analytical lens because of its closer alignment with the research aim and questions. Institutional theory is particularly effective in explaining stabilized patterns of innovation diffusion (Rogers et al., 2014) and conformity once technologies have become taken for granted within a field, but it is less precise in accounting for how specific expectations about emerging technologies are initially constructed, contested, and revised over time. To address this, the thesis conceptualizes diverse visions as micro-level processes through which institutional logics are constructed, negotiated, and enacted. More so, OVT foregrounds discourse, expectations, and narratives as central analytical objects and conceptualizes legitimacy as an ongoing and contested accomplishment rather than a static condition (Swanson & Ramiller, 1997; 2004). This makes OVT especially suited to examining how diverse smart grid stakeholders come to envision the role of predictive analytics in enhancing grid resilience under conditions of technological and institutional uncertainty. Importantly, OVT complements rather than replaces institutional theory, as shown by Wagner et al. (2018) the institutionalization of technological ideologies such as analytics through repeated articulation and socio-material reproduction. OVT thus provides the conceptual tools to capture these early and intermediate processes of sensemaking and mobilization, aligning with research on institutional logics that highlights how multiple, and often competing, logics shape organizational responses to new technologies (Berente et al., 2019).

Thus, OVT is particularly well-suited to addressing the second research question, which examines the interplay between expectations and thoughts about adoption and development. Unlike socio-technical perspectives that emphasize local enactment (Orlikowski & Scott, 2008), OVT operates at the organizational level and captures the inter-organizational coordination required in smart grids. This includes cross-organizational data sharing, regulatory alignment, industry standards, and long-term infrastructure investments. In this way, OVT enables analysis of how stakeholders' expectations are formed and negotiated, and how they guide collective action across organizational and institutional boundaries (Löwstedt, 1993; Swanson & Ramiller, 2004).

4 Method

This chapter outlines the methodological foundation and research design underpinning this thesis. It begins by articulating the philosophical standpoint that informs the study, clarifying the ontological and epistemological aspects that shape how actors involved in smart grids make sense of predictive analytics through their expectations, experiences, and considerations surrounding adoption. Building on this foundation, the chapter then justifies the overall methodological approach adopted to address the research questions. Furthermore, the chapter introduces and contextualizes the empirical setting through a detailed case description, outlining the characteristics of the Swedish smart grid context and the rationale for its selection. It then describes the data collection methods employed, including data sources, sampling strategies, and procedures for gathering empirical material. Finally, the chapter describes the data analysis used and addresses quality and ethical considerations, detailing how issues such as informed consent, confidentiality, and research integrity were managed throughout the research process.

4.1 Philosophical standpoint

This thesis, like any research examining how emerging digital innovations are envisioned, adopted, and reshaped through practice, is grounded in a philosophical tradition that foregrounds meaning, interpretation, and context (Merriam & Tisdell, 2016; Stake, 1978). This is particularly relevant when the study focuses not solely on technological outcomes but on how stakeholders' expectations of a technology shape their thoughts on adoption and development. In such settings, the research design aligns the researcher's worldview, methodological approach, and methods used to investigate how expectations and thoughts on adoption are constructed, negotiated, and enacted over time. Thus, the research questions (cf. Section 1.2) of this thesis examine how stakeholders understand, envision, and view the adoption of predictive analytics within the smart grid context, grounding my philosophical assumptions within an interpretive research tradition that assumes that reality is socially constructed, and there is no single objective truth (Creswell & Creswell, 2017; Merriam & Tisdell, 2016). Instead, there are multiple ways to understand the same event. In this view, researchers do not simply discover knowledge; they actively create or shape it through interpretation (Creswell & Creswell, 2017; Merriam & Tisdell, 2016). This perspective is well-suited to exploring how diverse actors, such as policymakers/regulators, grid operators, market actors, and energy users, develop and reconcile expectations regarding the role of predictive analytics in enhancing grid resilience.

This thesis's focus emerged from recognizing that the adoption of predictive analytics in smart grids is driven not only by technical capability but also by the alignment of expectations among heterogeneous stakeholders and by institutional readiness. These expectations concern anticipated benefits, skill demands, associated risks, regulations, cost feasibility, legitimacy, and contributions to a resilient energy future. Consequently, the study places particular emphasis on stakeholder interactions and on how expectations shape perceptions of adoption and use. Moreover, the empirical focus on the Swedish smart grid context reflects the assumption that expectations and thoughts about adoption are inherently situated phenomena. Consistent with qualitative and interpretive traditions, this study treats knowledge as context-dependent and shaped by institutional arrangements, societal conventions, and historically situated practices (Becker & Niehaves, 2007; Merriam & Tisdell, 2016). The meanings attributed to predictive analytics and thoughts about potential adoption are therefore understood in relation to the specific regulatory, organizational, and technological conditions of the Swedish smart grid context.

This orientation informs the study's ontological stance. Rather than assuming a single objective reality, the research adopts a constructivist ontology in which multiple realities emerge through stakeholders' experiences and interpretations (Becker & Niehaves, 2007; Creswell & Creswell, 2017). From this perspective, predictive analytics adoption and stakeholder expectations are not fixed phenomena but are continuously constructed through interactions among human actors (e.g., decision-makers, analysts, and engineers) and non-human elements (e.g., predictive models, data infrastructures, reports, policy documents, and analytical tools) within the smart grid (Orlikowski & Robey, 1991).

Epistemologically, knowledge about the interplay between expectations and thoughts on adoption is produced through the interaction between the researcher and the phenomenon under study (Becker & Niehaves, 2007; Creswell &

Creswell, 2017; Merriam & Tisdell, 2016). Thus, understanding how predictive analytics is envisioned and enacted in smart grids emerges through interpretive engagement with empirical material, where meaning is constructed through analysis rather than discovered as an objective fact. Because what constitutes successful or problematic adoption is understood through stakeholders' accounts and experiences, interpreted in relation to the sociotechnical configurations in which predictive analytics is embedded (Becker & Niehaves, 2007; Hirschheim, 1985).

Given the philosophical underpinnings discussed above, this thesis's underlying assumption is grounded in a *social constructivist tradition* (Becker & Niehaves, 2007; Hirschheim, 1985; Merriam & Tisdell, 2016; Orlikowski & Baroudi, 1991). Thus, this thesis acknowledges that the researcher is actively involved in making sense of the interplay between stakeholders' expectations and their views on the adoption of predictive analytics. It also examines how these expectations are articulated, legitimized, and revised as adoption unfolds. Meaning is thus co-produced through ongoing engagement with the research setting and its actors. Moreover, in terms of the logic of inquiry, the study adopts an interpretive case study, combined with an iterative approach between theory and empirical data (Langley, 1999; Walsham, 1995). This approach moves between organizing vision theory and empirical observations, allowing stakeholder expectations to be analyzed as evolving narratives that both shape and inform thoughts on adoption. Although individual studies referenced in this thesis may draw on different methodological approaches (for example, the action method in the first paper), the thesis, as a coherent whole, applies an iterative logic to integrate empirical findings and theoretical insights. Furthermore, examining the interplay between stakeholders' expectations and the adoption of predictive analytics in smart grids requires understanding multiple perspectives through sensemaking and socially constructed meanings (Hirschheim, 1985; Langley, 1999; Merriam & Tisdell, 2016). Moreover, predictive analytics in smart grids is socio-technically constructed, requiring analysis of how expectations are formed, contested, and adjusted through experience. Thus, qualitative methods are necessary to generate rich, contextualized insights into the dynamic relationship between technological innovation, stakeholder expectations, and adoption within the smart grid context.

4.2 Methodological Approach

Building on the study's ontology and epistemology outlined in the previous section, this thesis adopts a methodological approach that explicitly examines how meanings, expectations, and practices surrounding predictive analytics are constructed and enacted within the smart grid context. Methodology, in this sense, refers not simply to a set of techniques but to the overarching logic that links philosophical assumptions to research design, data collection, and analysis (Bryman, 2008; Mackenzie & Knipe, 2006). The methodology provides the rationale for why particular methods are appropriate for examining the research problem and how they collectively support the study's analytical aims. Thus, given the thesis's focus on how stakeholders involved in smart grids make sense of predictive analytics through their expectations, experiences, and considerations surrounding adoption, an interpretive case study approach (Walsham, 1995) is used. This is because interpretive case studies are particularly suitable for investigating complex, context-dependent phenomena in which multiple actors hold differing interpretations and causal mechanisms are intertwined with social, institutional, and technological conditions (Langley, 1999; Merriam & Tisdell, 2016; Stake, 1978; Walsham, 1995; Walsham, 2006). Moreover, the thesis does not seek generalizable laws but aims to generate in-depth, contextually grounded insights into how predictive analytics is understood, legitimized, and operationalized in practice. And considering that predictive analytics in smart grids cannot be meaningfully separated from the organizational, regulatory, and infrastructural contexts in which it is embedded. But rather a socio-technical innovation that emerges through the interaction of digital infrastructures, analytical models, organizational routines, policy frameworks, and stakeholder relationships. Hence, the choice for an interpretivist case study approach is justified as it enables the examination of these interdependencies as they unfold in a real-world setting, allowing the study to capture both expectations and experiences of adoption in the real world (Langley, 1999; Merriam & Tisdell, 2016; Stake, 1978; Walsham, 1995).

The study is designed as an embedded single-case study, focusing on the Swedish smart grid context as a theoretically and empirically rich setting. Sweden is a particularly relevant case because of its advanced digital infrastructure, strong policy emphasis on the energy transition, and active involvement of multiple stakeholders in smart grid initiatives. Within this single case, multiple embedded units of observation are examined, including policymakers and regulators, grid operators (TSO/DSO), market actors (energy management system), and other stakeholders involved in the development and use of predictive analytics. This design enables exploration of both shared and divergent expectations among actors and how these expectations influence thoughts on adoption.

Also, the study adopts Klein and Myers (1999)'s seven principles (Hermeneutic circle, contextualization, interaction between researchers and participants, abstraction and generalization, dialogical reasoning, multiple interpretations, and suspicion) as a guiding framework for conducting and evaluating the process. Thus, the data collection and analysis are guided by the principle that knowledge is co-produced through engagement between the researcher and the research setting (Langley, 1999; Merriam & Tisdell, 2016; Walsham, 2006). This approach is anchored on its flexibility and reflexivity, which enable iterative movement between empirical material and theoretical concepts (Arksey & O'malley, 2005; Klein & Myers, 1999). This is particularly important for examining the interplay between expectations and thoughts on the adoption of predictive analytics, where meanings and interpretations evolve as stakeholders gain experience with the technology. Also, the methodological approach is rigorous and ensures research quality and ethics, with strategies for ensuring credibility, dependability, and transparency (AIS, 2014; Klein & Myers, 1999; Vetenskapsrådet, 2025) embedded throughout the research process, alongside careful attention to ethical standards, and provides the foundation for the case study design.

4.2.1 Case Study Design

Consistent with the interpretive case study approach (Walsham, 1995) outlined above, this study adopts an embedded single-case study design (Yin, 2018) to examine how stakeholders' expectations shape perceptions of the adoption and development of predictive analytics within the smart grid context. An embedded case study design is particularly appropriate when the phenomenon of interest comprises multiple units of observation that are analytically distinct yet collectively constitutive of the overarching case. The overarching case in this thesis is predictive analytics in the Swedish smart grid, and the phenomenon is how stakeholders involved in the smart grid make sense of predictive analytics through their expectations, experiences, and considerations surrounding adoption. This phenomenon is inherently socio-technical and cannot be meaningfully separated from its real-world context, including regulatory frameworks, organizational arrangements, digital infrastructures, and stakeholder relationships (Yin, 2018). Accordingly, the study employs an interpretive case study approach (Langley, 1999; Merriam & Tisdell, 2016; Stake, 1978; Walsham, 1995), which is well-suited to understanding how different stakeholders interpret, negotiate, and enact the value and perceptions of adopting predictive analytics.

4.2.2 Description of the Swedish smart grid

In line with Yin's (2018) emphasis on grounding case studies in their contextual conditions, this study is situated within the development and contemporary digital transformation of Sweden's national power grid. The Swedish grid captures this transformation and reflects today's modern grids. It highlights how Sweden's electricity system has evolved from small, locally powered grids established after the first public power plant in Härnösand in 1885 (Svenska kraftnät, 2014) into a nationwide interconnected network spanning four electricity zones (Svenska kraftnät, 2021). This expansion, which began by linking local grids via high-voltage transmission lines, ensured that electricity generated in the hydro-rich north is supplied to the south (Liikamaa, 2019; Svenska kraftnät, 2014). Additionally, the expansion included integrating advanced information and communication systems, turning the grid into a smart grid that supports the integration of variable renewable energy, manages increasing system complexity, and employs sophisticated monitoring and defense features to maintain reliability amid rising demand and sustainability challenges (Idima et al., 2023; Lopez et al., 2018; Singh et al., 2025; Zohuri, 2023). In Sweden, Svenska kraftnät (SvK) owns and controls the national high-voltage transmission network, while regional and local DSOs, including Vattenfall Eldistribution, Ellevio, E.ON Elnät Sverige, and Tekniska Verken, operate and manage the distribution of low-voltage electricity to businesses and households (Liikamaa, 2019).

Sweden operates one of the world's oldest power grids, with the first public power infrastructure established in Härnösand in 1885 and early expansion to Stockholm by 1892 (Svenska kraftnät, 2014, 2021). Initially designed to supply electricity to a limited number of users and to power street lighting through the Stockholm Gasworks' electrical division, the grid has evolved over more than a century into a highly integrated national grid. Despite its robustness and historical reliability, significant parts of the transmission and distribution infrastructure are now approaching the end of their technical lifespan. This aging infrastructure, pressure from climate change, and growing electricity demand have accelerated the transition to a smart grid by integrating renewable energy and information and communication technologies, thereby shaping the technological, institutional, and temporal conditions that characterize the phenomenon under investigation (Yin, 2018). In the Swedish context, several interrelated pressures are driving the need for new approaches to grid management and coordination. These include an aging, capacity-constrained electricity infrastructure, accelerating electrification across sectors such as transport and industry, and the rapid growth of intermittent renewable energy sources. These developments are accompanied by evolving market and regulatory requirements for reliability, flexibility, and efficiency (Svenska kraftnät, 2022, 2024), as well as heightened societal expectations for a sustainable and resilient energy system.

Together, these pressures heighten the complexity and uncertainty of grid operations, thereby amplifying the importance of advanced forecasting, coordination, and decision-support capabilities. Predictive analytics has consequently emerged as a key digital innovation for anticipating demand peaks, managing variability in renewable generation, and informing both short-term operational decisions and long-term infrastructure investments. This is reflected in Sweden's ambition to establish a centralized data hub to improve market flexibility, electricity trading, and forecasting. At the same time, the role and value of predictive analytics are not self-evident; they must be articulated, legitimized, and enacted by multiple stakeholders operating under different constraints and expectations.

Moreover, the Swedish electricity system integrates structural and institutional practices into its energy transition, engaging energy management system providers, vehicle-to-grid initiatives, transmission system operators, and policymakers within a dynamic smart grid landscape shaped by technological change, regulatory reform, and sustainability ambitions. Thus, the Swedish case is evolving, with an organizing vision that advances digital innovation for the smart grid, emerging from stakeholders’ expectations and perspectives on the adoption of predictive analytics in real-world smart grid settings.

4.3 Data Collection Methods

To examine how stakeholders' expectations and views on the adoption of predictive analytics are constructed, enacted, and revised, this study employs a qualitative, multiple-method data collection strategy. Consistent with the interpretive and iterative process outlined earlier, the data collection involved semi-structured interviews, document analysis, and literature reviews (Arksey & O'malley, 2005; Merriam & Tisdell, 2016) to capture both discursive constructions of predictive analytics and stakeholders' views on its adoption in practice. Using multiple data sources enables methodological triangulation, enhancing the study's credibility and analytical depth by allowing insights to be examined across different forms of empirical material (Merriam & Tisdell, 2016). Together, these data sources provide insight into how predictive analytics is envisioned at the theoretical and policy levels, how it is framed and governed institutionally, and how it is understood and enacted by stakeholders within the smart grid context. This supports the study's aim of analyzing predictive analytics not only as a technical innovation but also as a socio-technical and institutional phenomenon shaped by expectations, legitimacy, and perceptions.

Moreover, within this single case, multiple embedded units of observation, involving different organizations, are examined at the organizational level to capture variation in expectations, experiences, and thoughts on adoption across the Swedish smart grid, which serves as the overarching case. First, an energy management system company is studied to examine the development, configuration, and deployment of predictive analytics solutions. This company develops advanced software platforms, large-scale batteries, and load management systems designed to support renewable energy integration and grid stability. Studying this company provides insight into how predictive analytics is envisioned, engineered, and operationalized within commercial and technical constraints. Second, the Swedish transmission system operator (TSO), responsible for ensuring that Sweden's electricity transmission system is secure, environmentally sustainable, and cost-effective over time, is selected as both an organizational unit and a building energy management platform. Third, stakeholders involved in vehicle-to-grid (V2G) initiatives, such as participants associated with the Swedish Electromobility Center and the BULT project (Sönne, 2023), as well as other stakeholders involved in the digitalization of sustainable power systems. These diverse actors offer perspectives on how predictive analytics is interpreted, adopted, and experienced within the smart grid, where forecasting demand, coordinating flexibility, and balancing grid stability are central concerns. In addition to stakeholders' perspectives, the study incorporates policy documents and annual reports as a process or program unit of analysis. It analyzes policy documents, reports, and strategic materials produced by grid operators (TSOs/DSOs), policymakers and regulators (e.g., Svenska kraftnät, Energiforsk), and market actors (e.g., Bixia, EMS, and building energy management) to understand how predictive analytics is framed, legitimized, and promoted within the Swedish energy sector. This document analysis is complemented by interview and observational data and reveals how expectations surrounding predictive analytics are articulated at the institutional and field levels.

Thus, examining these interconnected embedded units clarifies predictive analytics as both a technical forecasting tool and a sociotechnical mechanism that aligns diverse stakeholders around shared goals of grid resilience and sustainability (European Commission, 2022; Lopez et al., 2018). Overall, the embedded single-case design uses multiple data sources to enable a rich, context-sensitive examination of how the adoption of predictive analytics in smart grids unfolds through interactions among expectations, technologies, and stakeholder practices. By converging and diverging across multiple data sources, the study provides a nuanced account of how stakeholders in smart grids make sense of predictive analytics through their expectations, experiences, and considerations surrounding adoption. The next section provides an overview of data collection.

4.3.1 An Overview of the Data Collection Methods

Data collection was structured into three complementary phases: (1) a systematic literature review, (2) document analysis, and (3) semi-structured interviews. These phases are sequenced yet analytically interrelated through an iterative process. The literature review establishes the study's conceptual and theoretical foundations by mapping existing research on predictive analytics, smart grids, and socio-technical perspectives on digital innovation. The document analysis then situates these theoretical insights within the institutional and organizational context of the Swedish smart grid, examining how predictive analytics is articulated, justified, and governed in practice. Finally, semi-structured interviews capture how stakeholders make sense of predictive analytics through their interpretations, experiences, and reflections on its adoption and use within smart grid initiatives. Moreover, these methods produced published papers and contributed to the overall thesis research questions, as shown in Table 2. As illustrated in Figure 4, these phases collectively enable triangulation across academic discourse, institutional narratives, and stakeholders' experiences. This triangulated design allows the study to investigate how stakeholders make sense of predictive analytics; how, through stakeholders' expectations, predictive analytics is envisioned, implemented, and legitimized within the smart grid context; and how such expectations shape thoughts on adoption and development.

Table 2 Overview of Research Method and contribution to thesis

Method	Key Activities	Publication	Contribution to Thesis
Literature Review	Comprehensive review of 54 articles	Paper one	RQ1
Document analysis	Selected and analyzed 45 documents (policy documents, technical guidelines, project and annual reports)	Paper three	RQ2
Semi-structured interviews	Conducted 9 interviews with 12 participants	Paper two	RQ1 and RQ2

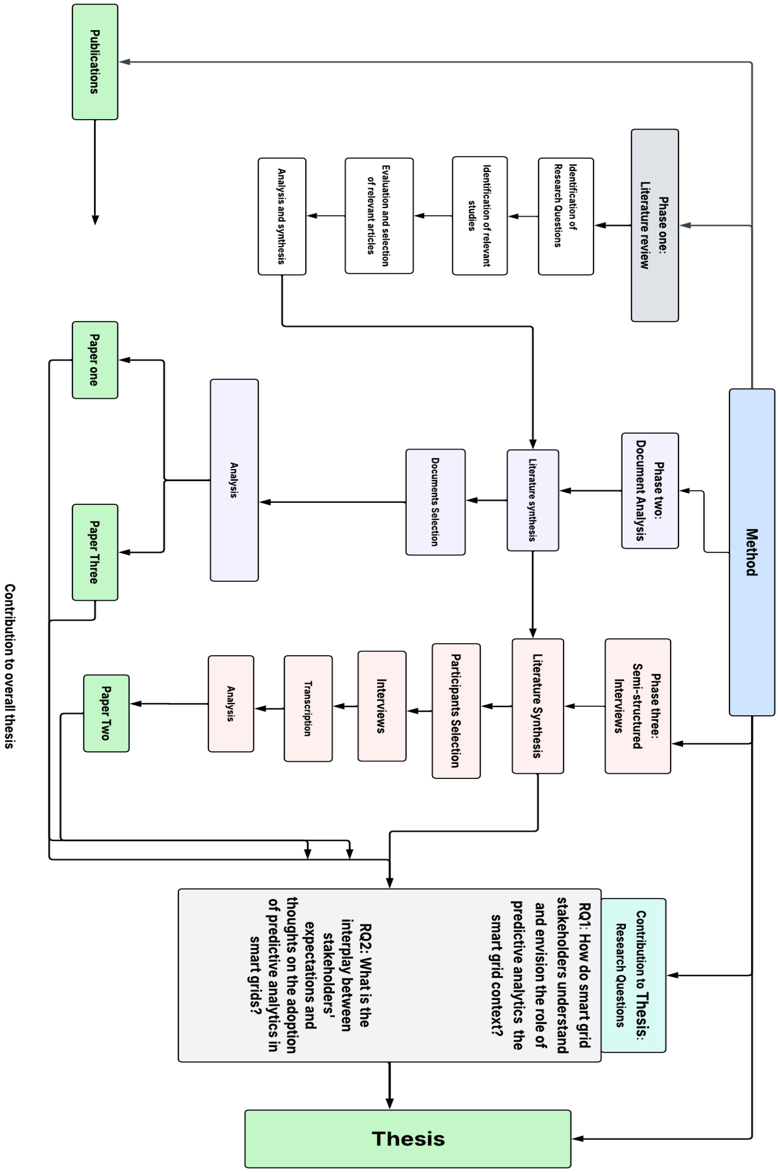

Figure 4 : An overview of the Thesis Data Collection method

4.3.2 Literature Review

The literature review serves as the analytical foundation of the thesis by systematically mapping prior research (Webster & Watson, 2002) relevant to predictive analytics, smart grid resilience, and information systems approaches to digital innovation. It encompasses scholarly work on advanced analytics and artificial intelligence in energy systems, smart grid development and resilience strategies, and Information Systems theories concerned with technology adoption, institutionalization, and stakeholder coordination (Berente et al., 2019; Currie, 2011; Leonardi, 2011; Orlikowski & Scott, 2008; Swanson & Ramiller, 1997; Venkatesh et al., 2003). Moreover, in addition to establishing the theoretical grounding for the study, the literature review supports an iterative process by sensitizing the researcher to key concepts and debates that inform the interpretation of the empirical material (Langley, 1999). It provides the conceptual basis for understanding predictive analytics as an ambiguous and evolving digital innovation whose value is shaped through discourse, institutional alignment, and practice. The review also identifies gaps in existing research, particularly between theoretical promises and operational adoption of predictive analytics. And how stakeholder expectations influence the adoption and long-term development of predictive analytics within complex, multi-actor energy systems. The review was followed by a document analysis discussed next.

4.3.3 Document Analysis

Document analysis examined how predictive analytics is framed, legitimized, and operationalized within the Swedish smart grid context. The analyzed materials included annual reports (n=15), project reports (n=16), regulatory guidelines and frameworks (n=8), and technical descriptions (n=7) produced by policymakers, grid operators, market actors, and research organizations engaged in electricity system management and digitalization, as seen in Table 3. In total, 46 documents, comprising approximately 2,329 pages, were analyzed, as shown in Appendix A. The documents were selected purposively based on the following criteria: (1) relevance to smart grid development and digitalization, (2) explicit discussion of predictive analytics (forecasting, predictive maintenance, real-time measurement, electricity consumption pattern and trends), data governance, flexibility, or resilience, (3) publication between 2015 and 2025 to capture contemporary institutional developments, and (4) provenance from authoritative actors (e.g., Swedish Energy Agency, transmission and distribution system operators, Swedish Energy Markets Inspectorate, EMS vendors, and non-profit, industry-owned research institute).

Table 3: Summary of documents analyzed

Document Type	Number of documents analyzed
Annual Report	15
Project Report	16
Regulatory guidelines/framework	8
Technical description	7
Total	**46**

4.3.4 Semi-Structured Interviews

Semi-structured interviews constitute the primary source of empirical data for understanding how stakeholders interpret and enact predictive analytics within the smart grid context. Using purposive sampling to capture information-rich perspectives (Tongco, 2007), interviews were conducted with actors from: (1) an Energy Management System (EMS) company, a technology provider that develops software and hardware to monitor, control, and optimize energy flows. In this study, EMS represents the commercial expertise required to balance supply and demand at the building or local level (2). Transmission system operator (TSO), responsible for managing the high-voltage "energy highways" that transport bulk power over long distances and across borders. TSO owns the national grid and are responsible for ensuring grid stability (3) Distributed system operator (DSO), an organization that is responsible for the "last mile" of electricity delivery and manages the low-to-medium voltage local networks that connect directly to homes and businesses (4) Building Energy management Platform, an integrated digital system that uses real-time data and automation to monitor, control, and optimize buildings' energy consumption and onsite resources and (5) stakeholders involved in vehicle-to-grid (V2G) initiatives.

Moreover, the nine interviews (two groups and seven individual), as seen in Table 4, were conducted, involving 12 participants in total, representing heterogeneous organizational roles (technical, managerial, research, and policy). This sample size is appropriate for qualitative case research with embedded units, where the aim is depth and variation rather than statistical representativeness. Moreover, variation was observed across organizational type (Policymakers/Regulators, Grid operators, and market actors), hierarchical level (engineers, CTOs, CEOs), and functional roles (development, implementation, policy, project coordination). Furthermore, saturation was assessed iteratively; after the sixth interview, no substantially new conceptual categories emerged, and the final three interviews served to confirm and refine existing themes, indicating theoretical saturation across embedded units (Merriam & Tisdell, 2016).

Table 4: Summary of interviewees

Interview type	**Participants (Roles)**	**Organization**	**Duration (Minutes)**
Group	Chief technology officer (CTO)	EMS	65
	Sales Engineer		
Individual	CTO	EMS	60
Individual	Research Lead	Electromobility center	60
Group	CTO	EMS	65
	Software developer	EMS	
	Research and Development engineer	EMS	
Individual	Project lead	Research institute	60
Individual	Research and Development engineer	EMS	60
Individual	Chief executive officer	Building Energy Management platform	30
Individual	Requirement engineer/project owner	Swedish Transmission system operator	60
Individual	Chief executive officer	Distribution system operator	70
		Total	530 (8 hours & 50 mins)

Also, to capture the complexities of grid stability across different scales, representatives from TSO and DSO were included, offering insights into high-voltage national networks and local distribution infrastructure, respectively. While researchers acted as proxies for the policymaking community, providing evidence-based perspectives on regulatory frameworks.

4.4 Data Analysis

The data analysis phase followed the data collection phase and focused on analyzing qualitative data in line with the study's interpretivist tradition, which assumes that reality is socially constructed and that meaning emerges through participants' interpretations of their experiences. Accordingly, the analysis emphasized identifying patterns of meaning rather than measuring objective variables and adopted an iterative thematic analysis approach across all data sources (Merriam & Tisdell, 2016). Abductive reasoning guided coding, and the study employed a hybrid analytical strategy that enabled movement between data and theory (Gioia et al., 2013; Morgan & Nica, 2020). Interview data were audio-recorded and transcribed verbatim using Microsoft Teams. The initial open coding was conducted manually in Microsoft Excel, followed by clustering codes into higher-level categories and themes. The literature review served as both a conceptual foundation and an analytical input and was conducted using a concept-centric approach (Webster & Watson, 2002). Key theoretical perspectives, debates, and knowledge gaps were identified, and concepts derived from the literature, together with OVT, informed sensitizing themes that guided subsequent empirical analysis while remaining open to refinement. Consistent with qualitative content analysis approaches (Erlingsson & Brysiewicz, 2017; Merriam & Tisdell, 2016), documents were read iteratively and coded to identify institutional priorities, governance arrangements, and dominant narratives surrounding predictive analytics. Analytical attention was given to articulated expectations (e.g., efficiency gains, flexibility, automation), legitimizing discourses (e.g., sustainability, security of supply), and implementation challenges (e.g., interoperability, regulatory uncertainty).

To enhance analytical clarity, key sensitizing concepts were operationalized into observable indicators. (1) Expectations were operationalized through articulated anticipated benefits (efficiency, accuracy, flexibility, automation), perceived organizational or system-level impacts, and future visions expressed by stakeholders. (2) Thoughts on Adoption were operationalized through indicators such as the integration of predictive models into operational decision-making, coordination routines among actors, technical integration into EMS platforms, and changes in organizational practices or workflows. This approach ensured consistency across the document analysis and semi-structured interviews, with predefined thematic areas, such as expectations, perceived benefits and challenges, implementation experiences, and cross-stakeholder coordination, while retaining flexibility to probe emerging issues (Adeoye-Olatunde & Olenik, 2021). This approach aligns with inductive qualitative research by foregrounding stakeholders' sensemaking processes and supporting in-depth analysis of how meanings and expectations evolve through interaction and experience (Merriam & Tisdell, 2016; Walsham, 2006). Thus, the analysis produced integrated themes across data sources, capturing both recurring patterns and divergent meanings in line with interpretivist assumptions of multiple realities.

Following Gioia et al. (2013)'s approach, the first-order codes were developed using terms close to participants' language (e.g., "trust in AI forecasts," "interpretable models," "manual overrides," "lack of coordination"). These codes were then grouped into second-order themes (e.g., predictive accuracy, organizational confidence in models, hybrid human-algorithm decision-making, coordination challenges). Finally, aggregate dimensions were developed (e.g., institutional expectations, socio-technical adoption), which yielded institutional narratives and experiential accounts. Similarly, the codes and themes were compared across sources, as shown in Table 5, to identify alignment and tensions, thereby supporting triangulation and interpretive depth (Merriam & Tisdell, 2016). This enabled iterative refinement of themes and reflected Langley (1999)'s view of theorizing as progressive abstraction from qualitative data. To ensure analytical rigor, reflexive memos were maintained throughout the process to document evolving interpretations and potential researcher bias. Credibility and trustworthiness were enhanced through triangulation, iterative engagement with the data, and transparent documentation of analytical decisions, consistent with Merriam and Tisdell (2016).

Although the study does not aim to build formal grounded theory, the coding logic proposed by Corbin and Strauss (2015) informed the progression from codes to integrated themes in an iterative and reflexive approach. This aligns with contemporary qualitative methodological advances, including reflexive thematic analysis (Braun & Clarke, 2019) and iterative thematic inquiry (Gioia et al., 2013; Morgan & Nica, 2020). Thus, insights from the document and literature reviews were triangulated with interview data through iterative comparison. Specifically, claims and narratives identified in policy and industry documents were compared with stakeholder accounts to identify convergence, divergence, and tensions as seen in Table 5.

Table 5 : An example of data analysis triangulation matrix

Theme	Literature review	Document analysis	Semi-structured interviews	Triangulation
Interpretation (Predictive accuracy)	Performance of AI/ML as a key indicator	Availability of quality training data	The need for harmonized data set for training	Divergence: Literature assumes improved accuracy with optimized AI/ML; but documents and interviews reveal the need for quality data
Legitimation (Trust in Predictive Analytics)	Explainable AI as the solution for stakeholder trust	Cannot adopt "black box" models due to liability if a predictive surge fails	Prioritize interpretable and basic model (auditing and human oversight)	Convergence, with interpretability emerging as a non-negotiable prerequisite for adoption.

4.5 Quality and Ethical Considerations

To ensure quality and ethical standards, the study was conducted in accordance with the General Data Protection Regulation (GDPR) and established ethical guidelines in research. The study's quality was guided by Klein and Myers (1999)'s seven principles (*hermeneutic cycle, contextualization, interacting with the subject, abstraction and generalization, dialogical reasoning, multiple interpretation and suspicion*), ensuring reflective design and execution through a critically engaged approach throughout the thesis process. More so, the study employs a qualitative case study methodology that integrates three complementary data collection methods: literature review, document analysis, and semi-structured interviews. The literature review serves as an initial interpretive lens, enabling the identification of existing theoretical perspectives on predictive analytics in smart grids and supporting the principle of abstraction and generalization (Klein & Myers, 1999). It further informs the development of interview protocols and sensitizing concepts that guide subsequent empirical inquiry. Similarly, document analysis contextualized the empirical setting within Sweden, drawing on organizational reports, policy documents, and strategic materials related to digitalization and predictive analytics. This method supports the principle of contextualization by situating stakeholder expectations within their institutional, cultural, and regulatory environment, while also enabling triangulation across data sources to enhance quality and credibility (AIS, 2014; Klein & Myers, 1999; Vetenskapsrådet, 2025). Finally, semi-structured interviews facilitated in-depth engagement with diverse stakeholders involved in the adoption of predictive analytics. This approach enables the exploration of multiple interpretations and supports dialogical reasoning by allowing the researcher to iteratively confront emerging findings with existing theoretical assumptions (Klein & Myers, 1999). The flexible nature of semi-structured interviews also aligns with the hermeneutic circle, as insights are continuously refined through movement between parts (individual accounts) and the whole (the broader socio-technical context). Together, these methods enable a rich investigation of the interplay between stakeholder expectations and the adoption of predictive analytics in the smart grid. By triangulating across literature, documents, and interview data, the study strengthens its quality, credibility, and dependability while maintaining transparency in the development of interpretations.

Also, the ethical considerations, including informed consent, confidentiality, and responsible data handling, were embedded throughout the research process in accordance with established qualitative research standards (Creswell & Creswell, 2017; Langley, 1999; Merriam & Tisdell, 2016), ensuring that the study is both methodologically rigorous and ethically sound. Informed consent was obtained from all participants, who were informed about the purpose of the study, data handling procedures, and their right to withdraw at any time. Personal and organizational identifiers were removed to ensure anonymity, and all data were securely stored and accessed only by the researcher. Furthermore, the research adhered to the ACM Code of Ethics and Professional Conduct (ACM, 2018), the AIS Code of Research Conduct (AIS, 2014), and the Swedish Research Council's Good Research Practice guidelines (Vetenskapsrådet, 2025). Employing reflexive practices throughout the research process to mitigate potential bias and ensure responsible, transparent, and ethical interpretation and reporting of findings (ACM, 2018).

Chapter 5

5 Summary of included papers

This chapter summarizes the three papers included in this thesis, providing an overview of each paper, its key findings, and its contribution to the thesis. Paper 1 analyzes AI-enabled predictive analytics in Swedish smart grids. Paper 2 examines co-creation in resilient distributed energy resources. Paper 3 addresses the trade-off between accuracy and transparency in predictive analytics. Together, these papers address complementary dimensions of predictive analytics in smart grids and collectively contribute to the thesis's overarching research objectives and theoretical framework.

5.1 Paper 1: AI-Enabled Predictive Analytics in Smart Grids: The Case of Sweden

5.1.1 Summary

The paper, published in *the Complex Systems Informatics and Modeling Quarterly Journal*, examines the integration of AI-enabled predictive analytics into smart grids (SGs) in Sweden, focusing on practical implementation strategies. It adopts an action research approach and concentrates on the first two phases of the action research cycle: diagnosis and action planning. The diagnosis phase includes a comprehensive review of 26 articles. Meanwhile, the action planning phase uses document analysis to propose strategies for implementing transparent AI in SGs, emphasizing explainable AI, robust data management, human-in-the-loop systems, and stakeholder collaboration. The study concludes that although AI has significant potential to optimize SGs, challenges such as limited transparency and real-world application remain.

5.1.2 Key findings

The paper study finds that AI-enabled predictive analytics can significantly enhance smart grid operations by enabling better outage prediction, demand response, fault diagnosis, and overall grid stability. However, challenges persist, particularly around the opacity of AI systems, which raises concerns about interpretability and trust. Also, the papers find that Real-world applications remain limited, with many solutions still in experimental stages. Thus, the study recommends adopting explainable AI techniques, strengthening data governance, integrating human oversight, and promoting stakeholder collaboration.

5.1.3 Contribution to thesis

The paper contributes to the thesis by emphasizing the importance of multi-stakeholder cooperation for implementing transparent AI in smart grids. It helps answer RQ1 by highlighting how stakeholders interpret predictive analytics as a crucial enabler of grid resilience, with applications such as outage prediction and stability control. It addresses critical transparency challenges by proposing strategies such as explainable AI and human-in-the-loop systems, while supporting the thesis's empirical goals through a structured action research framework that guides future implementation and investigation.

5.2 Paper 2: From Control to Co-Creation: Predictive Analytics in Resilient Distributed Energy Resources

5.2.1 Summary

The paper, a proceeding of the Australian conference on Information systems (ACIS2025) and published in *the AIS e-library*, investigates how predictive analytics is used, envisioned, and interpreted within DERs, through semi-structured interviews with smart grid stakeholders. The study examines how smart grid stakeholders envision, negotiate, apply, and experience predictive analytics in complex, real-world contexts. The study used semi-structured interviews to illuminate the evolving role of predictive analytics and its potential to transform DERs. The study also demonstrates that, despite growing industry discussion of advanced predictive analytics, most energy management systems still rely on basic statistical and rule-based models. This reliance is shaped by a combination of enabling and constraining factors, including data availability, system interoperability, and organizational capacity, which together influence the adoption and implementation of predictive tools.

5.2.2 Key findings

The key findings indicate that although advanced predictive analytics has significant potential to transform DERs, its practical application remains largely reliant on more basic statistical and rule-based models. These tools are used for a variety of tasks, including forecasting energy generation and consumption, optimizing energy storage strategies (such as arbitrage and peak shaving), and enabling cost minimization for consumers. The paper concludes that the adoption of predictive analytics is influenced by both enabling conditions, such as access to high-quality data, and constraining factors, such as device limitations and regulatory frameworks. It argues that advanced predictive analytics has the potential to foster a more collaborative and resilient energy ecosystem by empowering both grid operators and consumers.

5.2.3 Contribution to thesis

The paper "From Control to Co-Creation: Predictive Analytics in Resilient Distributed Energy Resources" contributes to the thesis by addressing RQ1: How do smart grid stakeholders understand and envision the role of predictive analytics in the smart grid context? The paper also contributes to RQ2: What is the interplay between stakeholders' expectations and thoughts on the adoption of predictive analytics in smart grids? by offering insights into how the legitimacy of predictive analytics in the smart grid is negotiated. Drawing on semi-structured interviews, the study shows that while predictive analytics is widely envisioned as transformative, current practice relies on simpler statistical models shaped by enabling and constraining conditions. By highlighting both the gap between vision and practice and the socio-technical strategies influencing adoption, the paper provides empirical grounding for the s central argument that predictive analytics functions as both a technical tool and a collaborative mechanism for building resilient smart grid ecosystems.

5.3 Paper 3: Predictive Analytics in Smart Grids: Examining the trade-off between Accuracy and Transparency

5.3.1 Summary

The paper submitted to the International Conference on Information Systems (ICIS2026) examines predictive analytics in smart grids, focusing on the stakeholders' frame accuracy and transparency trade-offs and how such trade-offs shape prioritization. Through a qualitative study that combines a scoping review and document analysis of policy, industry, and customer-oriented materials, the findings reveal that while accuracy remains the dominant discourse among technical and distribution systems operators, transparency is increasingly foregrounded in governance and societal legitimacy. Arguing that instead of treating accuracy and transparency as dual and competing imperatives, accuracy and transparency should be treated as complementary.

5.3.2 Key findings

The key findings show that predictive analytics in smart grids is shaped by differing stakeholder priorities across policymakers/TSOs, DSOs, and energy users. Stakeholders collectively frame predictive analytics around the themes of accuracy, transparency, and accountability, yet they attach different meanings and expectations to these concepts. Policymakers and TSOs emphasize market legitimacy, transparency, and societal accountability, advocating for interpretable models and clear documentation to maintain trust. In contrast, DSOs prioritize forecasting accuracy, operational efficiency, and competitive performance, often favoring technically precise models over full transparency. Energy users primarily value reliable service, fair billing, and understandable decision-making, linking transparency to their ability to interpret consumption and system decisions. These differing priorities create tensions between accuracy and transparency, and between efficiency and accountability. While stakeholders recognize these trade-offs, they remain only partially resolved, with interpretability and governance mechanisms emerging as compromise solutions. Overall, the findings show that the institutionalization of predictive analytics in smart grids depends on ongoing stakeholder negotiations to balance technical performance with legitimacy, trust, and fairness.

5.3.3 Contribution to thesis

The paper's findings support the overall thesis by showing that the role of predictive analytics in smart grids is collectively constructed through stakeholder interpretations and priorities. The findings show that stakeholders frame predictive analytics in relation to broader concerns about system performance, transparency, and institutional legitimacy. The paper contributes to answering RQ1 and RQ2 (cf. section 1.2). The findings reveal that stakeholders involved in smart grid understandings of predictive analytics hold varying views on adoption, and that these views are shaped by their roles within the smart grid. This highlights that, while predictive analytics in smart grids, as a digital innovation, is envisioned as a solution to uncertainty, its adoption is driven by competing expectations that are not only technical but also shaped by governance considerations, stakeholder expectations, and institutional negotiations within the evolving smart grid context.

5.4 Summary of Findings Across the Papers

Across the three papers, the findings highlight both the potential and the current limitations of predictive analytics in smart grids. The first paper demonstrates that AI-enabled predictive analytics can enhance grid operations by improving outage prediction, demand response, fault diagnosis, and overall grid stability. However, practical deployment remains limited because concerns about the opacity and interpretability of AI models undermine trust and accountability. As a result, the study emphasizes the importance of explainable AI, stronger data governance, human oversight, and stakeholder collaboration to support responsible adoption. The second paper shows that, despite the promise of advanced analytics, current applications in distributed energy resources (DERs) primarily rely on simpler statistical and rule-based models. These approaches are used for tasks such as forecasting energy generation and consumption, optimizing energy storage strategies, and enabling consumer cost minimization. The findings indicate that the adoption of predictive analytics depends on enabling conditions such as access to high-quality data, device capabilities, and supportive regulatory frameworks, suggesting that the transition toward more advanced analytics is gradual and shaped by broader system constraints. The third paper highlights that the development of predictive analytics in smart grids is also shaped by trade-offs between accuracy and transparency and by how these trade-offs influence stakeholders' prioritization. Policymakers, TSOs, DSOs, and energy users attach different meanings to accuracy and transparency, leading to tensions among technical performance, operational efficiency, and societal legitimacy. Together, these insights show that predictive analytics in smart grids is not only a technical innovation but also a socio-technical process shaped by how stakeholders make sense of it, informed by their expectations, experiences, and considerations surrounding adoption.

Chapter 6

6 Synthesis of Findings

This chapter synthesizes findings from the empirical studies and integrates insights across the three included papers. Guided by Organizing Vision Theory, sensemaking, and institutional perspectives, the chapter develops three integrative themes that explain how predictive analytics is envisioned, legitimized, and mobilized in smart grid contexts. Section 6.1 examines how stakeholders interpret the value and role of a shared vision of predictive analytics for grid resilience; Section 6.2 analyzes how legitimacy is negotiated in relation to the risks, compliance issues, and costs associated with predictive analytics; Section 6.3 explores how stakeholders mobilize resources through design choices and capacity-building for the adoption of predictive analytics, as it evolves from technological promise to an institutionalized capability.

6.1 Interpretation: Making sense of Predictive Analytics

Across the three included papers and the analysis of the empirical data, stakeholders consistently frame predictive analytics as a strategic response to increasing uncertainty in contemporary energy systems driven by renewable intermittency, decentralization, climate volatility, and evolving market dynamics. Policymakers, grid operators, and market actors frame predictive analytics as essential for forecasting demand, stabilizing renewable integration, detecting anomalies, enhancing demand response and flexibility, and supporting long-term infrastructure planning. One good example is an excerpt from Energiforsk's DIGIGrid project reports which frames digitalization as a critical enabler of grid transformation, stating that "*Digitalization of the electricity grids is an important tool, for the grid to be able to realize the potential that exists in the grid available resources today, and at the same time streamline the operation and maintenance of the grids*"(Kalhori et al., 2022, p. 9). The report notes that predictive maintenance and planning are key drivers of this digital transition, as its offers "better knowledge of the grid, operational optimization, long-term grid planning, and proactive maintenance" (Kalhori et al., 2022, p. 5). Through these narratives, predictive analytics is framed not merely as a technical capability but as a symbolic and strategic device that embodies data-driven decision-making, forecasting, and a shift from intuition to evidence.

Within these interpretive frames, predictive analytics signifies a move toward proactive rather than reactive management, positioning organizations as forward-looking, resilient, and innovative. As such, predictive analytics becomes a rhetorical solution to the organizational and infrastructural challenges posed by decentralized, data-rich energy systems. By promising anticipatory insight and enhanced control over uncertainty, it shapes stakeholders' collective imaginaries of a sustainable, adaptive, and intelligently managed energy future. These organizing visions reduce ambiguity about the purpose of predictive analytics while aligning it with broader ideals of modernization and system resilience. In line with Organizing Vision Theory, these interpretive frames perform critical functions: they shape how predictive analytics is understood, influence which use cases are prioritized (e.g., forecasting demand, predicting faults, optimizing assets), and determine whether it is perceived as a strategic, operational, or experimental innovation. Consequently, predictive analytics diffuses not only through its technical affordances but also through shared discourses that guide attention, legitimize investment, and coordinate innovation efforts across the energy sector. As renewable energy becomes more deeply integrated into smart grids, stakeholders increasingly frame predictive analytics as a key solution for managing photovoltaic (PV) integration and strengthening smart grid resilience. As one CEO of a distribution system operator explained, "*When assessing PV integration, we initially observed hosting capacity levels of around 25% in the low-voltage grid. However, this prompted further analysis into whether such levels were practically sustainable. We distinguished between hosting capacity and absorption capacity, emphasizing that the critical question is not only how much PV can be connected, but how much can be effectively absorbed and utilized locally*" (CEO of DSO). This perspective illustrates how predictive analytics is envisioned as a tool for aligning PV integration with actual system capabilities. Without such alignment, high levels of PV integration may create operational challenges rather than resilience benefits. As the CEO further noted, "*Our analysis showed that while hosting capacity exceeded 20%, the realistic absorption capacity was closer to 10–15% of annual energy demand. By prioritizing local consumption, first within the building, then among nearby users, and finally within the local grid, we were able to anticipate and manage PV integration levels. In practice, maintaining solar generation at approximately 10% of annual energy use demonstrates how predictive* *assessment and controlled integration can support a stable and balanced grid*" (CEO of DSO).

Moreover, the organizing vision of predictive analytics is constructed through shared meaning-making rather than predefined stakeholder roles. In early discourse, heterogeneous actors jointly frame what predictive analytics is and why it matters, using narratives, symbols, and dialogue to establish interpretive frameworks that enable coordination and implementation. This framing process underpins legitimacy and collective action across institutional, technical, and societal domains. Hence, within smart grid discourse, predictive analytics thus emerge as a central yet contested organizing vision, particularly in the context of AI. As Energiforsk's feasibility study report on AI application in nuclear plants describes AI as "*a virgin territory but… easy to find useful and realistic implementations*", highlighting both its novelty and perceived feasibility (Nygren et al., 2023). These narratives frame predictive analytics simultaneously as a pragmatic operational tool and as a symbol of digital and sustainable progress in energy transitions. This demonstrates how this vision materializes within a strong policy and innovation ecosystem in Sweden, where policy frameworks, grid operators, and technology providers collectively embed predictive analytics as a core strategy for balancing renewable generation and maintaining grid stability (Paper 1), aligning with broader European Union goals of a "digital green transition" (European Commission, 2022).

Moreover, predictive analytics is further materialized through stakeholders' shared vision of a Swedish national Data Hub, framed as a core digital infrastructure for consolidating metering data, standardizing information flows, and enabling supplier-centric markets, transparency, and competition. It was positioned as the digital foundation for future energy services and predictive analytics within the smart grid. This infrastructural imaginary is reinforced by a TSO requirements engineer, who stated: "*The vision was to establish a hub for central data and easy visualization of the grid through data harmonization and analytics… to provide a delivery structure that would ease communication and enhance flexibility, energy communities and energy sharing, and empower energy users*" (TSO requirements engineer). The interviewee highlighted the fragmented legacy market-communication architecture, in which retailers exchanged data with 150–170 grid owners via heterogeneous channels and text-file protocols, as a key barrier to advanced analytics. The Data Hub was thus envisioned as a harmonized data infrastructure enabling predictive coordination and data-driven market services. In this framing, shared data infrastructure was constructed as a necessary investment. The Data Hub served as a material anchor, translating predictive analytics from an abstract promise into a concrete pathway for smart grid coordination, enabling a shift from reactive grid management to predictive coordination of flexibility services, distributed energy resources, and energy communities.

However, framing predictive analytics as a panacea risks technological determinism and assumes that predictive systems alone can ensure resilience, thereby obscuring institutional dependencies, social dynamics, and data asymmetries. As emerging perspectives from Paper 2 (From Control to Co-Creation) illustrate, there is a shift from hierarchical control toward participatory co-creation, with predictive analytics supporting collaborative intelligence among policymakers, grid operators, market actors, and energy users. These reframing transforms predictive analytics from a purely technical outcome into a collective capability grounded in coordination, learning, and shared decision-making. Similarly, stakeholders in Sweden view predictive analytics for smart grids as central to both peak energy forecasting and reducing energy consumption. This is reflected in Svenska kraftnät's report on reducing gross electricity consumption during peak hours, which notes: "*as reductions are calculated by comparing actual gross electricity consumption for the identified peak hours with the gross electricity consumption forecasted by the transmission system operators, forecasts that are based on historical data and adjusted due to temperature differences*" (Svenska kraftnät, 2023, p. 1). While stakeholders envision predictive analytics as a tool for predicting the future, they also interpret it through the trade-off between accuracy and transparency, with priorities varying by organizational role and culture (Paper 3).

Thus, the interpretation of predictive analytics as an organizing vision within smart grids demonstrates an oscillation between optimism about its technical promise and caution regarding its social and institutional implications. Stakeholders articulate predictive analytics as a transformative capability, yet they simultaneously recognize that realizing this vision depends on data governance, institutional alignment, and infrastructural transformation. This theme illustrates how collective meaning-making shapes the trajectory of energy innovation and resilience planning, and how stakeholders negotiate trust and legitimacy in AI-enabled predictive models.

6.2 Legitimation: Alignment of Vision with broader operational concerns.

As predictive analytics moves from a rhetorical promise to an operational practice within smart grids, trust and transparency emerge as key mediating constructs that shape the legitimacy, acceptance, and sustainability of predictive models. Legitimacy in this context refers to the alignment among technical design, institutional expectations, and societal norms governing responsible energy innovation (Swanson & Ramiller, 1997). While accuracy and efficiency remain vital considerations for grid operations, they are also important justifications for investing in predictive analytics. Thus, legitimation is achieved when developers of predictive models can reassure stakeholders of the models' accuracy and transparency. Policymakers and energy users within smart grids increasingly demand predictive models that are transparent, auditable, and ethically governed, reflecting a shift from purely technical performance metrics among market actors toward a more comprehensive approach to socio-technical accountability. They navigate tensions between the efficiency promises of predictive analytics and concerns about transparency, accountability, and ethical governance. While predictive analytics can optimize operations and enhance system responsiveness, opaque "black-box" models raise questions about trust and alignment with public expectations.

The Energiforsk feasibility study explicitly acknowledges the need for organizational change to overcome practical constraints, noting that "*a future vision and challenges to reach that vision have been identified*" (Nygren et al., 2023). Similarly, the DigiGrid report highlights organizational and institutional barriers, stating that "*expertise, staffing, access to adequate system support, time, and financial resources are the most critical resources required to fulfill the long-term benefits of digitalization of the power grid*" (Kalhori et al., 2022). This observation aligns with Tekniska verken (2024) annual report, which highlights AI's transformative potential while identifying gaps in the organizational expertise and competencies needed for its effective use. The report notes that 2023 was "*the year the whole world talked about AI*," but the CEO in the same report warns that the energy industry faces significant challenges as "*new work areas, technologies, and requirements for competencies are increasing*" (Tekniska verken, 2024). Similarly, Svenska Kraftnät opts for a baseline forecast technique instead of advanced machine learning, stating that "*As an alternative, it would have been possible to potentially increase accuracy by using a large machine learning model with consumption change as output. These results would, however, be very difficult to interpret, justifying a simpler and more transparent approach*" (Svenska kraftnät, 2023, p. 4). These findings demonstrate that legitimacy is not just about the performance of technology but also about organizational alignment, associated risk, compliance issues, and the costs of adoption.

Furthermore, the opacity of AI algorithms, such as deep learning, underscores this tension over legitimacy. For instance, Paper 3 illustrates how the pursuit of predictive precision through complex machine learning introduces "epistemic opacity," constraining interpretability and diminishing operator confidence. This opacity not only challenges regulatory oversight but also erodes trust among energy users and institutional actors tasked with ensuring accountability in grid management. This is also noted in a report by RISE Research Institutes of Sweden, which states that while the broader energy sector envisions 'autonomous' smart grids, AI applications in nuclear plants must prioritize 'interpretability over raw predictive power' to maintain regulatory legitimacy (Sutfeld & Thore, 2025). This is further reinforced in an Energiforsk report on the use of big data, which notes that "*there is a notable divergence: where data scientists see 'optimization opportunities,' plant operators see 'potential points of failure' that require human-in-the-loop verification*" (Lindquist & Eriksson, 2026). Furthermore, Sutfeld and Thore (2025) their report notes that "*the legitimacy of AI in nuclear plants is not just about the algorithm's accuracy, but about 'on-premise' control, ensuring that safety-critical data never leaves the physical security of the plant*.". Across all three papers, the findings suggest that tensions between accuracy and transparency are discursively resolved by presenting this trade-off as a necessary socio-technical compromise. This framing performs a legitimation function in OVT by justifying the adoption of predictive analytics as both credible and responsible, thereby maintaining legitimacy without undermining its functional performance.

Similarly, the analysis of the findings shows that institutional culture further grounds legitimation and links the innovation to broader institutional risk. Paper 1 demonstrates that in Sweden's energy sector, long-standing traditions of public accountability and open data governance shape the development and deployment of predictive models. Compliance with transparency mandates and the GDPR embeds explainability directly in the model development cycle, ensuring that design choices reflect not only algorithmic efficacy but also societal norms of trust (Mikalef et al., 2019). This institutional anchoring transforms explainability from a technical afterthought into an integral principle of responsible AI design, aligning predictive analytics with normative expectations of fairness and accountability.

Thus, institutional culture further mediates legitimacy negotiation as trust in predictive analytics, especially in the era of AI, can be co-produced through participatory processes that extend beyond the algorithm itself. This highlights how stakeholder engagement, spanning policymakers, grid operators, and energy users, can generate legitimacy by aligning diverse interpretations to collectively frame the predictive analytics in the smart grid (Paper 3). Such participatory mechanisms move transparency beyond passive disclosure toward active dialogue about energy needs, production capacity, bias mitigation, and the ethical implications of automated decision-making (Volkova et al., 2022). Thus, by foregrounding human involvement and iterative explanation, transparency becomes a socially negotiated practice that fosters mutual accountability among stakeholders. Thus, the synthesis across papers 1 and 3 shows that legitimacy is not a static attribute but a continuously negotiated outcome that emerges through the interplay of design, regulation, and participation.

6.3 Mobilizing the Vision: Material Realization through Design Choices and Capacity-Building

Mobilization refers to the process through which predictive analytics transitions from conceptual vision to embedded organizational and infrastructural practice (Swanson & Ramiller, 2004). This stage operationalizes the organizing vision by translating strategic intent into concrete design choices, standards, and collaborative structures that enable adaptive and resilient smart grid implementation. Adopters mobilize market resources such as technologies, services, and skills, guided by the vision, while market actors align and develop offerings accordingly, with industry arenas such as conferences, seminars, and expos acting as key sites where the vision is materialized, showcased, and enacted (Swanson & Ramiller, 1997). The Energiforsk feasibility study report on artificial intelligence technologies in nuclear applications presents "*a step-by-step evolution roadmap and understanding of present implementable solutions*"(Nygren et al., 2023), illustrating how the vision is showcased and how stakeholders mobilize market resources, such as hardware, software, and skills, to operationalize predictive analytics through staged development pathways. It also maps applications intended to "*assist operation, technical, and maintenance staff in taking informed decisions regarding the operation, plant development, and maintenance*", demonstrating how technology innovation materializes and reshapes organizational routines and decision-support systems. Moreover, in Sweden, the organizing narrative of predictive analytics becomes actionable through shared technical standards, capacity-building initiatives, and co-creation platforms, such as the data hub, thereby mobilizing resources and technologies that align with organizational goals. This is reflected in Svenska Kraftnät's report, which adopts a baseline technique stating that "*The forecast consists of a 'baseline' forecast, which is the average for the same period during the reference period (the last five years), plus some adjustments. We chose the method partly because of transparency*" (Svenska kraftnät, 2023, p. 4). This shows how mobilization motivates policymakers, grid operators, and energy users to adopt predictive analytics to enable co-creation and joint decision-making on energy generation, distribution, and consumption (Paper 2).

Furthermore, Paper 1 provides empirical evidence of this mobilization in Sweden through national innovation policies and standardization initiatives led by Svenska Kraftnät, the authority responsible for ensuring that Sweden's electricity transmission system is safe, environmentally sound, and cost-effective today and in the future. This mobilization occurs through mechanisms such as regulatory sandboxes, public–private partnerships, and AI-enabled energy strategies that provide institutional scaffolding and encourage responsible experimentation and scalable innovation (Menazzi et al., 2023). These frameworks integrate technological development with governance legitimacy, ensuring that predictive analytics for critical infrastructure, such as the smart grid, evolve within a structured environment. This perspective is extended by emphasizing continuous organizational learning to keep pace with technological advances and evolving market trends, which demand the development of new and evolving skill sets (Paper 3). As the computational power of predictive analytics evolves alongside emerging technologies and streaming data, grid stakeholders must build capacity for ongoing monitoring, evaluation, and model retraining.

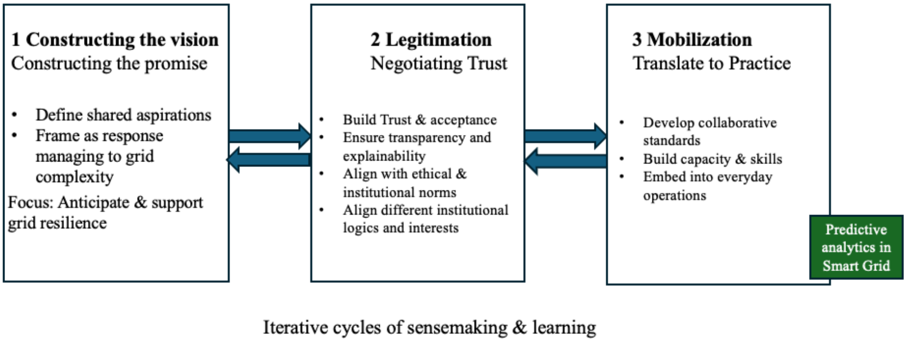

Figure 5 : Iterative process of organizing vision development for predictive analytics in smart grids

This dynamic process requires both technical proficiency and interdisciplinary literacy, uniting data scientists, engineers, system operators, and policymakers to sustain model reliability, cybersecurity, and social legitimacy. Thus, smart grid resilience emerges when predictive analytics is institutionalized as a shared socio-technical capability, distributed across a network of collaborating actors rather than confined to any single organization. It entails aligning with available technological infrastructure, regulatory frameworks, and human expertise to transform a technical system into a living, adaptive ecosystem capable of learning, coordinating, and recovering in real time.

Collectively, Sections 6.1–6.3 illustrate the evolving role of predictive analytics as an organizing vision for resilient smart grids, as shown in Figure 5. Vision construction captures how stakeholders articulate predictive analytics as a shared promise of anticipatory resilience. Legitimation underscores the importance of transparency, explainability, and ethical alignment for establishing trust and credibility. Mobilization shows how collaborative practices and institutional embedding translate this vision into operational routines. These themes mirror Swanson and Ramiller (1997)'s model of technology diffusion as a socio-discursive process, in which visionary narratives mobilize attention, legitimacy stabilizes participation, and mobilization embeds new practices within institutional structures. Through iterative cycles of sense-making, legitimation, and adaptation. Thus, the synthesis of findings (cf. chapter 6) reveals that successful integration of predictive analytics depends not only on algorithmic sophistication but also on social alignment, participatory governance, and institutional design.

7 Discussion

This chapter interprets the findings to advance understanding of predictive analytics as a digital innovation in smart grids. Rather than restating results, it explains how predictive analytics are constructed, legitimized, and embedded across organizational and institutional contexts. Drawing on Digital Innovation literature, the discussion adopts a thematic approach to answer the research questions. Accordingly, the chapter addresses the research questions by explaining how stakeholders envision predictive analytics as a future-oriented sensemaking tool for managing grid complexity and how their expectations recursively shape thinking about its adoption. Finally, it proposes a conceptual framework to guide the adoption of predictive analytics in smart grids.

7.1 Predictive analytics as a Future-oriented Sensemaking tool in Smart Grids

About RQ1: How do smart grid stakeholders understand and envision the role of predictive analytics in smart grids? The findings (cf. 6.1-6.3) and summarized in Table 6 indicate that stakeholders view predictive analytics as a future-oriented tool for determining grid scenarios through forecasting and prediction. This understanding of predictive analytics in smart grids goes beyond the artifact-centric view and instead emerges as a form of digital innovation within a complex socio-technical system. Aligns with the digital innovation literature's calls to shift attention from discrete technologies to the processes, infrastructures, and actor configurations through which digital innovations are constructed and stabilized (Nambisan et al., 2017; Nambisan et al., 2020). Accordingly, this study moves away from explaining adoption through technological superiority or performance improvements and instead examines how predictive analytics in smart grids evolves through a recursive interplay among expectations, institutional conditions, and organizational enactment. This shifts the analytical focus from "what the technology does" to "how the technology becomes meaningful, legitimate, and actionable" in practice. It also moves away from prior work that focuses primarily on improving model accuracy to address the critical need to bridge the gap between experimental success and practical adoption. Specifically, it examines how alignment or misalignment among technical capabilities, organizational structures, and stakeholder expectations influences whether predictive analytics is successfully adopted and sustained in practice, as in the work of Mikalef and Krogstie (2020) and Mikalef et al. (2018).

Table 6: Connecting Research Questions to Themes

Theme	Theoretical lens	Contribution to RQ1 (Understanding & Visions)	Contribution to RQ2 (Expectations–Adoption Interplay)
6.1 Interpretation	OVT; Sensemaking	Predictive analytics interpreted as a solution to resilient and digitalized grids; stakeholders interpret its role through existing operational and regulatory frames.	Visions articulated as guiding narratives that orient strategic planning and investment decisions
6.2 Legitimation	Sensemaking; Institutional Legitimacy	Stakeholders interpret risks, trust, explainability, and organizational readiness, shaping how predictive analytics is understood and evaluated	Legitimacy assessments constrain and enable adoption, influencing governance, regulatory alignment, and design choices
6.3 Mobilizing the Vision	OVT Mobilization; Sensemaking-in-Action	Predictive analytics understood as coordination and decision-support infrastructure enabling organizational and inter-organizational action	Vision translated into pilots, standards, governance structures, and skill development, shaping adoption trajectories

The findings (cf. sections 6.1-6.3) reveal that stakeholders envision the role of predictive analytics in smart through a sensemaking lens, interpreting it as an organizing vision that offers a shared interpretive frame for understanding digitalization and smart grid transformation. Through *interpretation (cf. section 6.1)*, predictive analytics is framed as a future-looking capability that enables proactive grid management, flexibility, and resilience. Stakeholders make sense of predictive analytics by linking it to familiar organizational concerns such as reliability, operational efficiency, and regulatory compliance, thereby anchoring the emerging technology within existing cognitive and institutional frames.

Therefore, through sense-making, stakeholders view predictive analytics as a forward-looking interpretive mechanism for navigating uncertainty in increasingly complex power systems. Rather than being adopted solely for its technical capabilities, it is framed as a digital innovation encompassing forecasting, asset optimization, and demand flexibility, offering a plausible and actionable narrative for managing grid complexity. This narrative aligns with Orlikowski and Gash (1994)'s technological frames, reducing ambiguity and enabling coordinated action among diverse actors. This interpretation aligns with digital innovation research, which emphasizes that technologies derive their meaning and value through ongoing interaction among actors, institutions, and infrastructures (Nambisan et al., 2017; Nambisan et al., 2020). In this sense, predictive analytics operates not merely as a tool but as an input into a downstream decision-making process, guiding collective responses to digital transformation. Moreover, consistent with broader innovation and diffusion perspectives (Rogers et al., 2014; Webster & Gardner, 2019), such interpretive framing is critical for aligning technological potential with institutional readiness, thereby influencing both the direction and pace of adoption in complex socio-technical environments.

Across the three themes (cf. section 6.1-6.3), predictive analytics is no longer seen merely as a technological promise but is increasingly understood as an institutionalized organizational capability embedded in smart grid routines, infrastructure, and governance arrangements. Stakeholders increasingly view predictive analytics as integral to the planning, operation, and regulation of smart grids, reflecting a stabilized organizing vision. This vision is enacted through shared expectations, regulatory frameworks, and infrastructural investments that align stakeholders' aspirations with practical adoption pathways. Thus, thoughts on the adoption of predictive analytics are shaped by stakeholders' expectations.

7.2 Expectations shaping interpretations and thoughts on Adoption

Regarding RQ2: What is the interplay between stakeholders' expectations and thoughts on the adoption of predictive analytics in smart grids? The findings (cf. section 6.1-6.3) show that stakeholders' interpretations of the value and role of predictive analytics, as well as their views on adoption, are shaped by their expectations. Thus, drawing on OVT dynamics and institutional theory (Powell & DiMaggio, 1991), the interplay between expectations and thoughts about adoption unfolds through processes of interpretation, legitimacy construction, mobilization, and institutionalization. The theme *of Legitimation (cf. 6.2)* shows that while stakeholders interpret and acknowledge predictive analytics *(cf. 6.1)* as a digital innovation capable of efficiency gains and resilience improvements in smart grid operations, they also engage in sensemaking around risks related to explainability, data governance, organizational capability, and regulatory fit. These interpretive processes shape whether predictive analytics is perceived as legitimate and actionable. Through *mobilization (cf. 6.3)*, expectations are not only translated into concrete adoption activities, such as pilot projects, data hubs, standardization efforts, and capacity-building initiatives, but they also begin to function as a social identity of boundary infrastructure. In line with Carlile (2002) a pragmatic perspective, expectations evolve and become embedded into the thoughts on adoption that enable coordination among different stakeholders by accommodating diverse interpretations while supporting shared action. As stakeholders engage in implementation, they continuously reinterpret predictive analytics in response to technical constraints and institutional requirements, illustrating how knowledge is transformed across boundaries rather than simply transferred. This ongoing reinterpretation Gal et al. (2005) highlights the dynamic nature of boundary objects as they become embedded within a broader social infrastructure and are shaped by stakeholders' expectations. Predictive analytics thus emerges as a boundary infrastructure that not only supports coordination but also shapes social identities and relationships among stakeholders, reinforcing its role as a collaborative forecasting environment that decentralizes decision-making and fosters mutual trust among energy participants (Liu et al., 2023; Liu et al., 2015; Valizadehhaghi, 2016). This interplay between expectations and thought on adoption is further articulated through the study's proposed conceptual framework.

7.3 A conceptual framework for implementing predictive analytics in smart grids

To further interpret the findings in relation to the research questions (RQ1 and RQ2), this study develops a kernel-theory-informed conceptualization of predictive analytics as a digital innovation. The framework, as shown in Figure 6, positions OVT as the central explanatory kernel, complemented by learning-oriented and infrastructural perspectives. In line with Hanseth and Lyytinen (2008), kernel theories provide generative and design-relevant explanations of socio-technical systems, particularly those characterized by heterogeneity, openness, and distributed control. Similarly, the conceptualization also builds on the work of Linden et al. (2007) which emphasizes that kernel theories guide inquiry by shaping how phenomena are interpreted, questioned, and iteratively revised. Within this framing, OVT (Swanson & Ramiller, 1997) explains how predictive analytics in smart grids emerges as a collectively constructed organizing vision, directly addressing RQ1. Stakeholders do not merely adopt predictive analytics based on predictive analytics technical properties; rather, they interpret and stabilize its meaning through discourse, promotion, and field-level sensemaking. This reinforces the finding that predictive analytics is understood as a shared yet evolving vision of digital transformation (Lakemond et al., 2025), anchored in existing institutional logics and projecting future capabilities. At the same time, integrating a learning-oriented kernel perspective extends the analysis of RQ2 by conceptualizing adoption as an ongoing inquiry process rather than a discrete decision. Discrepancies between expectations and realized outcomes trigger cycles of reflection, adaptation, and revision. This highlights that the interplay between expectations and thought on adoption is fundamentally recursive, where expectations both guide and are reshaped by implementation experiences.

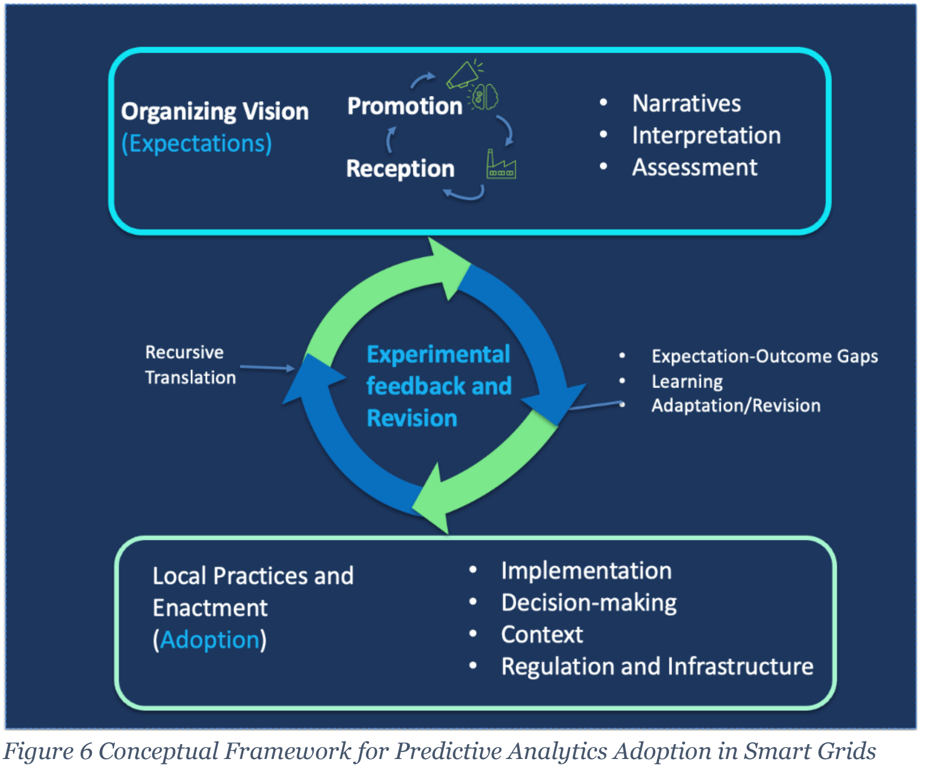

Figure 6 Conceptual Framework for Predictive Analytics Adoption in Smart Grids

Together, these kernel logics justify a framework that foregrounds process, recursion, and adaptation, aligning with digital innovation research that conceptualizes innovation as continuous recombination across evolving socio-technical configurations (Nambisan et al., 2017; Nambisan et al., 2020). Thus, it is conceptualized as a socio-technical coordination capability in the smart grid. The conceptual framework developed in this study positions predictive analytics as a sociotechnical coordination capability, linking organizing visions, recursive translation processes, and local enactment. This provides a more precise answer to RQ2 by explaining how expectations are translated into practice and subsequently stabilized. Specifically, organizing visions is discussed through competing expectations (van Lente & Bakker, 2010) about the potential of predictive analytics, which guide initial interpretations and strategic orientations. These expectations are then recursively translated through processes of experimentation, adaptation, and institutional alignment. Through this translation, predictive analytics evolves from an abstract vision into a boundary-spanning infrastructure that enables coordination across heterogeneous actors. Crucially, this process is not unidirectional. Local enactment, through implementation, use, and operational experience, feeds back into the vision, reshaping expectations and redefining what predictive analytics is understood to be. These iterative dynamic highlights that adoption is not a matter of implementation fidelity but of continuous alignment between evolving expectations and socio-technical conditions.

Hence, the findings from this thesis do not reduce predictive analytics to artificial intelligence alone. Instead, it draws on the capability maturity perspective articulated by Hansen et al. (2024) to frame predictive analytics as a multi-layered capability that develops incrementally across organizational, technological, and governance dimensions. In this sense, AI represents one advanced stage within a broader maturity trajectory rather than a prerequisite for predictive functionality. Therefore, organizations may operate effectively at different levels of maturity, ranging from rule-based automation and descriptive analytics to predictive modeling and AI-enabled prescriptive systems, depending on their infrastructural readiness, data governance frameworks, and workforce competencies. Thus, while El Rhatrif et al. (2024) identifying explainability as a precondition for responsible grid automation. This study argues that the actual implementation of predictive analytics requires integrating model types with organizational maturity and readiness. This aligns with the adoption of digital innovation, which depends on technology and institutional readiness (Benson, 2019; Webster & Gardner, 2019).

Accordingly, the conceptual framework presented in Figure 6 positions predictive analytics as a socio-technical coordination capability rather than a purely technical control instrument. It links organizing visions (shared expectations about predictive potential), recursive translation processes (where technologies are interpreted, adapted, and institutionalized), and local enactment through iterative feedback and learning loops. This framing enables stakeholders, including policymakers, grid operators, market actors, and energy users, to assess their current maturity level, identify infrastructural and skill gaps, and determine which analytical technologies are most appropriate for their present capabilities and strategic ambitions. In doing so, predictive analytics becomes a pathway for staged development and co-creation in smart grid transformation, rather than a one-size-fits-all AI solution. Moreover, the organizing vision and expectations layer of the conceptual framework highlights the importance for practitioners to articulate shared narratives about the role and value of predictive analytics. Since these narratives shape stakeholders' interpretation and assessment, they also influence legitimacy and acceptance. The framework further emphasizes recursive translation, where expectations are continuously translated into organizational practices through experimentation, evaluation, and revision. This implies institutionalizing co-creation mechanisms, shared data governance arrangements, and interdisciplinary capacity-building to support adaptive and learning-oriented smart grid operations.

At the level of local practices and enactment, thoughts on adoption depend on embedding predictive analytics into everyday operational routines, regulatory processes, and infrastructure design. This requires integrating predictive insights into operational workflows, market mechanisms, and planning activities to support real-time and strategic decision-making. Overall, the findings suggest that smart grid resilience depends less on algorithmic accuracy alone and more on the collective capacity of stakeholders to co-design, govern, and continuously revise predictive analytics systems. By linking expectations, translation, and enactment through experimental feedback loops, the framework provides a theoretical and practical roadmap for aligning technological innovation with institutional legitimacy and societal goals, highlighting the need for continuous alignment between system design and evolving stakeholder expectations in critical energy infrastructures.

Thus, resulting in practical implications for policymakers and regulators, grid operators (TSOs/DSOs), market actors (EMS, technology providers, and system developers), and energy users. For policymakers, the framework suggests establishing governance structures, regulatory sandboxes, and transparency requirements to support responsible experimentation with predictive analytics. For grid operators, the findings highlight the importance of embedding predictive models into operational decision-making processes and investing in organizational learning and interdisciplinary competencies. For market actors, the study emphasizes designing explainable and auditable analytics systems that align with institutional norms and stakeholder expectations. Finally, for energy users, participatory mechanisms and shared data infrastructures are critical for fostering trust, enabling flexible services, and supporting collaborative energy practices such as energy communities and demand response. Building on this theoretical grounding, the findings further show that predictive analytics evolves as an organizing vision that progressively materializes as a capability. However, this evolution is not adequately explained by a linear technological progression. Instead, it reflects a deeper transformation in how stakeholders conceptualize anticipation, coordination, and value creation in increasingly complex energy ecosystems. This directly addresses RQ1 by showing that stakeholders understanding shifts alongside technological possibilities, reinforcing the co-evolution of meaning and capability. Importantly, the study avoids reducing predictive analytics to artificial intelligence.

Chapter 8

8 Conclusions, Contribution, and Future Research Direction

This chapter summarizes findings of this thesis and articulates its key contributions and future directions. It begins by summarizing the main conclusions regarding the research questions, then outlines the theoretical and practical contributions to research on predictive analytics and smart grids. The chapter concludes by identifying limitations, explaining how the next phase of my PhD will build on these licentiate findings, and proposing directions for future research on the interplay among expectations, adoption, and the institutionalization of predictive analytics in energy systems.

8.1 Conclusions

Predictive analytics has emerged as a foundational capability in modern smart grids, offering tools to manage uncertainty, enhance flexibility, and support resilience. Yet this thesis demonstrates that predictive analytics, as discussed in the era of AI, is not solely about AI but has consistently evolved alongside emerging technologies. Moreover, predictive analytics is not only a technical tool but also evolves and shapes social and institutional phenomena. Through the lens of organizing vision theory, the thesis, a compilation and synthesis of two published articles and one submitted paper, was developed from a qualitative case study that involved an extensive review of the literature and a theoretical map of the evolving intersections of data-driven energy systems, energy management, AI applications, and responsible AI within smart grids. It can be concluded that stakeholder expectations, broader concerns about potential risks and costs, and institutional arrangements shape how predictive analytics is understood, adopted, and developed. The thesis is grounded in two research questions that highlight complementary dimensions of how stakeholders construct predictive analytics as an organizing vision tied to resilience, sustainability, and digital innovation. The interplay between stakeholders' expectations of digital innovation in smart grids and the ongoing adoption process influences reconfiguration, redesign, and new governance practices.

Moreover, the findings show that predictive analytics becomes durable not through technical capabilities alone, but through the collective sensemaking, negotiation, and mobilization processes that stabilize socio-technical innovations. Thus, the thesis contributes to theory, practice, and policy by offering a richer understanding of how predictive analytics evolves within complex energy systems and by outlining pathways for responsible and resilient predictive analytics in smart grid development. Furthermore, this thesis lays a conceptual foundation for understanding how predictive analytics in smart grids, as a digital innovation, provides insight into tensions surrounding transparency, legitimacy, and explainability, establishing the groundwork for subsequent empirical exploration. The case study also captures stakeholder experiences and perspectives on predictive analytics in a real-world smart grid setting. Semi-structured interviews with practitioners, operators, and policymakers within a case organization offer insights into how predictive analytics is perceived, operationalized, and governed in practice. These empirical insights deepen understanding of the socio-technical and institutional factors shaping adoption and collaboration across diverse stakeholder groups.

8.2 Theoretical Contribution

This thesis extends the explanatory power of OVT by demonstrating that predictive analytics in smart grids functions not only as a digital innovation but also as a sensemaking frame through which stakeholders interpret uncertainty and coordinate action. By integrating Weick (1995) the sensemaking perspective with institutional theory (Currie, 2011), the study shows how the organizing vision is constructed, negotiated, mobilized, and institutionalized into organizational routines and governance structures through competing expectations. This highlights the performative role of organizing visions in digitalization-enabled infrastructure transitions and advances understanding of how predictive analytics become embedded in critical infrastructure systems (Swanson & Ramiller, 1997; Swanson & Ramiller, 2004; Swanson et al., 2025). This widens the organizing vision theory beyond adoption hype cycles and strengthens its explanatory power in complex socio-technical systems with multiple actors co-shaping technological futures and constrained by regulatory and institutional barriers.

Moreover, this thesis reconceptualizes predictive analytics in smart grids as a socio-technical organizing vision that shapes collective frames about grid resilience and digitalization, defines legitimate and trustworthy practices, and structures long-term infrastructural and organizational investments. It further introduces expectation divergence as an evolutionary mechanism in innovation trajectories, showing that misalignments between anticipated potential outcomes and operational realities are not merely barriers but productive forces that reshape design requirements, governance practices, and institutional norms (Baskerville & Myers, 2009; Funk, 2019; Shi & Herniman, 2023). In this context, expectations operate as sensemaking devices that guide interpretation (Orlikowski & Gash, 1994) and justify investment, while unmet expectations trigger renegotiations of legitimacy and push systems toward redesign and realignment to achieve transparency, explainability, and participatory governance. Thus, deepening organizing vision theory and demonstrating that mobilizations are not a straightforward process, but are contested and constrained through competing and diverse expectations, as an evolutionary force, not just a barrier, in socio-technical innovation.

Furthermore, this thesis introduces predictive analytics as a boundary infrastructure (Linking IS and Energy Research) and contributes to a conceptual shift by illustrating how predictive analytics in smart grids function as a boundary infrastructure, a hybrid socio-technical system that connects diverse actors. It frames predictive analytics as a shared data/knowledge tool, a coordination mechanism across distributed energy resources, and an interpretive device that enables shared situational awareness and a governance tool that embeds transparency, risk norms, and accountability. This framing integrates work on boundary objects (Gal et al., 2005), digital infrastructures, and collaborative innovation, offering a new theoretical vocabulary. More so, it advances socio-technical perspectives on predictive analytics in the era of AI by showing that legitimacy and trust are co-produced through institutional culture, participatory design, and regulatory structures, not only through technical explainability mechanisms.

Overall, the thesis reframes predictive analytics in smart grids as a dynamic organizing vision, a sensemaking technology, and an inter-organizational capability whose legitimacy evolves through ongoing negotiation and institutionalization. It further demonstrates how predictive analytics enables resilient energy infrastructures and contributes to Green IS research at the intersection of digital innovation, AI governance, and sustainable energy systems.

8.3 Practical Contribution

This study concludes that thoughts on actual adoption of predictive analytics in smart grids depend less on technical optimization and more on aligning technological capabilities, organizational practices, and institutional conditions. For policymakers and regulators, the findings underscore the importance of establishing adaptive governance mechanisms, such as regulatory sandboxes, that enable experimentation while ensuring transparency and accountability. Grid operators are encouraged to move beyond pilot initiatives by embedding predictive analytics in core operational routines and investing in interdisciplinary competencies that integrate technical expertise with domain-specific knowledge. For technology providers, the study underscores the need to prioritize explainability, transparency, and institutional compatibility in system design rather than focusing solely on model accuracy. Finally, for energy users and market actors, the results highlight the value of participatory approaches and shared data infrastructures as key enablers of trust, collaboration, and flexible energy practices. Thus, the study offers a practical foundation for aligning predictive analytics initiatives with the broader socio-technical dynamics of smart grid transformation.

8.4 Future Research Direction

Building on the findings of this licentiate thesis, the next phase of my PhD will extend the study of predictive analytics in smart grids toward questions of security and resilience. This thesis has conceptualized predictive analytics not simply as a technical forecasting capability but as a socio-technical sensemaking mechanism through which actors interpret uncertainty and construct expectations about the future of grid operation and the adoption of innovation. Predictive models, data platforms, and analytical tools shape how grid operators, technology providers, and regulators interpret system dynamics and coordinate responses to anticipated/unforeseen changes. In this sense, predictive analytics functions as a boundary infrastructure that enables coordination across heterogeneous actors, expertise, and institutional contexts within the smart grid. Hence, as predictive analytics become increasingly embedded in grid operations, it also reshapes the security landscape of smart grids. The reliance on data-intensive infrastructures and algorithmically mediated decision-making introduces new vulnerabilities related to data integrity, system reliability, and algorithmic trust. The continuation of my PhD research will therefore examine how predictive analytics infrastructures shape processes of security, open innovation and governance in smart grids, focusing on how predictive systems mediate the interpretation of vulnerabilities, facilitate coordination between operational and cybersecurity actors, and influence how resilience and security are understood and managed as open innovation in smart grids continues.

Also, future research could further investigate the interplay between stakeholder expectations and the adoption of predictive analytics in smart grids by analyzing interaction patterns, coordination challenges, and enabling mechanisms among key actors. Such work can extend this thesis by generating actionable insights into how predictive analytics can be designed, governed, and enacted to support collaborative decision-making and resilient energy systems. Building on Organizing Vision theory (Swanson & Ramiller, 1997; Swanson & Ramiller, 2004), future studies should examine how organizing visions of predictive analytics evolve in other critical infrastructure domains, such as transport, water, and healthcare, to understand how expectations and legitimacy shape technology adoption in high-stakes contexts. Also, longitudinal research is needed to trace the divergence of expectations, the cycles of disillusionment, and iterative adaptation processes over time.

Moreover, given the Swedish empirical focus of this study, comparative cross-national research could reveal how institutional and governance structures influence the alignment between expectations and adoption in critical infrastructure. Furthermore, ethnomethodologically informed ethnographic studies (Srinivasan, 2007) could examine how stakeholder expectations are interpreted and enacted in operational settings, and how expectation–outcome gaps shape design choices, governance arrangements, and adoption practices. Such studies can advance IS scholarship on predictive analytics, boundary infrastructures, and socio-technical coordination in multi-actor digital infrastructures by revealing how organizing visions are translated into everyday practices.

References:

ACM, A. (2018). *ACM Code of Ethics and Professional Conduct*. Association for Computing Machinery. Retrieved January from https://www.acm.org/code-of-ethics

Adeoye-Olatunde, O. A., & Olenik, N. L. (2021). Research and scholarly methods: Semi-structured interviews. *Journal of the american college of clinical pharmacy*, *4*(10), 1358-1367.

AIS, A. (2014). *Code of Research Conduct - Association for Information Systems (AIS).* Association of Information Systems(AIS). Retrieved September from https://aisnet.org/page/AdmBullCResearchCond

Arévalo, P., & Jurado, F. (2024). Impact of artificial intelligence on the planning and operation of distributed energy systems in smart grids. *Energies*, *17*(17), 4501.

Arksey, H., & O'malley, L. (2005). Scoping studies: towards a methodological framework. *International journal of social research methodology*, *8*(1), 19-32.

Arnold, G. W. (2011). Challenges and Opportunities in Smart Grid: A Position Article. *Proceedings of the IEEE*.

Babayomi, O., Zhang, Z., Dragicevic , T., Hu, J., & Rodriguez, J. (2023). Smart grid evolution: Predictive control of distributed energy resources—A review. *International Journal of Electrical Power & Energy Systems*, *Vol. 147*. https://doi.org/https://doi.org/10.1016/j.ijepes.2022.108812

Barth, D., Cohen-Boulakia, B., & Ehounou, W. (2022). Distributed Reinforcement Learning for the Management of a Smart Grid Interconnecting Independent Prosumers. *Energies*, *15*.

Baskerville, R. L., & Myers, M. D. (2009). Fashion waves in information systems research and practice. *MIS Quarterly*, 647-662.

Bayindir, R., Colak, I., Fulli, G., & Demirtas, K. (2016). Smart grid technologies and applications. *Renewable and Sustainable Energy Reviews*, *66*, 499-516.

Becker, J., & Niehaves, B. (2007). Epistemological perspectives on IS research: a framework for analysing and systematizing epistemological assumptions. *Information Systems Journal*, *17*(2), 197-214.

Benson, T. (2019). Digital innovation evaluation: user perceptions of innovation readiness, digital confidence, innovation adoption, user experience and behaviour change. *BMJ health & care informatics*, *26*(1), e000018.

Berente, N., Lyytinen, K., Yoo, Y., & Maurer, C. (2019). Institutional Logics and Pluralistic Responses to Enterprise System Implementation. *MIS Quarterly*, *43*(3), 873-902.

Bessa, R. J., Rua, D., Abreu, C., Machado, P., Andrade, J. R., Pinto, R., Gonçalves, C., & Reis, M. (2018). Data Economy for Prosumers in a Smart Grid Ecosystem. e-Energy '18: The Ninth International Conference on Future Energy Systems., Karlsruhe, Germany

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). DIGITAL BUSINESS STRATEGY: TOWARD A NEXT GENERATION OF I NSIGHTS. *MIS Quarterly Vol. 37* (No. 2), pp. 471-482.

Bhattarai, B. P., Paudyal, S., Luo, Y., Mohanpurkar, M., Cheung, K., Tonkoski, R., Hovsapian, R., Myers, K. S., Zhang, R., & Zhao, P. (2019). Big data analytics in smart grids: state-of-the-art, challenges, opportunities, and future directions. *IET Smart Grid*, *2*(2), 141-154.

Boopathy, P., Liyanage, M., Deepa, N., Velavali, M., Reddy, S., Maddikunta, P. K. R., Khare, N., Gadekallu, T. R., Hwang, W.-J., & Pham, Q.-V. (2024). Deep learning for intelligent demand response and smart grids: A comprehensive survey. *Elsevier*, *15740137*. https://doi.org/10.1016/j.cosrev.2024.100617

Bose, B. K. (2017). Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems—Some Example Applications. *IEEE XPLORE, Proceedings of the IEEE*, *105*(11), 2262 - 2273. https://doi.org/10.1109/JPROC.2017.2756596

Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis. *Qualitative research in sport, exercise and health*, *11*(4), 589-597.

Bromberger, D. A., Garcia, V. J., Rodrigues, S. D., & Neves, L. S. (2026). A taxonomy for extreme weather events and their impacts on power systems: A comprehensive review of classification, effects, and mitigation strategies. *Renewable and Sustainable Energy Reviews*, *227*, 116498.

Bryman, A. (2008). Of methods and methodology. *Qualitative research in organizations and management: An International Journal*, *3*(2), 159-168.

Cao, H., Zhang, D., & Yi, S. (2023). Real-Time Machine Learning-based fault Detection, Classification, and locating in large scale solar Energy-Based Systems: Digital twin simulation. *Solar Energy*.

Carlile, P. R. (2002). A pragmatic view of knowledge and boundaries: Boundary objects in new product development. *Organization Science*, *13*(4), 442-455.

Chae, Y. T., Horesh, R., Hwang, Y., & Lee , Y. M. (2016). Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings. *Energy and Building*, *Vol. 111*, pp. 184-194.

Chen, L., Nath, R., Rocco, N., & Lidster, C. (2023). *A Sociotechnical Perspective on Predictive Analytics Implementation.* Hawaii International Conference on System Sciences (HICSS-56).2, https://aisel.aisnet.org/hicss-56/os/data_analytics/2

Corbin, J., & Strauss, A. (2015). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory, 4th Edition* (Vol. 2). Sage.

Creswell, J. W., & Creswell, J. D. (2017). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches FIFTH EDITION.* . SAGE Publications, Inc.

Currie, W. L. (2011). *Institutional Theory of Information Technology. The Oxford Handbook of Management Information Systems: Critical Perspectives and New Directions*. Oxford, New York: Oxford University Press.

Dhara, S., Shrivastav, A. K., & Sadhu, P. K. (2022). Smart grid modernization: Opportunities and challenges. *Electric Grid Mod*.

Diamantoulakis, P. D., Kapinas, V. M., & Karagiannidis, G. K. (2015). Big data analytics for dynamic energy management in smart grids. *Big Data Research*, *2*(3), 94-101.

Dwyer, C. (2011). Socio-technical systems theory and environmental sustainability.

El Rhatrif, A., Bouihi, B., & Mestari, M. (2024). AI-based solutions for grid stability and efficiency: Challenges, limitations, and opportunities. *Int. J. Internet Things Web Serv*, *9*, 16-28.

El-Hawary, M. (2016, 27-29 December 2016). *The Smart Grid—State-of-the-art and future trends* Eighteenth International Middle East Power Systems Conference (MEPCON), Cairo, Egypt.

Erlinghagen, S., & Markard, J. (2012). Smart grids and the transformation of the electricity sector: ICT firms as potential catalysts for sectoral change. *Energy Policy*, *51*, 895-906.

Erlingsson, C., & Brysiewicz, P. (2017). A hands-on guide to doing content analysis. *Afr J Emerg Med*, *7*(3), 93-99. https://doi.org/10.1016/j.afjem.2017.08.001

European Commission, E. C. (2022). *2022 Strategic Foresight Report: twinning the green and digital*
transitions in the new geopolitical context https://ec.europa.eu/commission/presscorner/api/files/document/print/en/ip_22_4004/IP_22_4004_EN.pdf

Faheem, M., Shah, S. B. H., Butt, R. A., Raza, B., Anwar, M., Ashraf, M. W., Ngadi, M. A. B., & Gungor, V. C. (2018). Smart grid communication and information technologies in the perspective of Industry 4.0: Opportunities and challenges. *Computer Science Review*.

Fan, J., & McDonald, J. (1994). A real-time implementation of short-term load forecasting for distribution power systems. *IEEE Transactions on Power Systems*, *9*(2), 988-994.

Ferreira, L. R., Aoki, A. R., & Lambert-Torres, G. (2019). A reinforcement learning approach to solve service restoration and load management simultaneously for distribution networks. *IEEE Access*, *7*, 145978-145987.

Funk, J. (2019). What's behind technological hype? *Issues in Science and Technology*, *36*(1), 36-42.

Gal, U., Yoo, Y., & Boland Jr, R. (2005). The dynamics of boundary objects, social infrastructures and social identities (Paper 57). *ECIS 2005 Proceedings. Retrieved from< http://aisel. aisnet. org/ecis2005/57*.

Garulli, A., Paoletti, S., & Vicino, A. (2014). Models and techniques for electric load forecasting in the presence of demand response. *IEEE Transactions on Control Systems Technology*, *23*(3), 1087-1097.

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.

Haefner, N., Parida, V., Gassmann, O., & Wincent, J. (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. *Technological Forecasting and Social Change*, *197*, 122878.

Hansen, H. F., Lillesund, E., Mikalef, P., & Altwaijry, N. (2024). Understanding artificial intelligence diffusion through an AI capability maturity model. *Information Systems Frontiers*, *26*(6), 2147-2163.

Hanseth, O., & Lyytinen, K. (2008). Theorizing about the design of Information Infrastructures: design kernel theories and principles.

Hernandez, L., Baladron, C., Aguiar, J. M., Carro, B., Sanchez-Esguevillas, A. J., Lloret, J., & Massana, J. (2014). A survey on electric power demand forecasting: future trends in smart grids, microgrids and smart buildings. *IEEE Communications Surveys & Tutorials*, *16*(3), 1460-1495.

Hirschheim, R. (1985). Information systems epistemology: An historical perspective. *Research methods in information systems*, *9*, 13-35.

Hsieh, J. P.-A., Rai, A., & Xu, S. X. (2011). Extracting business value from IT: A sensemaking perspective of post-adoptive use. *Management science*, *57*(11), 2018-2039.

Hu, J., & Vasilakos, A. V. (2016). Energy big data analytics and security: challenges and opportunities. *IEEE TRANSACTIONS ON SMART GRID*, *7*(5), 2423-2436.

IBM. (2025). *What is predictive analytics?* Retrieved October from https://www.ibm.com/think/topics/predictive-analytics

Idima, S., Nwatu, C. E., Adim, E. M., & Okwesa, I. J. (2023). Predictive analytics for aging US electrical infrastructure: Leveraging machine learning to enhance grid resilience and reliability.

José R., V.-C., & Zoltán, N. (2019). Reinforcement learning for demand response: A review of algorithms and modeling techniques. *Applied Energy, Elsevier*.

Kalhori, E., Werneskog, J., Barr, J., & Wolf, A. (2022). *DigiGrid – Digitaliserade och resurseffektiva elnät* (2022:895). E. AB. https://energiforsk.se/media/31876/digigrid-digitaliserade-och-resurseffektiva-elnat-energiforskrapport-2022-895.pdf

Kampars, J., Grabis, J., Pavlovs, V., Soloveja, G., & Stālmans, T. (2024). Predictive and optimisation models for AI driven electricity balancing platform. 2024 IEEE 65th International Scientific Conference on Information Technology and Management Science (ITMS),

Kehkashan, F., Hussain, S., Flavio, B. C., Abdullah, A. B., & Ling, A. W. (2024). Machine learning for power outage prediction during hurricanes: An extensive review. *The International Journal of Intelligent Real-Time Automation*.

Khalid, M. (2024). Energy 4.0: AI-enabled digital transformation for sustainable power networks. *Computers & Industrial Engineering*, *193*, 110253. https://doi.org/https://doi.org/10.1016/j.cie.2024.110253

Khan, M. A., Saleh, A. M., Waseem, M., & Sajjad, I. A. (2022). Artificial intelligence enabled demand response: Prospects and challenges in smart grid environment. *IEEE Access*, *11*, 1477-1505.

Kindong, T., Johansson, B., & Paulsson, V. (2024). A systematic literature review of AI-enabled predictive analytics in smart grids. *BIR-WS 2024, Prague, Czech Rep., September 11-13, 2024*, *3804*, 16-30.

Klein, H. K., & Myers, M. D. (1999). A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems. *MIS Quarterly*.

Kuster, C., Rezgui, Y., & Mourshed, M. (2017). Electrical load forecasting models: A critical systematic review. *Sustainable Cities and Society*, *35*, 257-270.

Lakemond, N., Holmberg, G., & Pettersson, A. (2025). Digital transformation in complex systems. *IEEE transactions on engineering management*, *71*, 192-204.

Langley, A. (1999). Strategies for theorizing from process data. *Academy of management review*, *24*(4), 691-710.

Le Coq, C., Holmberg, P., & Tangerås, T. P. (2025). Konjunkturrådets rapport 2025: Investeringar i elproduktion för en hållbar energiomställning. In: SNS förlag.

Leonardi, P. M. (2011). When Flexible Routines Meet Flexible Technologies: Affordance, Constraint, and the Imbrication of Human and Material Agencies. *MIS Quarterly*, *Vol. 35*(No 1), pp. 147-167.

Li, M., Mour, N., & Smith, L. (2024). Machine learning based on reinforcement learning for smart grids: Predictive analytics in renewable energy management. *Sustainable Cities and Society*, *109*, 105510.

Liikamaa, R. (2019). Electric power distribution in Sweden. In: RISE Research Institutes of Sweden AB.

Linden, L. P., Kuhn Jr, J. R., Parrish Jr, J. L., Richardson, S. M., Adams, L. A., Elgarah, W., & Courtney, J. F. (2007). Churchman's inquiring systems: Kernel theories for knowledge management. *Communications of the Association for Information Systems*, *20*(1), 52.

Lindquist, T., & Eriksson, M. (2026). *Uses for big data in the Nordic nuclear power plants: Experiences, challenges, and lessons learned* (2026:1166). E. AB. https://energiforsk.se/media/m2zhingx/2026-1166-uses-for-big-data-in-the-nordic-nuclear-power-plants.pdf

Liu, K., Wang, C., & Zhou, X. (2023). Decentralizing access control system for data sharing in smart grid. *High-Confidence Computing*, *3*(2), 100113.

Liu, T., Tan, X., Sun, B., Wu, Y., Guan, X., & Tsang, D. H. (2015). Energy management of cooperative microgrids with P2P energy sharing in distribution networks. 2015 IEEE international conference on smart grid communications (SmartGridComm),

Lopez, J., Rubio, J. E., & Alcaraz, C. (2018). A resilient architecture for the smart grid. *IEEE Transactions on Industrial Informatics*, *14*(8), 3745-3753.

Löwstedt, J. (1993). Organizing Frameworks in Emerging Organizations: A Cognitive Approach to the Analysis of Change. *Human Relations: Sage*, *Vol. 46*(No 4).

Mackenzie, N., & Knipe, S. (2006). Research dilemmas: Paradigms, methods and methodology. *Issues in educational research*, *16*(2), 193-205.

Marques, P. C., & Oliveira, P. A. (2024). Artificial intelligence technologies applied to smart grids and management. *Preprints*.

Menazzi, M., Qin, C., & Srivastava, A. K. (2023). Enabling resiliency through outage management and data-driven real-time aggregated DERs. *IEEE Transactions on Industry Applications*, *59*(5), 5728-5738.

Merriam, S. B., & Tisdell, E. J. (2016). Qualitative Research: A Guide to Design and Implementation.

Mesgari, M., & Okoli, C. (2019). Critical review of organisation-technology sensemaking: towards technology materiality, discovery, and action. *European Journal of Information Systems*, *28*(2), 205-232.

Meyer, M., Zapata, D., Kaltenpoth, S., & Müller, O. (2024). Benchmarking time series foundation models for short-term household electricity load forecasting. *arXiv preprint arXiv:2410.09487*.

Midttun, A. (1996). Electricity liberalization policies in Norway and Sweden: Political trade offs under cognitive limitations. *Energy Policy*, *24*(1), 53-65.

Mikalef, P., Fjørtoft, S. O., & Torvatn, H. Y. (2019). Developing an artificial intelligence capability: A theoretical framework for business value. International conference on business information systems,

Mikalef, P., & Krogstie, J. (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, *29*(3), 260-287.

Mikalef, P., van de Wetering, R., & Krogstie, J. (2018). Big Data enabled organizational transformation: The effect of inertia in adoption and diffusion. International Conference on Business Information Systems,

Mitchell, R. K., Agle, B. R., & Wood, D. J. (1997). Toward a theory of stakeholder identification and salience: Defining the principle of who and what really counts. *Academy of management review*, *22*(4), 853-886.

Molina, M., Gutiérrez, C., Ortega, M., & Sánchez, E. (2023). Summer heatwaves, wind production and electricity demand in Southern Europe: climatic conditions and impacts. *Environmental Research Communications*, *5*(8), 085005.

Morgan, D. L., & Nica, A. (2020). Iterative thematic inquiry: A new method for analyzing qualitative data. *International Journal of Qualitative Methods*, *19*, 1609406920955118.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*, *41*(1), 223-238.

Nambisan, S., Lyytinen, K., & Yoo, Y. (2020). *Handbook of Digital Innovation*. Edward Elgar Publishing Limited. http://ebookcentral.proquest.com/lib/linkoping-ebooks/detail.action?docID=6263922

Nygren, U., Börlin, S., Datta, P., Erman, M., Felix, K., Skogsmo, M., & Tenstam, J. (2023). *Feasibility Study on Artificial Intelligence Technologies in Nuclear Applications* (2023:923). E. AB. https://energiforsk.se/media/32289/feasibility-study-on-artificial-intelligence-technologies-energiforskrapport-2023-923.pdf

Olawumi, M. A., & Oladapo, B. (2025). Enhancing grid stability with machine learning: A smart predictive approach to residential energy management. *Energy and Buildings*, *338*, 115729.

Olufemi A., O., & Haoran, N. (2021). Artificial Intelligence Techniques in Smart Grid: A Survey *Smart Cities*. https://doi.org/https://doi.org/10.3390/smartcities4020029

Orlikowski, W. J., & Baroudi, J. J. (1991). Studying information technology in organizations: Research approaches and assumptions. *Information Systems Research*, *2*(1), 1-28.

Orlikowski, W. J., & Gash, D. C. (1994). Technological frames: making sense of information technology in organizations. *ACM Transactions on Information Systems (TOIS)*, *12*(2), 174-207.

Orlikowski, W. J., & Iacono, C. S. (2001). Research Commentary: Desperately Seeking the "IT" in IT Research-A Call to Theorizing the IT Artifact. *Information Systems Research*.

Orlikowski, W. J., & Robey, D. (1991). Information Technology and the Structuring of Organizations. *Information Systems Research*, *Vol. 2*(No. 2). https://doi.org/https://doi.org/10.1287/isre.2.2.143

Orlikowski, W. J., & Scott, S. V. (2008). 10 Sociomateriality: Challenging the Separation of Technology, Work and Organization. *The Academy of Management Annals*. https://doi.org/https://journals.aom.org/doi/10.5465/19416520802211644

Pandya, S. (2021). Predictive Analytics in Smart Grids: Leveraging Machine Learning for Renewable Energy Sources. *Int. J. Curr. Eng. Technol*, *11*(6), 677-683.

Parmar, B. L., Freeman, R. E., Harrison, J. S., Wicks, A. C., Purnell, L., & De Colle, S. (2010). Stakeholder theory: The state of the art. *Academy of Management Annals*, *4*(1), 403-445.

Pinzón, J. D., Osorno, T., Mola, J. A., & Valencia, A. (2020, 28 Sept.-2 Oct. 2020). Real-time Health Condition Monitoring of SCADA Infrastructure of Power Transmission Systems Control Centers. 2020 IEEE PES Transmission & Distribution Conference and Exhibition - Latin America (T&D LA),

Powell, W. W., & DiMaggio, P. J. (1991). *The new institutionalism in organisational analysis*. University of Chicago Press.

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In *An integrated approach to communication theory and research* (pp. 432-448). Routledge.

Sen, R., Heim, G., & Zhu, Q. (2022). Artificial Intelligence and Machine Learning in Cybersecurity: Applications, Challenges, and Opportunities for MIS Academics. *COMMUNICATIONS OF THE ASSOCIATION FOR INFORMATION SYSTEMS Vol. 51*(No. 1), pp. 179-209.

Shi, H., Xu, M., & Li, R. (2018). Deep Learning for Household Load Forecasting—A Novel Pooling Deep RNN. *IEEE TRANSACTIONS ON SMART GRID*, *Vol. 9*(pp 5).

Shi, Y., & Herniman, J. (2023). The role of expectation in innovation evolution: Exploring hype cycles. *Technovation*, *119*, 102459.

Shmueli, G., & Koppius, O. R. (2011). Predictive Analytics in Information Systems Research. *MIS Quarterly*, *35*(3), 553-572. https://doi.org/10.2307/23042796

Sifat, M. M. H., Choudhury, S. M., Das, S. K., Ahamed, M. H., Muyeen, S. M., Hasan, M. M., Firoj Ali, M. F., Tasneem, Z., Islam, M. R., Islam, M. R., Badal, F. R., Abhi, S. H., Sarkar, S. K., & Das, P. (2023). Towards electric digital twin grid: Technology and framework review. *Elsevier, Energy and AI*, *11*.

Singh, R., Arya, P. K., & Agrawal, A. (2025). The global energy landscape and the smart grid: a paradigm shift towards sustainability. *Green Machine Learning and Big Data for Smart Grids*, 221-234.

Sönne, M. (2023). *Better resilience with BULT*. Retrieved 10 September from

Srinivasan, R. (2007). Ethnomethodological Architectures: Information Systems Driven by Cultural and Community Visions. *JOURNAL OF THE AMERICAN SOCIETY FOR INFORMATION SCIENCE AND TECHNOLOGY*, *Vol. 58*(No. 5), pp. 723–733.

Stake, R. E. (1978). The case study method in social inquiry. *Educational researcher*, *7*(2), 5-8.

Sutfeld, L., & Thore, A. (2025). *On-Premise AI Solutions for Nordic Nuclear Applications: Report by RISE Research Institutes of Sweden* (2025:1093). E. AB. https://energiforsk.se/media/34237/2025-1093-on-premise-ai-solutions-for-nordic-nuclear-applications.pdf

Svahn, F., Mathiassen, L., & Lindgren, R. (2017). Embracing digital innovation in incumbent firms. *MIS Quarterly*, *41*(1), 239-254.

Svenska kraftnät, S. K. (2014). *Elnät i fysisk planering - Behandling av ledningar och stationer i fysisk planering och i tillståndsärenden. 2014.* (svensk energi, Issue.

Svenska kraftnät, S. K. (2021). *Grid development*. Retrieved December from

Svenska kraftnät, S. K. (2022). *National Grid: Reliable electricity supply*. Retrieved November from https://www.svk.se/en/national-grid/reliable-electricity-supply/

Svenska kraftnät, S. K. (2023). *Report on Reduction of Gross Electricity consumption during peak hours in Sweden for December 2022*.

Svenska kraftnät, S. K. (2024). National Grid: Operations and Electricity Markets.

Swanson, E. B., Ramiller, N., & Wang, P. (2025). Organizing vision revisited and reimagined for a changing world. *Journal of Information Technology*, 02683962251315765.

Swanson, E. B., & Ramiller, N. C. (1997). The Organizing Vision in Information Systems Innovation. *Organization Science 8*(5).

Swanson, E. B., & Ramiller, N. C. (2004). Innovating Mindfully with Information Technology. *MIS Quarterly*, *Vol. 28*(No. 4), pp. 553-583.

Syed, D., Zainab, A., Ghrayeb, A., Refaat, S. S., Abu-Rub, H., & Bouhali, O. (2020). Smart grid big data analytics: Survey of technologies, techniques, and applications. *IEEE Access*, *9*, 59564-59585.

Tan, B., Pan, S. L., Chen, W., & Huang, L. (2020). Organizational sensemaking in ERP implementation: The influence of sensemaking structure. *MIS Quarterly*, *44*(4), 1773-1810.

Tekniska verken, T. v. (2024). *2023 Års- och hållbarhetsredovisning: Arbete pågår. För en enkel, hållbar vardag och vår gemensamma framtid.* (Tekniska verkens års- och hållbarhetsredovisning 2023, Issue.

Thorén, C., Ågerfalk, P. J., & Rolandsson, B. (2018). Voicing the puppet: Accommodating unresolved institutional tensions in digital open practices. *Organization Studies*, *39*(7), 923-945.

Tona, O., & Carlsson, S. A. (2013). THE ORGANIZING VISION OF MOBILE BUSINESS INTELLIGENCE. European Conference on Information Systems,

Tongco, M. D. C. (2007). Purposive sampling as a tool for informant selection.

TT News Agency, T. N. A. (2025). *Thousands in Sweden will be without power tonight after Storm Johannes*. Retrieved 30th December from https://swedenherald.com/article/calmer-weather-but-warnings-remain-after-storm-johannes-hit-sweden

U.S. Department of Energy, U. S. D. o. E. (2009). *The Modern Grid Strategy: A Vision for the Smart Grid.*

Valizadehhaghi, H. (2016). Data-driven Predictive Analytics For Distributed Smart Grid Control.

van Lente, H., & Bakker, S. (2010). Competing expectations: the case of hydrogen storage technologies. *Technology Analysis & Strategic Management*, *22*(6), 693-709. https://doi.org/10.1080/09537325.2010.496283

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.

Vetenskapsrådet, V. (2025). *Good Research Practice 2024*. https://www.vr.se/english/analysis/reports/our-reports/2025-07-03-good-research-practice-2024.html

Volkova, A., Patil, A. D., Javadi, S. A., & de Meer, H. (2022). Accountability challenges of AI in smart grid services. Proceedings of the Thirteenth ACM International Conference on Future Energy Systems, Wagner, E. L., Newell, S., Ramiller, N., & Enders, J. (2018). From public ideology to socio-material reproduction of agile principles: The case of pivotal labs. *Information and Organization*, *28*(4), 192-210.

Walsham, G. (1995). Interpretive case studies in IS research: nature and method. *European Journal of Information Systems*, *4*(2), 74-81.

Walsham, G. (2006). Doing interpretive research. *European Journal of Information Systems*, *15*.

Webster, A., & Gardner, J. (2019). Aligning technology and institutional readiness: the adoption of innovation. *Technology Analysis & Strategic Management*, *31*(10), 1229-1241. https://doi.org/10.1080/09537325.2019.1601694

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, *Vol 26*.

Weick, K. E. (1995). *Sensemaking in organizations* (Vol. 3). Sage publications Thousand Oaks, CA.

Weick, K. E. (2012). Organized sensemaking: A commentary on processes of interpretive work. *Human relations*, *65*(1), 141-153.

Xu, X., He, S., Zhou, B., Wang, H., Jiang, H., Liu, C., Sun, B., Yin, T., & Yan, J. (2025). South European heatwaves and their impacts on the power system in 2022. *Journal of Geophysical Research: Atmospheres*, *130*(3), e2024JD042310.

Yan, J., Menghwar, M., Asghar, E., Panjwani, M. K., & Liu, Y. (2019). Real-time energy management for a smart-community microgrid with battery swapping and renewables. *Applied energy*, *238*, 180-194.

Yin, R. K. (2018). *Case study research and applications: Design and methods*. SAGE Publications, Inc.

You, J., Yin, F., & Gao, L. (2025). Escalating wind power shortages during heatwaves. *Communications Earth & Environment*, *6*(1), 245.

You, S., Zhao, Y., Mandich, M., Cui, Y., Li, H., Xiao, H., Fabus, S., Su, Y., Liu, Y., Yuan, H., Jiang, H., Tan, J., & Zhang, Y. (2020). *A Review on Artificial Intelligence for Grid Stability Assessment* 2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm),

Yu, N., Shah, S., Johnson, R., Sherick, R., Hong, M., & Loparo, K. (2015, 18-20 Feb. 2015). Big data analytics in power distribution systems. 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT),

Yu, Y., Lakemond, N., & Holmberg, G. (2024). AI in the context of complex intelligent systems: Engineering management consequences. *IEEE transactions on engineering management*, *71*, 6512-6525.

Zhang, J. Z., Srivastava, P. R., Sharma, D., & Eachempati, P. (2021). Big data analytics and machine learning: A retrospective overview and bibliometric analysis. *Expert Systems with Applications*, *184*, 115561.

Zhang, Y., Huang, T., & Bompard, E. F. (2018). Big data analytics in smart grids: a review. *Energy informatics*, *1*(1), 1-24.

Zhang, Z., Rath, S., Xu, J., & Xiao, T. (2026). Federated learning for smart grid: A survey on applications and potential vulnerabilities. *ACM Transactions on Cyber-Physical Systems*, *10*(1), 1-26.

Zhongtuo, S., Wei, Y., Zhouping, L., Lingkang, Z., Yifan, Z., Runfeng, Z., Yong, T., & Jinyu, W. (2020). Artificial intelligence techniques for stability analysis and control in smart grids: Methodologies, applications, challenges and future directions. *Applied Energy, Elsevier*

Zohuri, B. (2023). Navigating the global energy landscape balancing growth, demand, and sustainability. *J. Mat. Sci. Apl. Eng*, *2*(7).

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Licentiate Theses

1. **Johansson, Niklas E. (2004)** *Self-Service Recovery: Towards a Framework for Studying Service Recovery in a Self-Service Technology Context from a Management and IT Perspective,* Licentiate Thesis KUS 2004:3, Karlstad University.

2. **Ekman, Peter (2004)** *Affärssystem & Affärsrelationer: En fallstudie av en leverantörs användning av affärssystem i interaktionen med sina kunder,* Licentiate Thesis No.25, Mälardalens universitet.

3. **Wrenne, Anders (2004).** *Tjänsteplattformar: Vid utveckling av mobila tjänster inom telekommunikation,* Licentiatavhandling, KUS 2004:4, Karlstads universitet, Centrum för tjänsteforskning.

4. **Wismén, May (2004).** *Kunskapsprocesser inom hälso- och sjukvård: En studie av kunskapsintegrering mellan laboratorium och dess kunder*, Licentiatavhandling, KUS 2004:10, Karlstads universitet.

5. **Stoltz, Charlotte (2004).** *Calling for Call Centres: A Study of Call Centre Locations in a Swedish Rural Region,* Licentiate Thesis, No. 1084, IDA-EIS, Linköping University, Institute of Technology.

6. **Abelli, Björn (2004).** *Theatre Production: A System Development Process,* Licentiate thesis No. 30, Mälardalen University.

7. **Maaninen-Olsson, Eva (2004).** *Det gränslösa projektet: En studie om förmedling och skapande av kunskap i tid och rum,* Licentiatavhandling nr. 41, Företagsekonomiska institutionen, Uppsala Universitet,.

8. **Sällberg, Henrik (2004).** *On the value of customer loyalty programs: A study of point programs and switching costs,* Licentiate Thesis, No. 1116, IDA-EIS, Linköping University, Institute of Technology.

9. **Stockhult, Helén (2005).** *Medarbetaransvar - ett sätt att visa värderingar: En konceptualisering av medarbetarnas ansvar och ansvarstagande i callcenter,* Licentiatavhandling nr. 1, Örebro universitet, Institutionen för ekonomi, statistik och informatik.

10. **Vascós Palacios, Fidel (2005).** *On the information exchange between physicians and social insurance officers in the sick leave process: An Activity Theoretical perspective,* Licentiate Thesis, No. 1165, IDA-EIS, Linköping University, Institute of Technology.

11. **Keller, Christina (2005).** *Virtual Learning Environments in higher education:. A study of students' acceptance of educational technology*, Licentiate Thesis, No. 1167, IDA-EIS, Linköping University, Institute of Technology.

12. **Ahlström, Petter (2005),** *Affärsstrategier för seniorbostadsmarknaden,* Licentiatavhandling, No. 1172, IDA-EIS, Linköpings universitet, Tekniska Högskolan.

13. **Dahlin, Peter (2005).** *Structural Change of Business Networks: Developing a Structuration Technique,* Licentiate Thesis No. 49, Mälardalen University.

14. **Granebring, Annika (2005).** *ERP Migration Structure : An Innovation Process Perspective,* Licentiate Thesis No. 50, Mälardalen University.

15. **Cöster, Mathias (2005).** *Beyond IT and Productivity: How Digitization Transformed the Graphic Industry,* Licentiate Thesis, No. 1183, IDA-EIS, Linköping University, Institute of Technology.

16. **Horzella, Åsa (2005).** *Beyond IT and Productivity: Effects of Digitized Information Flows in Grocery Distribution,* Licentiate Thesis, No. 1184, IDA-EIS, Linköping University, Institute of Technology.

17. **Kollberg, Maria (2005).** *Beyond IT and Productivity: Effects of Digitized Information Flows in the Logging Industry,* Licentiate Thesis, No. 1185, IDA-EIS, Linköping University, Institute of Technology.

18. **Hansson, Magnus (2005).** *From Dusk till Dawn: Three Essays on Organizational Closedowns*, Licentiate Thesis, No. 3, Örebro University.

19. **Verma, Sanjay (2005).** *Product's Newness and Benefits to the Firm: A qualitative study from the perspective of firms developing and marketing computer software products,* Licentiate thesis, No. 54, Mälardalen University.

20. **Sundén, Susanne & Wicander, Gudrun (2005).** *Information and Communication Technology Applied for Developing Countries in a Rural Context: Towards a Framework for Analyzing Factors Influencing Sustainable Use*, Licentiate thesis, KUS 2006:69, Karlstad University.

21. **Käll, Andreas (2005).** *Översättningar av en managementmodell: En studie av införandet av Balanced Scorecard i ett landsting,* Licentiatavhandling, No.1209, IDA-EIS, Linköpings universitet, Tekniska Högskolan.

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23. **Flodström, Raquel (2006).** *A Framework for the Strategic Management of Information Technology*, Licentiate Thesis, No.1272, IDA-EIS, Linköping University, Institute of Technology.

24. **Werelius, Sofie (2006).** *Consumer Business Relationship with Retailer and Etailer for the Purchase of Clothing: A Network Perspective*, Licentiate Thesis No. 45, Uppsala University, Department of Business Studies.

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29. **Numminen, Emil (2008).** *Software Investments under Uncertainty: Modeling Intangible Consequences as a Stochastic Process*, Licentiate Dissertation Series, No. 2008:7, Blekinge Institute of Technology.

30. **Bergqvist, Linda (2008).** *A Conceptual Framework for Studying the Successful Outcome of the IS Outsourcing Process from a Relationship Perspective,* Licentiate Thesis, KUS 2008:30, Karlstad University, Information Systems, Faculty of Economic Sciences, Communication and IT.

31. **Wingkvist, Anna (2008).** *The Quest for Equilibrium. Towards an Understanding of Scalability and Sustainability for Mobile Learning*, Licentiate Thesis, No. 08118, Växjö University, Center for Learning and Knowledge Technologies, Department of Information Systems, School of Mathematics and System Engineering.

32. **Sundberg, Klas (2009).** *Atlas Copcos strategi och styrning: Verktyg som ger guld***,** Licentiate Thesis, No. 48, Uppsala universitet, Företagsekonomiska institutionen.

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