Leveraging advanced analytics to develop and evaluate energy efficiency services and products

Andreas Weigert

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Erstgutachter: Prof. Dr. Thorsten Staake

Zweitgutachter: Prof. Dr. Frédéric Thiesse

Mitglied der Promotionskommission: Prof. Dr. Dominik Herrmann

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ORCID iD des Autors: 0000-0002-8093-3710

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Dedicated to those who are mindful, listen, and truly care.

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German summary (Zusammenfassung)

Zwei disruptive Transformationen, die Energiewende und die Digitalisierung, stellen die Gesellschaft und die Energieversorger vor große Herausforderungen und bieten gleichzeitig große Chancen. Insbesondere die Dezentralisierung der Energieerzeugung und die Elektrifizierung von Großverbrauchern wie Heizungen oder Fahrzeugen (Colle 2020; BDEW 2021) lassen neue Geschäftsfelder rund um den Vertrieb solcher Systeme sowie umfassende Dienstleistungskonzepte entstehen und können die Rolle der Energieversorger vom Energieanbieter hin zum Online-System-Anbieter verändern (Requejo et al. 2019; Colle 2020). Gleichzeitig generieren die Digitalisierungsbestrebungen der Energieversorger neue und potenziell wertvolle Kundendaten. Neben neuen Kundeninteraktionsdaten aus den klassischen Geschäftsfeldern (BDEW 2021) werden für eine zunehmende Anzahl von Haushalten Verbrauchsdaten durch Smart Meter generiert (Tounquet und Alaton 2020; BFE 2021; EIA 2022), die insbesondere für Großverbraucher wie beispielsweise Wärmepumpen indikative Muster betreffend Systemzustand und Nutzung verfügbar machen und damit helfen können, Optimierungspotenzial zu heben. Darüber hinaus entstehen durch die Aktivitäten in den neuen Geschäftsfeldern Datensätze aus der Planung und dem Vertrieb von Dezentralisierungs- und Elektrifizierungslösungen sowie aus der Durchführung von Energieeffizienzdienstleistungen. Aufgrund des beratungsintensiven Charakters vieler dieser Produkte und Dienstleistungen (Gram-Hanssen et al. 2017) enthalten diese Daten häufig implizit teures Expertenwissen.

Die Nutzung dieser Datensätze mit Hilfe von Datenanalyse und Künstlicher Intelligenz (DA&KI) birgt daher ein großes Potenzial. Für Unternehmen könnten diese Technologien insbesondere bei der Entwicklung neuartiger Produkte und Dienstleistungen, bei der Automatisierung von Aufgaben und bei der Erweiterung menschlicher Fähigkeiten hilfreich sein (Brynjolfsson und Mitchell 2017). Kunden könnte die Nutzung von DA&KI dabei helfen, dass wichtige Produktmerkmale, wie z.B. eine hohe Energieeffizienz, ein hoher Nutzungsgrad erneuerbarer Energie und niedrige Betriebskosten auch tatsächlich erbracht werden. In der Praxis ist dies für eine wichtige Kerntechnologie der Energiewende häufig nicht der Fall: So liegt z.B. die Effizienz von Wärmepumpen im Betrieb regelmäßig unter den Erwartungen (Puttagunta et al. 2010; Caird et al. 2012; Gleeson und Lowe 2013; Yin et al. 2019; Qiao et al. 2020; Chesser et al. 2021; Gao et al. 2021; O'Hegarty et al. 2022).

Allerdings zeigt sich, dass zahlreiche Energieversorger Schwierigkeiten bei der Erschließung des Potenzials von DA&KI in neuen Geschäftsfeldern wie der Energieeffizienzberatung oder dem Verkauf und Service haben, wodurch viele Daten ungenutzt bleiben (BDEW 2021). Ein wesentlicher Faktor, der viele Energieversorger bei der Erschließung dieses Potenzials hemmt, ist das Fehlen von Analyseexperten (McKinsey 2018; BDEW 2021). Diese werden folglich vor allem in den traditionellen Geschäftsbereichen eingesetzt (BDEW 2021). Dies führt dazu, dass es für Energieversorger eine zentrale Herausforderung ist, geeignete Anwendungsfälle für die Datenanalyse in neuen Geschäftsfeldern zu identifizieren. Auch in der Forschung liegt der Schwerpunkt von Anwendungsfällen für die Nutzung von Smart-Meter-Daten vorwiegend in den traditionellen Geschäftsbereichen wie z.B. der Stabilisierung des Stromnetzes (Fischer und Madani 2017), nicht aber in der Energieeffizienzberatung von Wärmepumpen, und es gibt nur wenige Beispiele, die erste Schritte in diesem Kontext gezeigt haben (z.B. Fei et al. 2013; Taylor et al. 2014; Hopf et al. 2018b). Eine weitere Herausforderung besteht darin, dass viele dieser neuartigen Datensätze ein begrenztes Volumen aufweisen, d.h. sie umfassen oft nur einige hundert Transaktionen und wenige Datenfelder, was ein Hindernis bei ihrer Nutzung darstellen kann. Trotz ihres Potenzials bleiben kleine Datensätze in vielen Organisationen ungenutzt (Wilson und Daugherty 2020), was insbesondere für Energieversorger bei der Entwicklung neuer Geschäftsfelder gilt (BDEW 2021).

Vor diesem übergeordneten Hintergrund ist das Ziel dieser kumulativen Dissertation, einen differenzierten Blick auf zwei typische Anwendungsfälle im Kontext von neuen Geschäftsfeldern von Energieversorgern und der Energiewende zu werfen, die Energieeffizienzberatung von Wärmepumpen und dem Vertrieb von Dezentralisierungs- und Elektrifizierungslösungen. Ein Schwerpunkt der Arbeit liegt darin, die Möglichkeiten von prädiktiver Datenanalyse zur Kundenselektion auf Basis typischer Energieversorgerdaten zu untersuchen, wie z.B. Smart-Meter-Daten, Beratungsprotokollen aus der Energieeffizienzberatung von Wärmepumpen oder Onlinekonfigurationen für Dezentralisierungs- und Elektrifizierungslösungen. Die untersuchten Daten umfassen dabei typische Fälle, in denen nur begrenzte Datenmengen zur Verfügung stehen. Um das Themenfeld ganzheitlich zu adressieren, besteht die kumulative Thesis aus einem einführenden Kapitel und fünf Forschungspapieren, die wie folgt in zwei Kapitel unterteilt sind.

Kapitel 1 beleuchtet die Möglichkeiten der Datenanalyse für die Bereitstellung von Energieeffizienzdienstleistungen. Zunächst wird das erzielte Einsparpotenzial einer Energiesparkampagne für professionell inspizierten Wärmepumpen eines Energieversorgers untersucht, große Heterogenität im Einspareffekt nachgewiesen und Möglichkeiten zur Identifikation von Vielsparern anhand einfacher Wärmepumpencharakteristika und Stromverbrauchsdaten aufgezeigt. Darauf aufbauend werden prädiktive Verfahren untersucht, die eine Ableitung von wichtigen Wärmepumpencharakteristika für die Energieberatung auf Basis von Smart-Meter-Daten ermöglichen. Die Arbeit zeigt, dass bereits wenige hundert Labels sowie viele in der Praxis üblich auftretende Varianten von Smart-Meter-Daten für eine zuverlässige Vorhersage ausreichen. Das Kapitel schließt mit einer Studie, in der daran anknüpfende Möglichkeiten zur digitalen Energieberatung untersucht werden. Ein Schwerpunkt liegt dabei auf der Entwicklung eines Frameworks zur Analyse typischer Wärmepumpenprobleme im Feld und den Möglichkeiten der Problemerkennung durch Smart-Meter-Datenanalyse sowie der Eignung von Inspektionsprotokollen als begrenzte Datenquelle für die Labelgenerierung. Darüber hinaus werden Möglichkeiten der Einbindung von Endnutzern in die Problemerkennung und -lösung untersucht. Angewandt auf Felddaten aus über 200 professionellen Inspektionen ermöglicht das Framework eine Bewertung der nächsten Schritte in der digitalen Energieeffizienzberatung für Wärmepumpen.

Kapitel 2 vermittelt einen Einblick in die Datenanalyse zur Vertriebsunterstützung von Dezentralisierungs- und Elektrifizierungslösungen. In diesem Kapitel werden Fallstudien für zwei typische Produkte der Energiewende mit hohem Individualisierungsgrad und entsprechendem nachgelagerten Beratungsaufwand betrachtet. Das Kapitel demonstriert, wie Produktberater durch prädiktive Analysen auf Grundlage begrenzter Daten aus Online-Konfiguratoren bei der Identifizierung relevanter Kunden unterstützt werden können. Darüber hinaus liefert das Kapitel für diesen Anwendungsfall empirische Evidenz dafür, dass der Aufbau von analytischen Fertigkeiten und die Realisierung von Wertschöpfungsmechanismen bereits im Umfeld begrenzter Datenmengen möglich ist. Dies kontrastiert die vorherrschende Meinung, dass große Datensätze eine Schlüsselvoraussetzung hierfür sind.

Die Erkenntnisse aus dieser Dissertation tragen in vielfältiger Weise zum aktuellen Stand der Forschung und zu einer fundierten Entscheidungsgrundlage für die Praxis, insbesondere für Energieversorger und politische Entscheidungsträger, bei. Sie zeigen nicht nur den Nutzen von Datenanalysen zur Identifizierung besonders geeigneter Kunden in den neuen Geschäftsfeldern von Energieversorgern auf, sondern leisten auch einen Beitrag für einen zielgerichteteren Einsatz wertvoller und knapper Expertenressourcen. Darüber hinaus erlaubt das entwickelte Framework zur Analyse von Wärmepumpenproblemen im Feld einen Blick in die Zukunft und beschreibt Möglichkeiten zur Digitalisierung der Energieeffizienzberatung. Die Arbeit liefert eine Bewertung für ein breites Spektrum an möglichen Ansätzen und betont insbesondere die Rolle der automatisierten Problemerkennung auf der Basis von Inspektionsprotokollen und Smart-Meter-Daten sowie die Möglichkeit verschiedener Grade der Einbeziehung von Endnutzern in die Problemerkennung und -lösung, die mithilfe von assistierenden Informationssystemen möglich werden könnte. Die vorgeschlagenen Ansätze könnten eine vielversprechende Alternative oder Ergänzung zu einer teuren Vor-Ort-Beratung durch Experten darstellen. Abschließend liefert die Arbeit eine Reihe von Hinweisen für politische Entscheidungsträger, die beim Design von Energieeffizienzprogrammen für Wärmepumpen berücksichtigt werden sollten, um einen kosteneffizienten Einsatz von Fördermitteln zu gewährleisten. Daneben erweitert die Arbeit die Informationssystemforschung um einen Beitrag, der für einen beispielhaften Fall aus dem Energieversorgersektor zeigt, dass für die Wertschöpfung durch Datenanalysen nicht unbedingt große Datenmengen notwendig sind.

Insgesamt veranschaulicht diese kumulative Dissertation das Potenzial prädiktiver Analyse für die Entwicklung neuer Geschäftsfelder von Energieversorgern auf Basis von typischen und kleinen Datensätzen, um bedeutsame Unternehmensziele (z.B. Geschäftstransformation und ein effizienter Einsatz von Unternehmensressourcen) und gesellschaftliche Ziele (z.B. Energiewende) voranzutreiben. Die Dissertation zeigt für relevante Anwendungsfälle auf, wie Energieversorger bereits vorhandene Datensätze für die Entwicklung neuer Geschäftsfelder nutzen können und liefert Energieversorgern Argumente und Ansätze, auch mit begrenzten Datensätzen Datenanalyseinitiativen zu starten.

Introductory paper

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1. Introduction

Two disruptive developments, the energy transition and digitalisation, pose significant challenges for utility companies. At the same time, both transformations also offer new business opportunities through the decentralisation of energy production and the electrification of large energy consumers such as heating systems and vehicles (Colle 2020; BDEW 2021). In light of these developments, utility companies are confronted with new business models and new competitors (Requejo et al. 2019). In this context, some companies strive for a more intelligent use of energy, for example, by aggregating energy from photovoltaic systems, battery-electric vehicles, and heat pumps (Requejo et al. 2019), while other companies focus on specific products (e.g. a heat pump or a battery storage) and develop accompanying services, for example, by providing a turnkey installation, operation, efficiency monitoring, and maintenance of a solution (Requejo et al. 2019; Colle 2020). Given these developments, some utility companies are now better described as 'online consumer retailer[s] rather than a traditional retail power provider[s]' (Requejo et al. 2019, p.3).

At the same time, digitalisation efforts lead to more data being available to utility companies. Starting from their core business, utility companies conduct digital innovation projects to reduce costs and increase customer satisfaction (Requejo et al. 2019). Typical endeavours include the development of new platforms for customer interaction, the provision of services for account management, and access to consumption and billing data (BDEW 2021). Such endeavours result in a plethora of additional customer interaction data. For instance, utility companies derive new data from pre-sales activities in which users configure decentralisation and electrification solutions online. Such data are frequently augmented by experts when offering a system, which necessitates an extensive exchange of information with customers, including the collection of detailed data on building characteristics and customer preferences (Gram-Hanssen et al. 2017). In addition to sales activities, the advent of digital metering technology (i.e. smart meters) has enabled an increasing number of utility companies to collect energy consumption data from residential households in near real-time (Tounquet and Alaton 2020; BFE 2021; EIA 2022). These sensors generate information on energy consumed on household level, which is typically aggregated across all electric devices. Their data also contains patterns that are particularly indicative of large energy consumers, such as heat pumps. In particular, when combined with data from activities in the new business fields, sensor data has the potential to be of significant value. For instance, energy efficiency consulting typically results in comprehensive reports covering pictures of the inspected entity, calculations, problems, and recommendations (Sprehn et al. 2015).

Utilising such data with methods from data analytics and artificial intelligence (DA&AI) could have a profound impact on the development of new business activities, as DA&AI allow companies to extend human capabilities, develop new products, services, and processes, and even automate some particularly suitable tasks or processes (Brynjolfsson and Mitchell 2017). From the customer perspective, DA&AI could also help to ensure that important product and service features of electrification and decentralisation solutions such as high energy efficiency, high utilisation rate of renewable energy, and low operational costs are actually realised. Achieving these features is critical not only to satisfying customers who have already invested in such technologies, but also to building trust in many planned projects. However, in the field, it has been shown that this is often not the case. For example, the energy efficiency of heat pumps during operation, a key technology in the energy transition, often falls short of expectations (Puttagunta et al. 2010; Caird et al. 2012; Gleeson and Lowe 2013; Yin et al. 2019; Qiao et al. 2020; Chesser et al. 2021; Gao et al. 2021; O'Hegarty et al. 2022). While uncovering efficiency problems of heat pumps through data analysis solutions was previously the preserve of heating manufacturers, the advent of smart meters and the resulting indicative consumption patterns could pose a strategic advantage for utility companies, as these data potentially allow them to develop cross-manufacturer analytical solutions covering heat pumps regardless of their age and IoT capability.

However, many utility companies are still struggling to initiate data analytics initiatives using their newly collected data. A recent study analysing the utilisation of data analytics in German, Swiss, and Austrian (GSA) utility companies shows that the primary fields of DA&AI lie in their traditional business, for example, in price analysis and demand forecasting to support energy retail and risk management (BDEW 2021). In contrast, DA&AI is less used in new business fields, for example, by using smart meter data to provide energy efficiency recommendations or to support sales and service (ibid.). The study also points out that even a quarter of utility companies in the GSA region see little benefit arising from data analytics and concludes that 'data treasures are often not exploited' (p. 21, ibid.).

This thesis takes the view that multiple factors contribute to the underutilisation of data treasures in emerging business fields. First, many utility companies lack the necessary resources to initiate data analytics initiatives, i.e. digital experts. Closely related, feasibility studies are missing that demonstrate how analytics can assist utility companies in these new business fields and serve as a blueprint. Second, many of the newly available data sources in these business areas tend to be limited in volume, which makes them less attractive for companies that are still at the infancy of their data analysis endeavours. These aspects will be detailed below before introducing the thesis's overall research theme.

First, utility companies face organisational challenges in finding suitable digital experts, such as data scientists, who do not perceive utility companies as digital and thus attractive companies (McKinsey 2018). Consequently, they are only slowly starting to build data analytics skills in their employees and to set up initiatives between business and data scientists to solve problems with data analytics (BDEW 2021). However, having employees with domain knowledge and analytical skills is crucial for building data analytics competencies (Ghasemaghaei et al. 2018). As a result, utility companies lack use cases that demonstrate how data analytics can leverage and support these new business fields. In the field of digital energy efficiency services, the lion's share of utility companies in the GSA region do not provide customers with energy efficiency recommendations based on smart meter data (BDEW 2021). This situation is even more severe for applications focusing on heat pumps for space and water heating. Academia has primarily investigated the role of heat pumps and smart meters for traditional business fields of utility companies, namely maintaining electricity grid stability, incorporating renewable energy and fluctuating electricity rates (Fischer and Madani 2017). In this context, only a few studies focus on using such data to reveal information relevant for heat pump replacement marketing (Fei et al. 2013) or energy efficiency (Taylor et al. 2014; Hopf et al. 2018b), but do not show the actual value of such information for energy consultancy. Finally, it remains unclear if and how end users could be involved in energy consultancy with the help of derived information on their installation.

Second, in terms of volume, utility companies often collect data on a relatively small number of customers or decision points, processing only hundreds of transactions with attributes in the tens. Such low data volumes are characteristic of many of the emerging data sources for decentralisation and electrification products and services. For example, energy-efficiency consulting is typically provided only once per customer every few years, while planning a new heat pump or photovoltaic system may happen once every fifteen years or more due to long lifetimes (Bundesverband Wärmepumpe e.V. 2014; Marinelli et al. 2019). Also, the number of potential transactions is often limited as many utility companies, especially in Germany (Beier et al. 2020) and Switzerland (BFE 2018), are small and serve small regional markets. Due to the novelty of many decentralisation and electrification products and services, the resulting data sets can be considered rare and historical data tend to be limited in volume. Activities in these areas often result in data sets that contain expert knowledge, e.g., from sales agents or energy consultants, who documented information expensive to derive, and thus generated valuable pieces of information that can be a source for deriving labels for prediction tasks. One additional complexity is that these data sets are often difficult to process, as they lack digitisation, standardisation, and integration. Many utility companies describe such data silos between different units, along with non-uniform databases, as a major barrier to DA&AI initiatives (BDEW 2021). One example is reports from energy efficiency consulting that contain important information about appliances which experts found in laborious on-site inspections at the customers' sites. However, these reports, if digitised at all, often do not capture information in a form that allows its direct use for analytical purposes. The potential of such sources lies in combining them with additional data sources such as smart meter data, where they can serve as potential labels for machine learning tasks. However, best practice in the utility industry describes the availability of large volumes of data as a core requirement before embarking on DA&AI initiatives (BDEW 2020). Such recommendations are partly due to a biased focus on data-hungry AI methods (e.g. deep learning), which require tens of thousands of data points (Bach et al. 2017) and are ineffective with only hundreds of data points (Kraus et al. 2020). However, many less data-hungry methods exist that can help initiate analytical steps, build analytics competencies, and assess project feasibility.

As long as utility companies lack feasibility studies and are in the early stages of building data analytics capabilities, they may avoid data analytics projects with limited data sources despite their potential opportunities. To address the first aspect, this thesis explores use cases relevant to business transformation and an important societal environmental goal, the energy transition. This thesis investigates the feasibility of data analytics initiatives in new business areas focused on energy efficiency services and decentralisation and electrification solutions. In particular, this thesis poses the following overarching research theme:

Exploring approaches to leverage data analytics for consultancy-intensive efficiency products and services in the context of utility companies and limited data environments.

To respond to this research theme, this thesis investigates two application areas, namely the provision of energy efficiency consultancy services, and the sales of energy decentralisation and electrification solutions. Both application areas are typical examples of new business fields of utility companies in the context of the energy transition. Additionally, both application areas include extensive consulting services that require highly qualified experts, who often represent the bottleneck in the provision of these products and services given the shortage of skilled workers in the energy transition (HPA 2020; Ecoplan 2021; Nowak 2021; BMWK 2022; Branford and Roberts 2022; Hilpert 2022). Finally, these application areas deal with cases where limited but potentially valuable data are available.

Cumulatively, the thesis comprises this introductory paper and two chapters that provide more detailed insights into the application areas (see Figure 1). The introductory paper includes a background section on analytical approaches for heat pump energy efficiency consultancy and on value creation from data analytics. It then discusses the methodology and data analysis methods used in this thesis, summarises the main findings of the five papers, and describes the overall contributions and implications. The introductory paper concludes with limitations, future research directions, and a short conclusion.

The introductory paper is followed by Chapter 1, which examines consultancy-intensive services, using the example of energy efficiency consulting for heat pumps. The chapter explores the possibilities of DA&AI based on smart electricity meter data to evaluate and improve a heat pump inspection campaign (*Paper I*) and demonstrates the predictability of several heat pump characteristics and the suitability of smart meter data and other data sources for this purpose (*Papers II–III*). The chapter concludes with a study outlining further steps to digitalise consultancy services aimed at improving heat pump efficiency. This study identifies typical heat pump problems in the field and proposes a multi-dimensional classification scheme that allows problems to be analysed in terms of their readiness for implementation in digital services. The study focuses on the potential recognisability of heat pump problems using either smart electricity meter data or guided homeowners as well as possible solving strategies (*Paper IV*).

Finally, Chapter 2 focuses on two consultancy-intensive businesses, the sales of a solution for the decentralisation of energy supply (i.e. photovoltaic systems) and sales of a solution for the electrification of large consumers (i.e. heat pumps). Moreover, it discusses for the business cases analysed, whether value creation mechanisms and data analytics capabilities can be formed with limited data (*Paper V*).

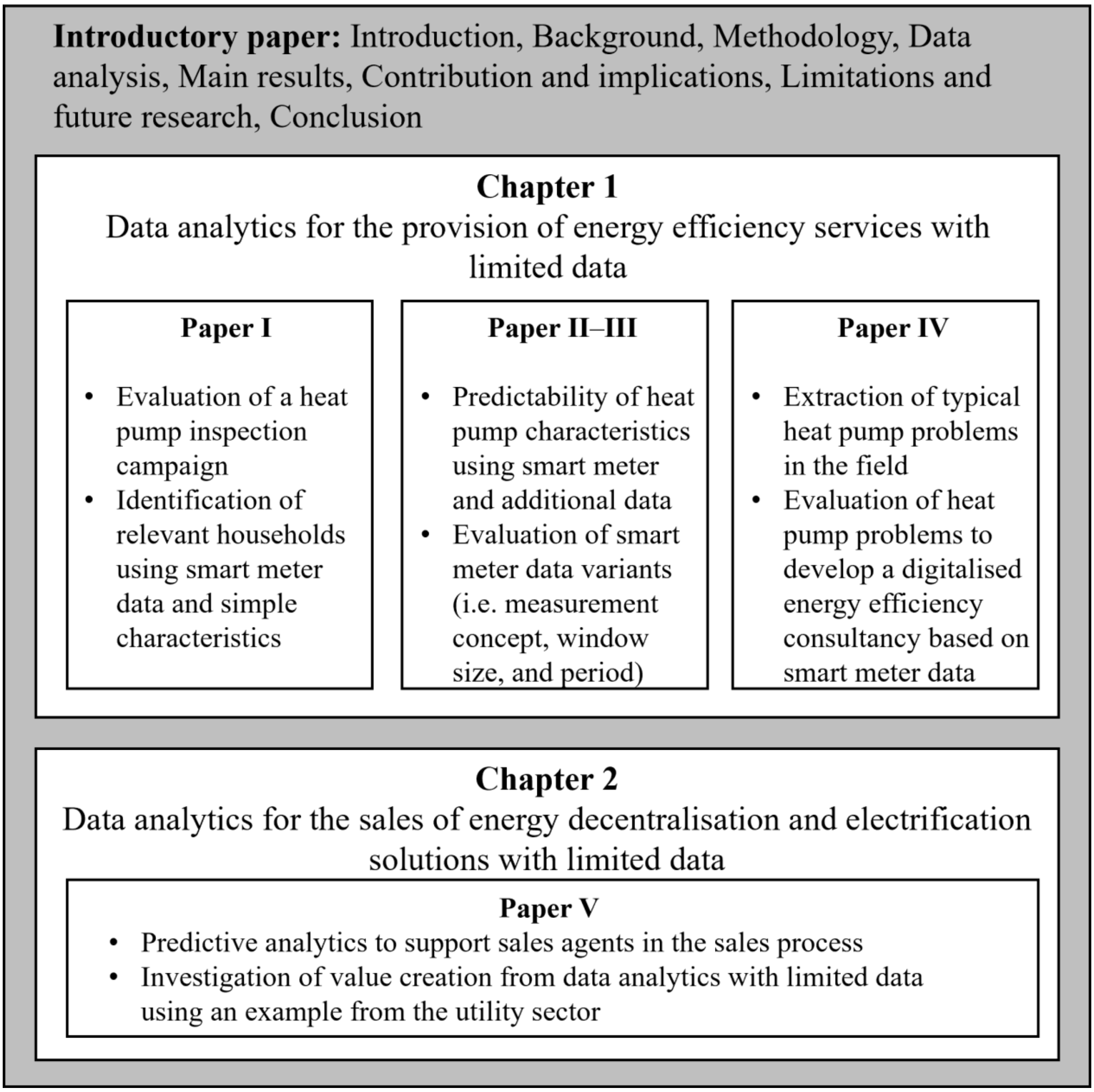

Figure 1: Structure of this dissertation

2. Background

This section comprises of two subsections. The first subsection provides an overview of related work in energy efficiency consultancy with a focus on heat pumps and smart electricity meter data. The second considers the theoretical foundations of data value creation through data analytics in organisations. Each subsection outlines research gaps and derives research questions. The first subsection reviews sensing approaches for heat pump energy efficiency consultancy, emphasising the potential of smart electricity meters. It notes that heat pumps can benefit from consultancy due to various issues and summarises methods to extract relevant information from smart meters. The subsection highlights that predicting heat pump characteristics using smart meter data has been underexplored, identifies important prediction problems and data challenges, and discusses approaches for detailed identification of heat pump problems using smart meters. It emphasises the need for more knowledge about specific field problems to better involve end users in the consultancy process. The second subsection introduces the concepts of 'big data' and 'limited data', noting that utility companies possess valuable limited data sources.[1] It summarises key frameworks for business value creation through IT, highlighting resources, capabilities, and value creation mechanisms, and concludes that the capabilities and mechanisms to support predictive analytics with limited data remain unclear.

2.1. Smart meter-based energy efficiency consultancy for heat pumps

2.1.1. Sensing approaches for heat pump consultancy

Measurement data are the foundation for data-driven energy efficiency consultancy and fault detection for heat pumps. Various types of sensors enable measuring states of the heating system and connected components which can be categorised into two basic approaches: multiple sensing, which allows measuring internal and sometimes external components of the heating system, and in single sensing, where the entire heating system is measured externally with a smart electricity meter. Both approaches are detailed below.

Modern heat pumps typically employ multiple sensing technologies, including temperature sensors, pressure sensors, and power meters. An increasing number of heat pumps utilise these sensing technologies to generate and transmit valuable data. However, this approach is often not the default case, and many systems from smaller vendors lack advanced sensing functions or IoT functionalities entirely. Manufacturers tend to avoid incorporating sensors due to various costs associated with measuring, recording, and storing data, unless there is a clear business case (Nowotny 1985; Katipamula and Brambley 2005a; Kim and Katipamula 2018; Zhao et al. 2019). Conversely, customers are sensitive to initial costs (Zhao et al. 2019) and may be reluctant to purchase the often separately sold IoT component necessary for data transmission. Even if data are measured and transmitted, they are stored in proprietary

[1] The elaborations in the second subsection correspond in large part to those of my co-authors in Paper V and were slightly complemented to provide a more nuanced picture of situations with limited data in in utility companies. Paper V describes the utility company as vendor of durable sales goods for renewable energy systems.

platforms of manufacturers and often not accessible to third parties such as utility companies. Generally, suppliers tend to favour proprietary solutions, believing that they offer greater customer retention potential compared to services on interoperable platforms (Fleischle and Kaniut 2019). Standards for such platforms are still in development (Nowak 2021; Scotton and Nowak 2021). Moreover, many already installed heat pumps, particularly those of an older, less efficient design, are of interest for energy consultancy. However, these heat pumps do not measure or transmit data. Waiting for solutions that use integrated multiple sensing technologies will leave behind a significant number of households for data-driven energy consultancy until their systems are replaced in the next decade[2]. Therefore, a manufacturer-independent sensing strategy appears to be a promising avenue for developers of energy consultancy services. Utility companies are already laying the groundwork for this by deploying smart electricity meters.

Smart electricity meters can be classified as single sensing approaches that measure and record electrical data in real-time (e.g. voltage, frequency, and consumption) in buildings, apartments, or even single appliances such as heat pumps, and transmit the data accordingly (Jixuan Zheng et al. 2013). Utility companies will soon have access to vast amounts of electricity consumption data. Across the EU (including the UK), the adoption of this technology grew to 34% in 2018, with an anticipated penetration rate of 77% by 2024 (Tounquet and Alaton 2020). In the US, the roll-out of smart meters reached 69% in 2021 (EIA 2022). The introduction of smart metering technology has coincided with a surge in the deployment of heat pumps. Focusing on the Swiss market[3], official statistics allow us to estimate the proportion of residential buildings with both a heat pump and a smart electricity meter installed, and thus to estimate the number of clients who might be interested in energy efficiency services tailored to heat pumps.[4] Figure 2 indicates that utility companies could hold heat pump data from 21.3% of residential buildings by 2027, highlighting the substantial market potential for developers of heat-pump-centred efficiency services.

[2] The lifespan of heat pumps typically exceeds 15 years (Bundesverband Wärmepumpe e.V. 2014; Marinelli et al. 2019)

[3] The Swiss market was used as example since all studies in this dissertation were conducted with Swiss utility companies.

[4] This estimation is based on the following numbers: In the beginning of 2021, the penetration rate of smart electricity meters reached 20.2% (BFE 2021), while 17.0% of the residential buildings used heat pumps as primary heating system (BFS 2022), resulting in an overall market potential of 3.4%. By the end of 2027, there is an obligation for Swiss utility companies to reach a roll-out of 80% for smart electricity meters (BFE 2021). With an anticipated increase to 26.7% of buildings utilising heat pumps for primary heating, utility companies could access heat pump data from 21.3% of all residential building. This calculation is based on three assumptions: First, the 80% roll-out rate of smart meters will be reached. Second, the sales figures of heat pumps in the years 2022–2027 will be 28,583 per year (the average of the sales figures in 2019; 2020; 2021; 23,980; 28,064; 33,704 (see FWS 2022)). Third, the number of 1,774,161 residential buildings in Switzerland will stay constant (see BFS 2022).

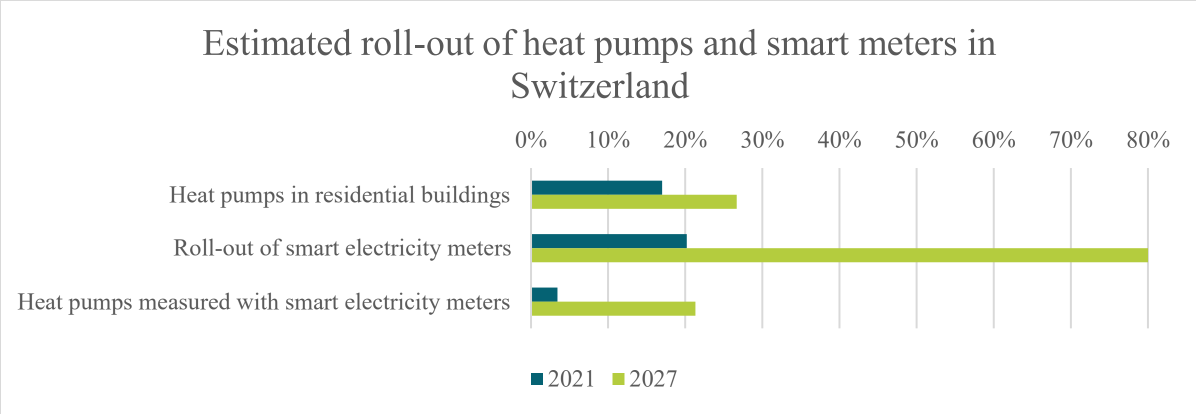

Figure 2: Estimated availability of smart meter data measuring heat pumps in Switzerland

2.1.2. Energy consultancy for heat pumps and potential improvements

Given the work principle of heat pumps, i.e. moving energy from a heat reservoir (the primary energy source) to a building with the help of a compressor using electricity (the secondary energy source), even small performance issues can increase the electricity demand considerably over the system's lifetime. Overall, one study estimates that the energy required to operate heat pumps amounts to 30% while maintenance and replacement account for 20% of the lifetime costs (Marinelli et al. 2019). However, it has been observed that the performance of heat pumps is often lower than expected for different heat pump types (e.g. ground source, air source) in various settings (e.g. residential, commercial) and regions (e.g. EU, USA, China) (Puttagunta et al. 2010; Caird et al. 2012; Gleeson and Lowe 2013; Yin et al. 2019; Qiao et al. 2020; Chesser et al. 2021; Gao et al. 2021; O'Hegarty et al. 2022). The literature so far, summarised in Table 1, notes a multifaceted set of factors rather than one unique cause for increasing operation, maintenance, and replacement costs.

Table 1: Problem categories of heat pumps found in literature

Problem category	Typical examples	Related studies
Planning and design	Wrong system capacity, wrong ductwork sizing	(Russ et al. 2010; Miara et al. 2011; Domanski et al. 2014; Miara et al. 2017; Gao et al. 2021; Decuypere et al. 2022)
Manufacturing quality	Not closing valves, faulty temperature sensors	(Russ et al. 2010; Miara et al. 2011; Günther et al. 2014; Madani and Roccatello 2014; Miara et al. 2017; Qiao et al. 2020)
Installation and maintenance	Refrigerant over- or undercharge, non-condensable gases, sensor mounting	(Russ et al. 2010; Miara et al. 2011; Günther et al. 2014; Domanski et al. 2014; Miara et al. 2017; Winkler et al. 2020; Bellanco et al. 2022)
Configuration of parameters	Non-ideal heating curve, night-setback, and charge pump settings	(Russ et al. 2010; Miara et al. 2011; Caird et al. 2012; Günther et al. 2014; Miara et al. 2017; Gao et al. 2021; Günther et al. 2020)
User training	Lack of understanding of heat pump work principles, inadequate briefing of settings like holiday mode	(Russ et al. 2010; Miara et al. 2011; Caird et al. 2012; Miara et al. 2017; Qiao et al. 2020; Gao et al. 2021; Decuypere et al. 2022)

Considering the initial three categories, manufacturers, planners, and installers play a pivotal role in enhancing the performance of heat pumps before a system enters operation. After system installation, the last two categories, improving parameter configuration and user training, seem promising for after-sales energy efficiency consultancy and can often be resolved during a single visit. Both categories also do not require hardware adjustments or new parts that require additional experts such as installers and technicians, which can be an implementation hurdle for heat pump owners due to the scarcity of experts (HPA 2020; Ecoplan 2021; Nowak 2021; BMWK 2022; Branford and Roberts 2022; Hilpert 2022). While some projects have examined the impact of various problems on energy efficiency (e.g. Russ et al. 2010; Miara et al. 2011; Miara et al. 2017; Günther et al. 2020), less is known about the overall saving potential through parameter configuration and user training. One study examined an energy audit programme of a US-based utility company, which included walk-through inspections through buildings, tests of the building envelope and ductwork, and suggestions for users' behaviour improvements (Taylor et al. 2014). The authors found an average saving potential of 3.2%. However, the described intervention took place in a region with different climate conditions compared to central Europe[5], and did not focus on heat pumps solely. The data analysed (billing records of classical meter readings) lacked the opportunities afforded by more detailed smart electricity meter data. Further knowledge is required about the potential of energy consultancy focusing on user training and the fixing of easy-to-solve heat pump configuration issues. This thesis addresses this knowledge gap by formulating the following research question:

RQ-1: *How much do on-site energy efficiency inspections for heat pumps decrease a household's electricity consumption?*

Although many of the above listed studies identify diverse issues that can lower the performance of heat pumps considerably, many systems in the field actually work properly. This presents a challenge for consultants and customers alike in determining the profitability of energy efficiency consultancy at the outset. Hence the question of which customer should participate in consultancy may be just as critical as how many customers participate (Taylor et al. 2014). In this context, consultants identified household characteristics related to occupants, dwelling, electric appliances, and heating systems available as potentially helpful in selecting high-potential customers before they start inspection (Beckel et al. 2012). While a series of papers have been dedicated to the predictability of such characteristics using smart electricity meter data (e.g. Beckel et al. 2013; Beckel et al. 2014; Hopf et al. 2018b) with some works even covering heat pump related characteristics (Fei et al. 2013; Hopf et al. 2018b; Ray et al. 2019), only a few works investigated the actual value of such characteristics for energy efficiency campaigns in the field. For example, in the case of customised home energy reports, Hopf (2019) found that the activation (open and click rate) is similar between participants who received a personalised report based on stated characteristics (e.g. household type and size, space and water heating types) and those who

[5] The climate zone in Florida, USA is subtropical to tropical, while the climate zone in Switzerland is temperate.

received a report based on the same characteristics predicted. Taylor et al. (2014) demonstrated that in three cases—sales programs for old heating, ventilation, and air conditioning systems (HVAC), attic insulation installation, and comprehensive energy audits—only households with low initial energy performance showed significant energy savings and that prior information can help in pre-selection. Referring again to the energy audit case described previously, the authors revealed that only half of the participants with a high prior consumption explained the overall statistically significant saving of 3.2%. However, addressing only high-consumers would have led to an average saving between 4.7–5.8%. To test the value of smart meter data and heating system characteristics, this thesis examines the following research question:

RQ-2: *Can easy-to-obtain information (e.g. using smart meter data and heating system characteristics) help to identify households with high energy-saving potential?*

2.1.3. The prediction of heat pump characteristics

Previous research in the field of household characteristics prediction has predominantly focused on occupant-related properties (e.g. number of adults, social class), dwelling attributes (e.g. house type, building age), and non-heating system appliances (e.g. electricity consumers, cooking type, light bulbs) (Beckel et al. 2013; Beckel et al. 2014; Beckel 2015; Hopf et al. 2016a; Hopf et al. 2016b; Sun et al. 2019; Yan et al. 2020; Cui et al. 2022). Only a few works paid attention to properties related to heating systems or heat pumps: Kozlovskiy et al. (2016) show that the age of a gas heating system can be predicted better than chance using annual gas consumption data. Other studies assess the predictability of space and water heating types, but they only distinguish between electric and non-electric systems, leaving uncertainty about heat pumps (Hopf 2018; Hopf et al. 2018a). Delving into heat-pump specific characteristics, Fei et al. (2013) demonstrate the predictability of heat pump existence but use relatively coarse-grained daily electricity meter data, leaving potential room for improvement. Ray et al. (2019) employ an analysis using a 5-minute resolution, which is typically unavailable on a large scale for utility companies. Finally, Hopf et al. (2018b) assess the predictability of the space- and water heating types (based on the classes electric storage, heat pump, and others), the age of the heating system (new, average, old), and heat pump existence using 15-min smart electricity meter data. There is potential for enhancement, considering that heat pump-related performance metrics, such as AUC values, range from 0.66 to 0.68, and the proposed model for the age of the heating system is not tailored to heat pumps.

Furthermore, there are two additional characteristics potentially valuable for energy efficiency services. The first is the heat pump type, which describes the reservoir used to extract heat. This can be either air source or ground source and it is valuable to know given that systems using different heat reservoirs typically differ in their efficiency rating (e.g. Marinelli et al. 2019; Mouzeviris and Papakostas 2021; Sadeghi et al. 2022). The second is the modulation type, which can be either variable or fixed. Variable speed heat pumps adjust the speed of the compressor in response to heat demand fluctuations, thereby affecting power consumption. Conversely, fixed speed heat pumps operate the compressor at a constant speed, resulting in a fixed power level, with on-off cycling in response to heat demand changes. Knowledge about fixed speed pumps is valuable for energy efficiency services or the sales of a replacement system since they are typically older and less efficient (Zhao et al. 2003; Shao et al. 2004; Aprea et al. 2006; Bagarella et al. 2016; Dongellini and Morini 2019; Mahmoud et al. 2021; Szreder and Miara 2020) compared to variable speed heat pumps that have fewer cyclic losses (Dongellini and Morini 2019). Knowledge about variable speed heat pumps is potentially valuable, as the modulation capability may enable digital services for optimal control (Pean et al. 2019; Péan et al. 2019; Betzold et al. 2020; Langer and Volling 2020) or integration of photovoltaic systems (Fischer et al. 2015).

The predictability of both characteristics has to the best of my knowledge not been investigated. This thesis builds upon earlier works on heating system characteristics prediction, replicating them on new data sets and testing further characteristics that are interesting for developing energy efficiency services, relevant for future sales (i.e. replacement), or additional services (e.g. optimal control, photovoltaic integration), and examines the following research question:

RQ-3: *To what extent can heat pump related characteristics (i.e. the existence, reservoir, age, modulation type) be predicted based on smart electricity meter and additional data?*

When it comes to the prediction of heat pump characteristics, there are several challenges related to the use of smart electricity meter data and additional data that potentially affect the predictive power of prediction models. In its pure form, smart meter data are time series data and consist of a timestamp and the measured electrical data (Jixuan Zheng et al. 2013). However, in the field, a wide variety of smart meter data exist and the data available differ regarding the measurement concept (what is measured), the window size of the time-series used for feature extraction (how much data is available), and periods available (i.e. heating vs. non-heating period). Moreover, since consumption patterns of heating system characteristics vary within a season, additional data sources like weather and geographical energy efficiency data could help. These challenges are outlined below and the research question RQ-3 is further detailed.

Challenge regarding the measurement concept of smart electricity meter data

The measurement concept describes the measured entity such as a building, a part of a building, or a specific appliance. A building can have one or more meters installed. From a data analytics perspective, multiple meters are preferable over a single meter as they provide a more accurate picture of the usage of appliances as shown in Figure 3 (a), showing load curves from three different measurement concepts. The left and the middle plots show a case in which two meters are installed in a building, one measures a heat pump, and a second measuring all other appliances (e.g. light, entertainment, cooking). The two load curves differ in many points in time. While the left plot shows the consumption of a heat pump and clearly indicates operational patterns that can be attributed only to one appliance, this is more challenging for the middle plot (i.e. building) which mixes consumption patterns of many appliances.

The right plot displays a scenario with a single meter, blending the heat pump with all building appliances, resulting in some additional noise alongside the heat pump load curve.

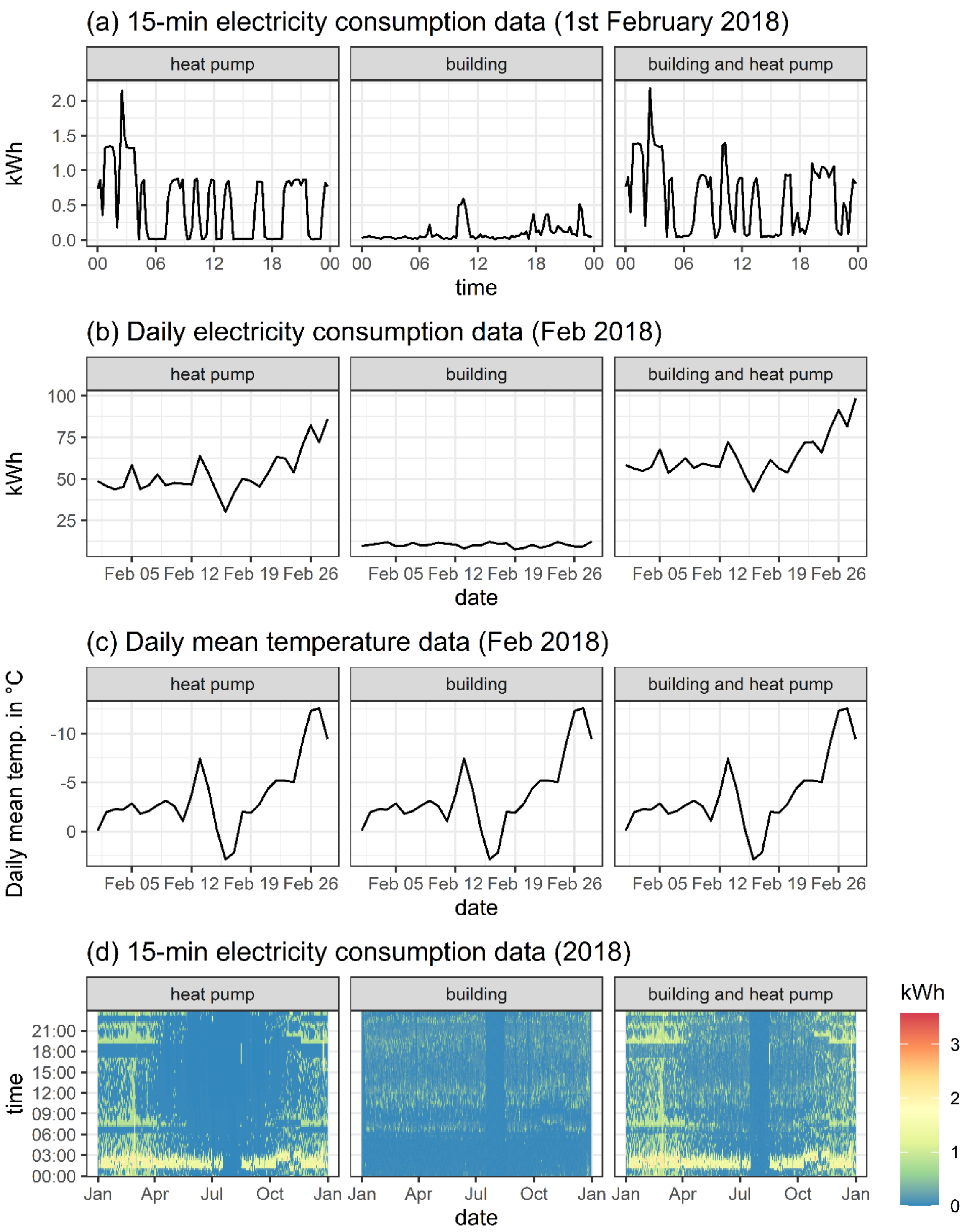

Figure 3: Electricity consumption data from smart meters and weather data showing different measurement concepts and data granularities

In practice, heat pumps are measured with different concepts. One common approach is to install multiple meters in buildings with multiple independent parties to ensure fair consumption charging. This can involve separate meters for two apartments in a semi-detached house and additional meters for shared spaces or large appliance, such as heat pumps. In the case of single-family houses, an individual meter for a heat pump may be installed to receive discounted electricity tariffs in return for providing grid flexibility (i.e. the opportunity to lock consumption at certain times) (Dott et al. 2018, pp.70–71). On the other hand, many single-family homes may forego additional meters due to cost factors such as high acquisition[6] and operational expenses, low overall consumption, and the use of photovoltaic systems for self-consumption (Finanztip 2022). Hence, two heat pump measurement concepts are common: measuring the building and heat pump together, or measuring the building and heat pump separately. Consequently, smart meter data analytics for heat pumps should be able to work on aggregated data to reach as many households as possible. However, this aspect, has—to the best of my knowledge—not been investigated. To address this challenge, the following research question is formulated:

RQ-3a: *How does the measurement concept (i.e. separate vs. mixed measured heat pumps) influence the prediction of heat pump characteristics?*

Challenge regarding the window size of smart electricity meter data

Regarding the number of data available, it is necessary to slice time-series into a defined window size to derive features for predictive models. Slicing a time-series into a week from 15-min data results in 672 measurements; for a month, it ranges from 2,688 to 2,976, and for a year, it totals about 35,040 measurements. More data in form of a larger window size should lead typically to better predictions. Previous work, however, focused on using only a single week to derive features (e.g. Beckel et al. 2013; Beckel et al. 2014; Hopf et al. 2018b; Hopf et al. 2016b) or used majority voting approaches to combine single-week into multiple-week predictions (Beckel et al. 2014; Beckel 2015; Hopf et al. 2018b). At least for majority voting, there seems to be a saturation effect after combining more than 15 single-week predictions (Hopf et al. 2018b). When it comes to window sizes, it is not clear whether larger sizes like a month or a year are helpful (Beckel 2015; Hopf et al. 2016b). Knowing the required window size is also important for utilities that have just recently started to deploy smart meter and have not yet collected large amounts of time series data. To examine this challenge, the following research question is formulated:

RQ-3b: *How does the window size (i.e. a week, month, year) used to derive features from smart electricity meter data influence the prediction of heat pump characteristics?*

Challenge regarding the selection of period in time of smart electricity meter data

Another important aspect is the selection of a suitable period in time for a time series. This is crucial for the prediction of heating system characteristics given their different operation modes during the year, which is visible in Figure 3 (d). The graph shows the 15-min consumption values over one year and for the different times of the day. One can see a 'blue egg' of low consumption values in the middle of the

[6] The cost for installing a smart electricity meter is about 180–200 € in the EU (EC 2019)

figure, showing from left to right the influence of the varying outside temperature and thus heat demand reflected in electricity consumption within a year. The left part of the egg shows the first transition period from April to May, when the number of heating hours (and thus electricity consumption) in the middle of the day slowly decreases. The centre of the egg shows a non-heating period from May to September. In the second transition period from September to October, the number of midday heating hours slowly increases again. Given these varying consumption patterns, the selection of the time-series period might influence the prediction performance of heating system characteristics. Previous work has shown a seasonal effect of the period selected for prediction on characteristics like the space heating type and the existence of a heat pump (Hopf et al. 2018b). However, this study covers only a single year leaving uncertainty about multi-year periods. Knowing suitable periods is also important for utilities that have just recently started to deploy smart meters and have not yet collected data from different periods. Hence, this thesis replicates this analysis, extends it to a multi-year period and formulates the following research question:

RQ-3c: *How stable is heat pump characteristics prediction (i.e. the heat pump existence) over time?*

Challenge regarding the value of additional data sources

Although smart electricity meter data are the core data asset for utility companies to develop energy efficiency services, it can be useful to augment these data with additional data. In particular, weather data appears to be promising for predicting heat pump characteristics, as the heat demand of a heat pump, and therefore the electricity consumption, follows the outside temperature (i.e. lower temperature, more heat demand). This can be seen in the left plots of Figure 3 (c–d), which show the daily electricity consumption data and the weather data for February 2018. In household classification research, Beckel (2015) showed that enriching smart electricity meter data with weather data marginally improves the predictability (about 0.3% percentage points) but did not focus on heating system-related characteristics. Hopf et al. (2018b) showed that weather data can complement smart electricity meter data for the prediction of heating system related characteristic (space- and water heating type, age of heating system) and the existence of a heat pump but it is not stated to what extent weather data improves the prediction over using pure smart electricity meter data. Fei et al. (2013) showed the superiority of electricity features combined with weather features over general electricity wavelet features for the prediction of heat pump existence. However, their work uses comparatively coarse-grained daily consumption and weather data. Furthermore, it has been shown that geographical (Hopf et al. 2016a; Hopf 2018), real estate (Hopf 2018), statistical and governmental data (Hopf et al. 2018a) combined with smart electricity data are helpful for the prediction of household characteristics. However, the investigated data sources do not contain data energy-efficiency relevant information related to the heating system. A new data set described by Klauser and Schlegel (2016) containing such data seems promising. This thesis replicates existing research and extends it by examining the following research question:

RQ-3d: *How does additional data sources (weather, geographical energy efficiency) influence the prediction of heating system characteristics (i.e. heat pump existence)?*

2.1.4. From heat pump characteristics to heat pump problem recognition and solving

While the research strand on household classification described above has demonstrated the predictability of household and some heating system or heat pump related characteristics using smart electricity meter data, less attention has been paid to analytical solutions that provide guidance on specific problem recognition and solving. However, data available to utility companies (e.g. smart electricity meter data, energy consultancy reports) can potentially be used for this purpose as well. In comparison, the research strand on HVAC applications provides an extensive overview of automated fault detection and diagnostics using integrated multiple sensing of heating systems, but naturally did not address the use of smart electricity meters for this purpose (e.g. Katipamula and Brambley 2005a; Katipamula and Brambley 2005b; Zhao et al. 2019; Kim and Katipamula 2018; Li and O'Neill 2018). This strand of research provides utilities with insights into effective practices and highlights challenges faced by the HVAC industry, particularly the scarcity of accessible training data in the form of field labels, which utility companies could potentially address with their new data sources, as outlined below.

Various fault detection methods have been proposed. Essentially, they can be distinguished by the way fault detection models are built, which is either knowledge-driven (i.e. based on a priori knowledge) or data-driven (i.e. deriving rules from empirical sensor data) (Katipamula and Brambley 2005a). Recent works favour data-driven methods over knowledge-driven methods (Katipamula and Brambley 2005a; Kim and Katipamula 2018) due to their predictive superiority and functionality with fewer sensors (Zhao et al. 2019). This aspect is crucial for utilities, as they only have data from a single type of sensor available (i.e. smart electricity meter). An important category of data-driven methods is classification, which aims to distinguish whether faults have occurred or not (Zhao et al. 2019). Classification methods require a sufficient number of labels for training, which can be generated by simulation, created in the laboratory, or collected in the field. However, these approaches vary in quality and associated cost per label. While the generation of labels by simulation is comparatively cheap, the effectiveness of models built on simulated data may not translate effectively to real-world situations (Bode et al. 2020) compared to labels generated in a laboratory setting or collected in the field (Li and O'Neill 2018; Zhao et al. 2019). A likely reason for this is that many of the methods tested are specific to the laboratory training data of a single system type (Katipamula and Brambley 2005b). In comparison, collecting field labels based on maintenance, warranty, or efficiency consultancy reports, for example, is time-consuming and costly (Li and O'Neill 2018; Zhao et al. 2019). This technique is superior in terms of accurately representing real-world operational contexts across different manufacturers and systems (Li and O'Neill 2018). This is particularly relevant for utility companies, as their business is usually focused on a regional market with a variety of systems and manufacturers. Moreover, utility companies that already provide energy efficiency consulting services for heat pumps may have historical field data on actual faults in reports that they could use to extract labels. Despite the described advantages of this approach, not much is known about the probability of faults or fault combinations in the field (Li and O'Neill 2018; Bellanco et al. 2021). This makes it difficult to determine how labels could be generated efficiently, i.e. how many reports need to be analysed to extract a given number of labels. Only a few studies provide knowledge about fault probabilities. Madani and Roccatello (2014) examine the most frequent and costly faults of heat pumps from Swedish manufacturers. However, they categorise problems at the component level rather than specific heat pump problems. Furthermore, as they focus on warranty-related issues, the problems identified are mostly hard faults (i.e. those that lead to direct system breakdowns), which are more likely to be recognised by heat pump owners (and led to the warranty claim), rather than soft faults that lead only to a drop in performance (Bellanco et al. 2021). Aguilera et al. (2022) present the occurrence of some specific problems in the field, but their analysis focuses on large heat pumps (e.g. for district heating, industrial processes), which are typically different from smaller residential installations. To examine the opportunity of field data collection on problems for a wide range of residential systems and heating system manufacturers, with a focus on efficiency-related soft problems, the following research question is formulated:

RQ-4: *What typical problems do experts uncover during energy efficiency consulting for heat pumps, and what potential benefits result from solving them?*

For the development of automatic fault detection approaches, not only a sufficient number of labels, but also the availability of sensor data is crucial. However, so far it is unclear whether typical smart electricity meter data have value beyond predicting heating system characteristics for specific heat pump problem recognition. The value and application areas of electricity meter data typically increase with more detailed data granularity (Carrie Armel et al. 2013). For example, at a high data granularity of 2 seconds, it is even possible to identify the TV program being watched (Greveler et al. 2012). However, approaches using fine-granular data from about 1 minute to kHz resolution typically belong to the field of non-intrusive load monitoring (e.g. Angelis et al. 2022) and are for utility companies typically not adaptable due to data protection regulations, e.g. in Germany (Deutscher Bundestag 2023). Typical smart electricity meters in the EU measure data at intervals of 15-min, 30-min, or hourly intervals, but most countries in the EU and Switzerland default to 15-min intervals (BFE 2014; Merino and Ebrill 2018). While already annual electricity consumption data allow for the prediction of some household characteristics (Hopf et al. 2016a), higher granularity data, such as daily, bi-daily, 60-min, 30-min, or 15-min intervals, improve prediction accuracy (Beckel 2015; Hopf et al. 2018b; Yan et al. 2020). This has also been confirmed for some heating system characteristics (Hopf et al. 2018b). However, there is further potential in 15-min data for energy efficiency consultancy, which is illustrated in Figure 3. Consider only the left diagrams showing the consumption of a separately measured heat pump; (a) shows 15-min consumption data over a period of one day, while (b) shows daily consumption data over one month. While (b) provides less information and only shows the variation of daily consumption patterns within a month, the higher granularity of (a) clearly shows the on-off-cycles of the heat pump during the day and one peak at 3am, most likely due to regular hot water heating or disinfection (i.e. heating the water in the tank above a certain temperature to kill germs). This peak can be further examined in (d), which shows the 15-min consumption values over a year and for the different times of the day. Here we can see a continuous consumption pattern visually detectable by a yellow horizontal bar which is 'thick' over 1am and 3am and 'long' over the entire year. This yellow bar is most likely the hot water production that is executed to a fixed schedule. Moreover, the already described 'blue egg' shows the different transition phases of the year describing overall heating patterns. In sum, given these visual patterns, it seems feasible that advanced classification approaches could derive further heat pump related characteristics from 15-min smart meter data, such as problems related to hot water production plans or other issues.

While the value of such automated recognition approaches to derive further characteristics may be helpful in attracting high-potential households, enriching the picture of a planned consultancy for consultants, and reducing the time spent on manual on-site inspection, the role of end users in this context is less explored. Some studies highlight the need for better advice and increased knowledge for end users (e.g. Caird et al. 2012; Miara et al. 2017; Decuypere et al. 2022), as well as the willingness of many users to proactively improve the efficiency of their system (Miara et al. 2017). Providing feedback on heating systems to potential end users has been shown to be advantageous on system performance in two simulation studies (Sauer et al. 2007; Sauer et al. 2009). In the field, systems from end users with a deeper understanding achieved higher system efficiencies (Caird et al. 2012; Qiao et al. 2020; Gao et al. 2021). In this logic, information systems utilising automatic fault detection could provide information about recognised problems to end users (i.e. homeowners) and involve users in the consultancy process by confirming potentially found problems, manually checking additional typical issues, and even solving simple problems themselves.

Achieving this goal, requires a clear understanding of which typical problems encountered in field installations could potentially be recognised and solved, either by smart meter data analytics or manually by the end user themselves. However, previous research so far has not covered these questions. Therefore, two additional research questions are formulated:

RQ-5: *How can heat pump owners recognise heat pump problems, and how can information systems (i.e. smart-meter-based detection and assisted recognition) support this process?*

RQ-6: *How can heat pump problems be solved, and how can information systems support this process?*

2.2. Data analytics for value creation

2.2.1. The need for a focus shift from big to limited data

Big data is often defined as information assets that are characterised by high occurrences of 'V's, namely a high *volume* of data, e.g. measured in terabytes or petabytes, a high *velocity* of data describing the speed at which data is generated, and a high *variety* describing the different data formats such as structured, semi-structured and unstructured data (Laney 2001; Gartner [no date]). Extended versions also cover *veracity*, describing the quality and trustworthiness of the data, and *value*, describing potential insights and benefits from the analysis, such as the predictive power (e.g. Kaisler et al. 2013; Rouhani et al. 2017).

Although these attributes characterise information assets in a multifaceted way, big data descriptions often focus on volume (Manyika et al. 2011). It is striking that many works (e.g. Fan et al. 2015; Rouhani et al. 2017; Zhang et al. 2018) use a volume-centred definition and focus on the maximum technical limits, which are constantly changing due to improvements in hardware and software (Zhang et al. 2018). For example, they refer to 'the amount of data just beyond technology's capability to store, manage and process efficiently' (Kaisler et al., 2013, p. 994) or to 'data sets with sizes beyond the ability of common software tools to capture, curate, manage, and process the data within a specified elapsed time' (Bharadwaj et al., 2013, p. 477).

Such upper limits of hardware, software or budget are usually difficult to overcome, but it is often possible to process and analyse at least a subset of the data, which can mitigate the consequences of these limitations. However limitations also exist at the lower end of data volume, which is equally relevant for companies and noted by Wilson and Daugherty (2020, p.3) as follows: 'For every big data set (with one billion columns and rows) fueling an AI or advanced analytics initiative, a typical large organization may have a thousand small data sets that go unused.'

However, the use of such data sets has been frequently recognised as a significant challenge (Brodley et al. 2012; Baier et al. 2019; Someh et al. 2020). It is primarily companies in data-intensive (Tambe 2014), IT-intensive (Wu et al. 2020), or highly competitive sectors (Müller et al. 2018) that have been the main beneficiaries of DA&AI initiatives to date. Likewise, best practices for data analytics in the utility industry note the necessity of having 'a large amount of data to achieve good results. If data is not available in sufficient quantities, the use of AI is questionable (we are talking about thousands to hundreds of thousands of data sets for very complex problems)' ([Translated by the author] BDEW 2020, p.23). They highlight the problem's complexity as a factor influencing the volume requirements. Although many data assets from utility companies such as smart electricity meter data qualify as big data because many sensors generate large volumes and high velocities (Zhang et al. 2018), the value of such data sets can often only be achieved by linking and analysing them with considerably smaller data sets that contain labels necessary for machine learning tasks. These are typically expensively to generate, and often require the participation of experts or customers. These data sets cover, for example, survey data, reports, and notes from energy consulting or sales activities for decentralisation and electrification solutions.

However, determining the suitability of data sets based on a minimum volume for analysis in advance is complex, as studies from different fields show: Estimates range from as few as ten observations for fault diagnosis in machines (Indira et al. 2010), to under a hundred in biomedicine using logistic regression (Motrenko et al. 2014), and several thousand for discrete choice analysis (Alwosheel et al.

2018). Examples of work using data from utility companies—for example, the case of predicting efficiency-relevant characteristics based on smart electricity and survey data—show sufficient results based on only a few hundred data points (e.g. Beckel et al. 2013; Beckel et al. 2014; Hopf et al. 2018b). These works show that sticking to such rather conservative recommendations on the necessity of large data volumes (i.e. thousands or more data points) as mandatory criterion for data analytics projects is questionable. Nevertheless, research on the value creation from data in organisations concentrates on large data volumes (e.g. Ghasemaghaei et al. 2018; Mikalef and Krogstie 2020; Elia et al. 2020).

As it appears difficult to assess the complexity of a problem in advance, it is necessary to provide additional guidance to utility companies by investigating specific cases. Therefore, this thesis tests the feasibility of selected cases and limited data sets relevant for new businesses of utility companies. For this purpose, this thesis formulates the field assumption that especially such small data assets can be valuable to analyse, and thus focuses on such limited data from the utility industry, by which data collections are meant that are small in volume—i.e. entries (rows) in databases in the order of hundreds—and limited in variety—i.e. attributes (columns) in the order of tens[7].

2.2.2. Factors influencing value creation through data analytics

The need for gaining a deeper understanding of conditions under which investments in information systems technology lead to productivity gains was one of the key topics in information systems research from an early stage (Brynjolfsson 1993). A theoretical framework that is often used to better understand the determinants of firm competitive advantage in the information systems discipline is the resource-based view (Melville et al. 2004; Schryen 2013), which emphasises a firm's internal resources and capabilities as the main source of its competitive advantage (Wernerfelt 1984; Barney 1991; Teece et al. 1997). To capture value, resources and capabilities should be valuable, rare, difficult to imitate, and organised (Kennedy 2020). In general, internal resources describe tangible (e.g. property, plant, equipment) and intangible assets (e.g. knowledge, and skills) that a firm owns, while capabilities describe routines or collections of routines that allow the firm to effectively use its resources to achieve desired outcomes (Winter 2003; Kennedy 2020). A capability is dynamic—and therefore particularly valuable—if it allows to 'extend, modify or create ordinary capabilities' (Winter 2003, p.991).

Bharadwaj (2000) used the resource based view to define resources and capabilities related to information technology as 'firm's ability to mobilize and deploy IT-based resources in combination or copresent with other resources and capabilities' (p. 171), and further detailed them as IT infrastructure, human-based IT resources, and IT-enabled intangibles. Several works have built on this conceptual understanding to shed light on value creation through big data analytics (e.g. Gupta and George 2016; Ghasemaghaei et al. 2018; Mikalef et al. 2018; Ghasemaghaei 2019; Mikalef and Krogstie 2020). However, these works point out that the resources required for analytics differ from those of conventional information technology resources, stressing the importance of data, big data infrastructure,

[7] This definition from limited data is taken from Paper V.

and fostering a data-driven culture. Finally, Ghasemaghaei et al. (2018), found that the capability of *data analytics competence* is an important factor in influencing decision-making performance. They define it as 'a firm’s ability to deploy and combine data analytics resources for rigorous and action-oriented analyses of data' (p. 103). This capability can be considered dynamic as it enables the modification of other capabilities (Ghasemaghaei et al. 2018; Ghasemaghaei 2019; Kristoffersen et al. 2021).

However, even if an organisation has built up resources and capabilities, this does not automatically translate into strategic value (Sirmon et al. 2007; Grover et al. 2018). Two conceptual frameworks are helpful to better understand how strategic value can be realised through big data and analytics (Grover et al. 2018; Zeng and Glaister 2018). First, Grover et al. (2018) propose a conceptual framework (Figure 4) that aims to bridge the gap between formed capabilities and value targets of organisations (e.g. organisational performance, products and service innovation, business process improvement) with a number of value creation mechanisms. They suggest twelve mechanisms for bridging this gap, namely, transparency, access, discovery, experimentation, prediction, optimisation, customisation, targeting, learning, crowd-sourcing, monitoring, and proactive adaptation. Second, Zeng and Glaister (2018) propose a conceptual framework (Figure 5) that describes two modes of mechanisms that use either internal data, which enables transaction-driven value creation (i.e. a focus on data analysis to achieve exclusive economic gains), or external data, which enables relation-driven value creation (i.e. a focus on data collaboration with partners for mutual economic gains). Focusing on internal data, they describe four distinct mechanisms, namely, democratise data, contextualise data, experiment with data, and execute data insight. The above-described mechanisms from Grover et al. (2018) and Zeng and Glaister (2018) are structurally comparable and are therefore mapped and described in detail in Table 2.

The extensive body of literature on data analytics resources and capabilities frequently ignores the aspect that even limited data can serve as a valuable resource for companies seeking to establish competitive advantage. Therefore, this thesis discusses whether the formation of resources and capabilities related to data analytics (i.e. analytics competency) is possible even with limited data for the case of selling decentralisation and electrification solutions. Since the investigation of value creation mechanisms in firms within limited data has received minimal attention, it also discusses whether value creation mechanisms described in Table 2 can contribute to the achievement of value targets even when only limited data are available for the analysed utility company case.

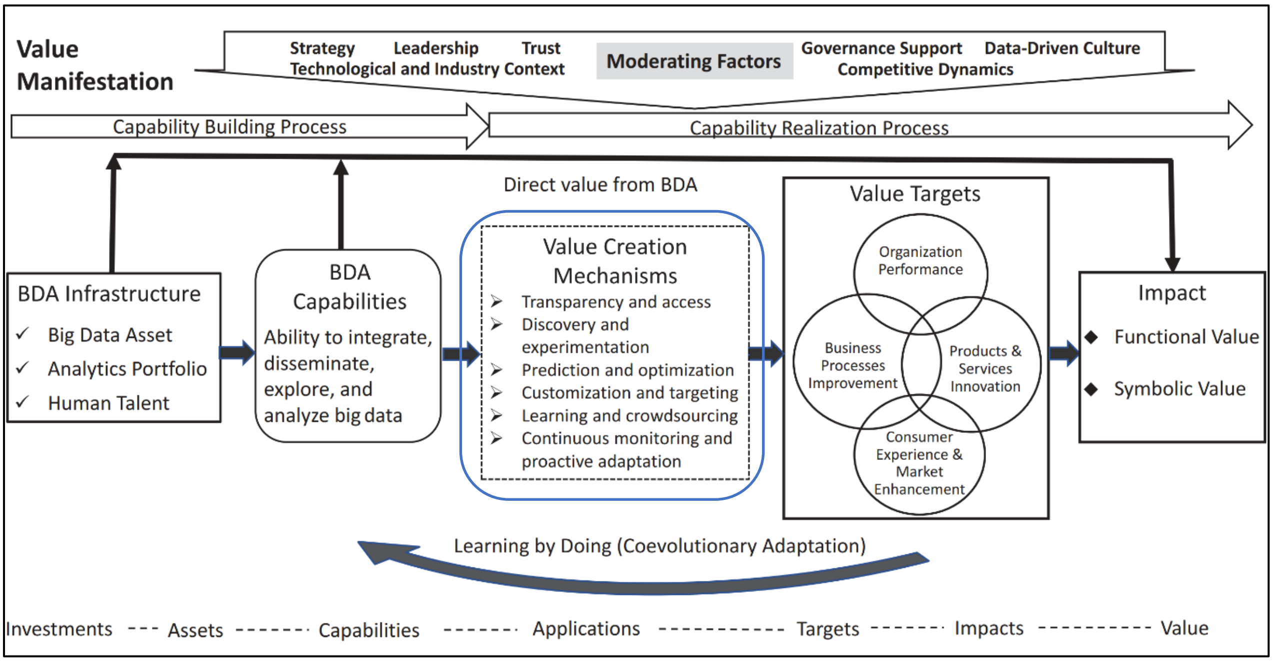

Figure 4: Grover et al. (2018, p.398) framework describing value creation through big data analytics

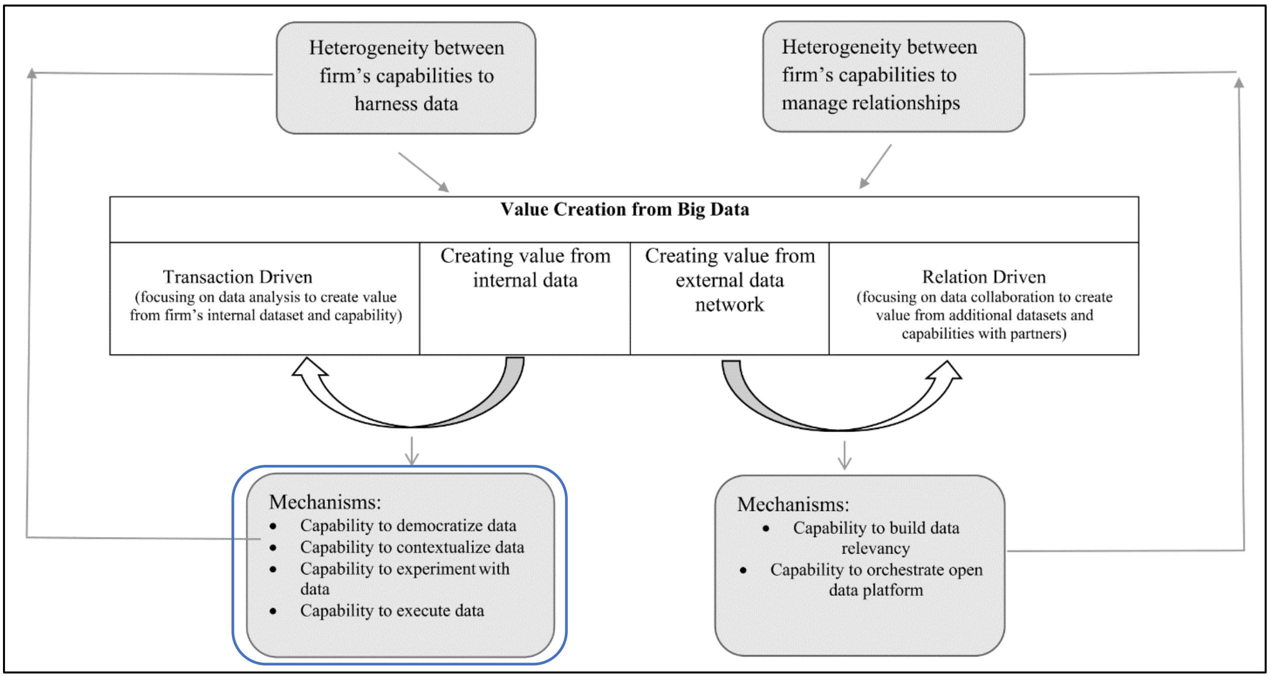

Figure 5: Zeng and Glaister (2018, p.114) framework describing value creation through big data analytics

Table 2: Mapped value creation mechanisms from Zeng and Glaister (2018) and Grover et al. (2018) frameworks

Internal value creation mechanisms following Zeng and Glaister (2018)	Value creation mechanisms following Grover et al. (2018)
Democratise data: 'integrate data across the firm and enable a wider range of employees to access and understand data where it is needed at any given time.' (p. 120).	**Transparency and Access**: 'The ability to generate descriptive data and disseminate them widely across a firm not only allows consistency in viewing the data but also facilitates a more complete visibility of the firm's business processes and outcomes.' (p. 401)
Contextualise data: 'assign meaning as a way of interpreting the data within which an action is executed.' (p. 124)	**Discovery**: 'digging into data for both deep and pragmatic insights can yield important outcomes for various BDA targets.' (p. 401)
Experiment with data: 'promote "trial and error", cultivate an inquisitive attitude towards data, encourage continuous experimenting with the data and monitor the changes.' (p. 126)	**Experimentation**: 'big data can involve many small experiments. For instance, running longitudinal experiments can provide insights into causality that may have strong implications for the delivery of customer services, among other targets.' (p. 401)
Execute data insight: 'transform data insights into actions that lead to identification of new opportunities that increase the customer's willingness to use/pay and thus for creating value.' (p. 127)	**(Machine) learning, and proactive adaption, and prediction**: 'determining probabilistic outcomes for the future on which present-day action' (p. 401) **Optimisation**: 'determine the 'best path' forward—something that was largely suboptimized and dependent on managerial judgment in the recent past.' (p. 401) '**Customisation** of products and services' (p. 401) '**Targeting** different market segments with digitally versioned products' (p. 401)

3. Methodology

This thesis uses a plethora of methods to investigate opportunities that arise for utility companies in new business fields from limited data sources. This section describes the research approaches, followed by the research methods, and the data collection techniques. Table 3 summarises the research methodology.

Table 3: Research methodology used in this thesis

	Paper I	Paper II	Paper III	Paper IV	Paper V
Research approach	Quantitative research	Quantitative research	Quantitative research	Mixed method	Mixed method
Research method	Quasi experiment	Predictive analytics	Predictive analytics	Case study	Case study embedding predictive analytics
Data collection					
Heat pump inspection report	✓	-	-	✓	-
Smart electricity meter data	✓	✓	✓	(✓)	-
Weather data	✓	✓	-	-	-
Geographical data	-	✓	-	-	-
Online sales configurators	-	-	-	-	✓
Interviews	-	-	-	✓	✓
Ground truth data	-	✓	✓	-	✓

3.1. Research approach

Typical research approaches in the information systems discipline cover quantitative, qualitative, mixed-method approaches that combine the former, and design science (Recker 2013, p.36). To respond to the research questions, this thesis uses quantitative and mixed method approaches which are described below.

At its essence, quantitative methods utilise quantitative data, i.e. numbers that are analysed to respond to research questions (Recker 2013, p.66). They are well suited for the exploration of analytical solutions to develop and assess energy efficiency services and products in the utility industry that centre on numerical data. In particular, numerical data analysed are empirical measurements from smart electricity meters or information systems (e.g. online configurators for electrification and decentralisation solutions) used to evaluate the effect of providing an energy efficiency service, and study empirical phenomena such as the predictability or potential predictability of information relevant for the sales of energy efficiency products and services. Hence, Papers I–V use mainly or in parts quantitative methods.

In comparison, 'qualitative methods focus on text, most importantly text that captures records of what people have said, done, believed or experienced about a particular phenomenon, topic, or event' (Recker

2013, p.88). Moreover, they allow researchers to combine the analysis of multiple sources of data that have been collected in a natural setting (Recker 2013, pp.88–89). For example, they allow researchers to analyse textual data such as interview data, focus group discussions, and reports altogether, and help to answer how analytical systems are perceived by organisations or what potential lies in data assets for developing energy efficiency services. Studies that combine qualitative and quantitative approaches are called mixed-method approaches and are used in Papers IV–V.

3.2. Research methods

3.2.1. Quasi experiment

An experiment is a research method that allows researchers to examine cause and effect relationships by giving subjects of one group (the treatment group) some sort of treatment and withholding treatment from another group (the control group) while at the same time maintaining control over other potential confounding factors (Recker 2013, p.82). Three criteria help to differentiate between different types of experiment designs, namely, how subjects are assigned to groups (random or not), when observational data are collected (pretest or pretest and posttest), and if single or multiple observations 'O' per participant are available (i.e. a time series of consumption values from continuously measuring a heating system) (Campbell and Stanley 1963).

How participants are assigned to a treatment condition allows researchers to differentiate so-called 'true experiments', in which participants are randomly assigned to a treatment or a non-treatment condition, from 'quasi experiments' which lack random assignment. Random assignment allows to better control for differences among the investigated subject (e.g. participant, building, and heating system characteristics) that could interfere with the treatment. However, in practical settings—such as the study described in Paper I—random assignment is often not possible (Recker 2013, pp.82–83) which makes quasi experiments the best alternative possible. Since quasi experiments generally lack the full control of true experiments (Campbell and Stanley 1963, p.34) and are more prone to increased selection bias (Recker 2013, p.85), it is crucial to choose a quasi-experimental design that is capable of ensuring internal validity (i.e. confounded effects) and external validity (i.e. representativeness or generalisability).

Based on these criteria, one can differentiate three types of quasi experiment designs (Table 4) which differ in their extent of being able to control possible threats to internal and external validity. One speaks of a *time series design*, when pretest and postest observations are only available for a treatment group and one has several observations per participant. This design generally fails to ensure internal validity by controlling for history (i.e. effects of weather or season) and for instrumentation effects (i.e. changes in calibration) but one must also be careful about external validity, e.g., interaction effects of selection and testing biases with the experimental variable (Campbell and Stanley 1963, pp.39–41). A *non-equivalent control group design* describes a situation in which only a single pretest and posttest observation per participant is available, but a researcher has data for a treatment and a control group.

This design is generally prone to internal invalidity by regression-to-the-mean effects (i.e. groups have been selected on the basis of extreme values), interaction of selection and maturation effects, and in cases of external invalidity by interaction effects of selection and testing biases with the experimental variable (Campbell and Stanley 1963, pp.47–50). The last type is the *multiple time-series design,* a mixture of the other two designs. This type considerably reduces the number of the possible threats to internal validity described above. It can be used if several observations per participant are available for a treatment and a control group (Campbell and Stanley 1963, p.37ff).

Table 4: Quasi-experimental designs following (Campbell and Stanley 1963)

Experimental design	Groups without random assignment	Pre-test observation measurements	Intervention	Post-test observation measurements
Time series design	Treatment group	O O O O	Treatment	O O O O
Non-equivalent control group design	Treatment group	O	Treatment	O
	Control group	O	No treatment	O
Multiple time-series design	Treatment group	O O O O	Treatment	O O O O
	Control group	O O O O	No treatment	O O O O

Notes: The observations O in this table indicate, by way of example, whether single or multiple observations per participant are available before and after the intervention.

Paper I uses the multiple time series quasi experimental design as research method to analyse (i) the effect of energy efficiency consultancy for owners of heat pumps and (ii) whether data from smart electricity meters can be used to pre-select customers with high saving potential. The quasi-experimental design is chosen since a random assignment was not possible due to the complexity of collecting empirical data in the field. Having a measurement infrastructure (i.e. smart metering) installed months before the treatment occurs (i.e. the efficiency consultation) is difficult in a situation where the market penetration of both heat pumps and smart meters in the field is still rising from smaller rates. Therefore, existing data were taken from an ongoing efficiency campaign. Moreover, for legal reasons, customers could not be refused to receive the treatment (i.e. the heat pump inspection), since customers were mandated to pay a special surcharge on the electricity price that finances exactly such efficiency services. Although self-selection is often a threat to external validity, this is not the case in this setting because the study evaluates the efficiency of the status-quo approach (i.e. heat pump inspection by self-selection) with an alternative selection mechanism based on smart meter data.

The multiple time-series design rather than a *time series design* or a *single-value non-equivalent control group design* was chosen as it combines the advantages of the other two designs and allows researchers to better control for factors that can jeopardise internal validity, such as history effects, instrumentation, regression-to-the-mean, and selection-maturation interaction effects (Campbell and Stanley 1963, pp.55–57). In particular, this design allows researchers to control for history effects of heating systems, which naturally occur due to seasonal consumption fluctuations between the heating- and the non-heating period and weather conditions. Although this design generally allows to cope with regression-to-the-mean effects to answer (i), it was necessary to control for this effect when answering (ii) since some pre-selectors were built on above-/below-median pretest consumption values.

3.2.2. Predictive analytics

Analytics is a scientific process that allows researchers to transform data into insights to make better decisions and includes three broad areas: descriptive, predictive, and prescriptive analytics (Wang et al. 2019). Predictive analytics aims to answer the question 'What will happen?' and is an important research method in various research disciplines. In the information systems discipline Shmueli and Koppius (2011) describe predictive analytics as 'statistical models and other empirical methods that are aimed at creating empirical predictions (as opposed to predictions that follow from theory only), as well as methods for assessing the quality of those predictions in practice (i.e. predictive power)' (p. 554). Basically, such statistical models first try to infer patterns and rules from a data set that consists of independent variables (also predictor variables or features) and a known outcome variable (also ground truth data or labels). In the second step, the inferred rules (i.e. the model) allow researchers predicting instances for which only independent variables are given.

This research method enables researchers assessing the predictability or unpredictability of empirical phenomena (Ehrenberg and Bound 1993; Shmueli and Koppius 2011). Such a phenomenon can be, for example, providing guidance for a business or organisation that is interested in which data available to them can be used to predict future human behaviour (i.e. customer choice of products, churn) and showing the strategic value (i.e. the practical relevance) that arises from such predictions (e.g. Kitchens et al. 2018). Moreover, assessing the predictability of phenomena is also important in the intersection of the information systems discipline with further disciplines that consider 'energy' as a major topic of interest (e.g. Energy Informatics, Smart Grid Community). Several studies have developed empirical predictive models and methods to create benchmarks for the predictability of phenomena in the energy efficiency context. Examples are the predictability of household characteristics relevant to energy efficiency (Beckel et al. 2014; Hopf et al. 2018b), the energy performance of buildings (Wenninger and Wiethe 2021; Wederhake et al. 2022), and information important for smart electricity grids (Wang et al. 2019).

Three papers use predictive analytics as a research method. Papers II–III use predictive analytics to investigate the phenomenon of predicting heat pump characteristics that can support energy efficiency consultancy based on data available to utility companies such as smart meter data (section 3.3.2), weather data (section 3.3.3), and geographical energy efficiency data (section 3.3.4). Moreover, ground truth data were collected using metadata from smart electricity meter, questionnaires, and expert interviews (section 3.3.7). Paper V uses predictive analytics as an embedded unit of a case study. The investigated phenomenon is the usage of predictive analytics in a case where only limited data are available (i.e. the energy decentralisation and electrification solutions). For this purpose, data available from two online sales configurators (section 3.3.5) were enriched with ground truth data from a customer relationship management system and questionnaires (section 3.3.7) to predict whether a sales talk with a potential customer would follow the use of the configurator and whether a sale would be concluded. The predictions aided the company in prioritising potential customers and determining which ones warranted investing valuable planning time from experts.

3.2.3. Case study

A case study allows researchers to study phenomena (i.e. a case) related to information systems within their natural setting (e.g. case site such as a firm or organisation) over a period of time. (Recker 2013, p.95). Case studies can be differentiated into a single case or multiple cases, and if they embed a single unit of analysis (i.e. holistic) or multiple units (Yin 2018, p.51 f). One major concept that case studies enable is data triangulation that allows researchers to 'perusing, and relating, multiple sources of evidence about a particular phenomenon or topic […] to gain a more nuanced picture of the situation, and increase reliability and validity of […] findings' (Recker 2013, p.91). Two papers study data analytics case studies representative of utility companies with limited data.

Paper IV uses a holistic single-case study design to investigate the opportunities from smart meter data analytics for heat pump problem detection. In detail, the study reveals typical problems and suggests a classification scheme for their analysis with the goal of developing information systems that help users—even beyond experts—in recognising and solving relevant problems. The selected case is a single utility company in the Zurich region of Switzerland that provides various energy efficiency consultancy services to its customers. For this purpose, the study investigates heat pump inspection protocols from a reporting tool for energy efficiency consulting (section 3.3.1) as well as data from several expert interviews and observational data from inspections that were accompanied by the researcher (see section 3.3.6). The study generates and analyses several constructs in a mixed-method approach: A content analysis (see section 4.3) is used to extract and count the occurrence of typical heat pump problems (construct 'list of problem classes'). Moreover, the study develops a classification scheme that allows researchers to analyse problem classes with respect to problem recognisability, solving, and potential benefits (construct 'classification scheme'). Both constructs were validated and applied in several interviews with energy consultants (construct 'list of classified problem classes'). Finally, a descriptive analysis of this construct is triangulated with data from the interviews and with observational data to evaluate potential problem recognisability and solvability using analytical solutions and various user groups.

Paper V utilises an embedded single-case study design to investigate the feasibility of supporting sales agents with predictive analytics in the sales of decentralisation and electrification solutions. Furthermore, it investigates the process of value creation through data analytics for the case of a utility company. In detail, the study explores which organisational capabilities and mechanisms for creating business value support the application of predictive machine learning methods with limited data available. The selected case is a single utility company in Central Switzerland that sells energy decentralisation and electrification solutions to building owners and introduced online sales configurators for heat pumps and photovoltaic systems. The configurators allow potential customers to configure their system and get a pre-offer. Both application areas serve as two distinct embedded units for a predictive data analytics project (section 3.2.2). Within this project, supervised machine learning (section 4.2) is applied using online sales configurator data (section 3.3.5) and ground truth data (section 3.3.7). The case study utilises data triangulation and embeds multiple sources of evidence into the analysis. Specifically, the study analyses the analytics project together with interviews and focus group discussions (section 3.3.6), and further material (emails, flipchart notes, slide decks, meeting notes, etc.) that were collected during and after conducting the project.

3.3. Data collection

To respond to the research questions, the studies in this thesis employ various data collection approaches and utilise various original data sources from utility companies, as elucidated in the following sections.

3.3.1. Heat pump inspection reports

In general, home energy inspection or audit reports are generated as a result of self-audits performed by homeowners or through professionals (i.e. energy consultants) who analyse the building or devices with the aim of improving energy efficiency (Sprehn et al. 2015). One subtype of home energy reports—and the one analysed in this thesis—focuses on buildings that use heat pumps as their primary heating system. Two studies analyse report data from an energy efficiency campaign for heat pumps that was conducted from a Swiss utility between the years 2015 and 2021. In this campaign, professionals with specialised knowledge about heat pumps conducted on-site inspections and documented the outcome of the consultation in reports. The utility provided 228 reports, approximately half of the reports as text documents (e.g. PDFs) and the other half as a database excerpt of a digital reporting software. The reports contain structured (i.e. checkboxes) and unstructured elements (i.e. text fields) to detail the different topics. The reports contain information regarding the investigated building and heating system including auxiliary systems (e.g. the hot water and heat distribution system) and the found overall efficiency of the system. Furthermore, the reports contain information about identified problems and implemented changes to improve the efficiency, and general recommendations for the client to improve the system efficiency.

Two papers use data from the heat pump inspection reports. Paper I uses the inspection date to separate electricity consumption data into a baseline and a treatment phase, which allows researchers to analyse the saving effect of the heat pump efficiency campaign using linear panel data regression (section 4.1). Furthermore, the study uses six basic characteristics from the investigated buildings and heating systems as possible pre-selection criteria to determine heat pumps with high saving potential. Paper IV focuses on the documented problems in the text fields and structured elements. It extracts problems from each report by applying a content analysis (section 4.3) to generate a list of problem classes and to count their frequency. The list serves as input to further investigate the heat pump problems using interviews (section 3.3.6).

3.3.2. Smart electricity meter data

Smart electricity meter data describe electrical data (e.g. voltage, frequency, and consumption) measured in buildings, apartments, or similar locations and typically consist of a unique identifier, a timestamp, and the measured electrical data (Jixuan Zheng et al. 2013). Please refer to the 'Background' section for a detailed overview of the electrical measurement data, and to the 'Ground truth data collection' section below for a description of metadata from smart electricity meters.

Four papers constituting this thesis use or refer to the electrical measurement data of smart meters, which come from two different utility companies in Switzerland. Paper I analyses long-period monthly electricity consumption data in a panel data analysis (section 4.1) in two forms. First, to estimate the saving induced by an energy saving campaign for heat pumps, and second, to infer criteria and test their value for pre-selecting heat pumps with high saving potential. Papers II–III use both 15-min consumption data to derive features for supervised machine learning (section 4.2) and predict basic heat pump characteristics. The studies also investigate the role of different measurement concepts, window sizes, and additional data (e.g. weather data) on the prediction performance. Paper II uses 15-min mixed electricity consumption data and a window size of one week. The study tests the predictability of three heat pump characteristics, and examines two aspects of the prediction performance. First, it tests the benefit of additional data sources (weather and geographical energy efficiency data), and second the seasonal impact of the chosen week in a multiple year setup. Paper III analyses the smart meter data together with experts to derive class labels for one heat pump characteristic and uses the consumption data for prediction. Furthermore, the study tests prediction performance for three different window sizes (data of one week, one month, and one year) and two different measurement concepts (aggregated smart meter data and separate heat pump data). Lastly, Paper IV refers to electricity meter data in an abstract form. Smart meter data are not directly analysed in this study; instead, experts from a utility were interviewed to evaluate which heat pump problems likely create patterns in aggregated 15-min smart meter data.

3.3.3. Weather data

Weather describes the 'short-term state of the atmosphere—in the past, present, or future […] in terms of temperature, precipitation, humidity, cloudiness, wind, and other variables. […] In order to make sense, descriptions of weather always include both time and location' (NOAA Climate.gov 2022). Two papers use historical weather data in this thesis. Both are public data sets and contain time-series data from ground-based weather stations. Weather data are strongly correlated with consumption data of smart electricity meters that measure heat pumps, which is exemplarily shown in Figure 3 (a) and (b) for one winter month. This correlation can either help in deriving features or in controlling for this external factor when investigating the effect of a heat pump inspection campaign.

Paper I uses the 'TabsD' data set from (MeteoSwiss 2017). This data set contains pre-processed and interpolated daily air temperature values in a 1 x 1 km grid over Switzerland. Daily values are used to calculate a temperature-dependent indicator for heat demand, the so-called heating degree days, which are an important parameter that influences the heat demand of a building. This study connects weather data to other data using both time and location (i.e. closest grid point). The main purpose of using this type of weather data is to control for heat pump consumption increases or decreases due to seasonal variations. Paper II uses the 'Integrated Surface Database' data set from (NOAA 2021) that provides raw hourly weather data from different weather stations around the world. Four weather variables (temperature, wind, speed, air pressure, and precipitation) from six weather stations in the region of interest were averaged, and missing values were linearly interpolated. The main purpose of using weather data in this study was to generate features for supervised machine learning and test their potential in improving prediction performance.

3.3.4. Geographical energy efficiency data

Geographical data are digital information that refer to a spatial location on the earth’s surface. A special type of geographical data is the *solar cadastre data set*, which describes energy-efficiency relevant information and unifies data from several sources, such as 3D models of buildings, official housing registers, shading, and weather data (Klauser and Schlegel 2016). The main purpose of the data set is to provide estimates for the potential of roofs and facades of Swiss buildings to produce electricity and for heating and domestic hot water purposes. Paper II uses three features from this data set, namely, the basal area of the building, the estimated energy demand for hot water and room heating, which are assumed to improve the prediction quality of basic heat pump characteristics.

3.3.5. Online sales configurators

An online sales configurator is an information system that allows companies to propose customised and personalised products and services to potential customers and assist them in decision-making (Abbasi et al. 2013). Ultimately, it is an 'knowledge-based software application that supports a potential customer, or a sales-person interacting with a potential customer, in completely and correctly specifying a product solution within all the possible solutions offered by a company' (Sandrin 2017, p.177). Paper V uses 5,038 individual configurations entered by potential customers in two web-based sales configurators: The first information system contains configurations from typical decentralisation solutions for energy supply (i.e. photovoltaic systems), and the second contains electrification solutions for large consumers (i.e. a heat pump). The main goal of the configurators was to attract new customers. For this purpose, potential customers enter basic information about the planned project, various building characteristics, and constraints (e.g. roof characteristics, the space area to be heated, characteristics of the old heating system) in the online configurator. The configurators create a non-binding preliminary offer based on this data, precise enough to give potential customers a rough overview of the feasibility of their planned project, costs, and benefits. However, the company must conduct further time-intensive and thus expensive activities to create an official offer. For example, specialised sales agents must collect further information on-site and use additional specialised software to plan a system. Hence, the motivation to use online configurators for the vendor is rather an initial step in attracting potential customers to initiate sales talks and further activities that may end in an actual sales transaction rather than a system that 'completely and correctly specifying a product solution' (Sandrin 2017, p.177).

3.3.6. Interviews

Interviews are a data collection technique in which an interviewer asks individuals questions. One can differentiate between structured, semi-structured, and non-structured interviews, and between single-person-interviews (i.e. a single expert) and multiple-persons-interviews (e.g. focus group discussions) (Ciesielska and Jemielniak 2018, p.78ff). Two studies in this thesis use semi-structured interviews which include open and closed questions. Paper IV uses single-person interviews to collect data from energy efficiency consultants at a utility to develop, validate, and apply a classification scheme for typical heat pump problems. For the expert interviews, two energy consultants were selected who have together more than ten years of experience and have conducted more than two hundred heat pump inspections. As a preparation for the interviews and to collect additional empirical observations, the researcher accompanied the experts individually for two heat pump inspections. Five semi-structured interviews (individually held with the two experts) were conducted that resulted in about ten hours of material, a validated classification scheme for typical heat pump problems, an improved list of typical heat pump problems, and an applied classification scheme for typical heat pump problems. Paper V utilises two forms of interviews, single-person interviews and focus group discussions with participants of a data analytics project (i.e. a utility company selling energy decentralisation and electrification solutions and a software company). Altogether, the study collects data in seven semi-structured interviews and twelve focus group discussions with participants of the data analytics project (e.g. head of the sales department, sales agents, software consultants, and data scientists).

3.3.7. Ground truth data collection

Having a sufficient number of a known outcome variable (also ground truth data or labels) is a key requirement for many machine learning tasks. However, more recent applications of machine learning lack a history of accumulating training data over decades, and thus have little or no training data available, which makes collecting labels a key challenge in many application areas (Roh et al. 2021). Since little training data regarding heat pump characteristics or heat pump sales are publicly available, this thesis analyses the predictability of these phenomena. In such case, one can use different techniques to collect ground truth data; for example, derive existing labels from internal resources or manual labelling techniques (Roh et al. 2021). The papers constituting this thesis use and combine different techniques to derive labels from existing transactional data (i.e. a CRM system and from smart meter metadata), and use two different manual labelling approaches (self-labelling from sales configurators or smart meter users based on questionnaires, and experts interviews), see Table 5. The following section describes the internal data sets and manual labelling approaches used to derive several dependent variables.

Table 5: Ground truth data collection method

Paper	Case	Collection technique	Subjects in original data set or invited in survey	Subjects relevant for analysis due to participation on survey and connectable to feature sets N	%	Created dependent variables
II	Basic heat pump characteristics	• Deriving internal labels from smart meter metadata • Manual labelling from smart meter users using a questionnaire	3,636	397	11%	• Heat pump existence • Heat pump type (reservoir), • Heat pump age
III	Basic heat pump characteristics	• Manual labelling based on expert interviews	226	171	76%	• Heat pump modulation type
V	Heat pump sales	• Existing internal labels from CRM data	2,093	2,093	100%	• Heat pump sales talk initiation
		• Manual labelling from sales configurator users using a questionnaire	1,797	238	13%	• Heat pump actual purchase
	Photovoltaic sales	• Existing internal labels from CRM data	2,945	2,945	100%	• Photovoltaic pump sales talk initiation
		• Manual labelling from sales configurator users using a questionnaire	2,466	560	23%	• Photovoltaic actual purchase

Customer relationship management data

Customer relationship management systems (CRM) allow companies to collect data about existing and potential customers (i.e. prospects) and often include basic information such as addresses, demographic information), and historic transactions such as acquisition sources and sales activities (Kumar and Reinartz 2018, p.159). The latter can be utilised to serve as labels for machine learning tasks. Paper V uses data from a CRM system to derive ground truth data on conducted sales talks with potential customers that were acquired through the online sales configurator channel previously. The study derives two instances of the dependent variable *sales talk initiation*: one for users of heat pump sales configurator and one for users of the photovoltaic system sales configurator. The CRM data could not be used to derive the second dependent variable, *actual purchase*, as only a few transactions were available at that time, which made it necessary to collect data using a questionnaire (see below).

Metadata from smart electricity meters

Metadata from smart meters contain textual descriptions and notes from the grid operator and describe what is measured on a specific metering point. Since one building can have several meters, the 'what' is often further specified and contains information about the part of the measured building (e.g. an apartment on the ground floor, 2nd floor etc.) or information about larger devices (e.g. electric boiler, heat pump, photovoltaic system) that are measured. Such data allow, to a certain extent, to derive ground truth data (i.e. labels) about the *existence of heat pumps* (i.e. positive labels). Operators of meters can gain information about already installed heat pumps when they install new metering points (which is currently done during the roll-out of smart meters). Afterwards, grid operators potentially gain information about newly installed heat pumps from installers who are often obligated to report installations due to grid stability reasons (Dott et al. 2018, p.70). Since heat pumps operate for a long lifetime, one can assume that a label about the existence of a heat pump derived from metadata is true for several years[8].

However, one must be careful about the precision of such data regarding the non-existence of heat pumps (i.e. negative labels), since reporting from heat pump installers can happen late in practice or not at all. The pure fact that metadata does not contain information about a heat pump does not necessarily mean that no heat pump is installed, even though it is likely given their low market penetration. This situation was also found in Paper II, in which the actual number of heat pumps derived from smart metadata differed from a questionnaire that was used as a supplementary ground truth data collection method: While the utility had only information about 51 installations, 90 customers stated that they had a heat pump. Therefore, labels about the non-existence of heat pumps should be retrieved using alternative methods, such as questionnaires.

[8] Please note that the average lifetime of a heat pump is about 15–20 years (Bundesverband Wärmepumpe e.V. 2014)

Questionnaires and expert interviews

Manuel labelling is the most accurate ground truth data collection technique but also an expensive form that often requires domain knowledge (Roh et al. 2021).

Paper II uses a questionnaire to derive three different characteristics of heat pumps that serve as ground truth data from smart meter users. For this purpose, all residential customers of the utility that had a smart meter installed in February 2018 (3,636 customers) were invited to participate on a survey and were asked several questions about their heating system. In particular, users were asked which type of primary heating system they use. If they selected systems other than a heat pump, they served as negative labels for the *heat pump existence*. If they selected 'heat pump', users were asked when they had installed the system, and what heat reservoir the system uses. 397 survey participants provided data on their heating system. From this data, three dependent variables were derived, the *heat pump existence*, the *heat pump age*, and the *heat pump type (reservoir)*.

Paper III uses expert interviews to derive one single characteristic of a heat pump, the *heat pump modulation type*. For this purpose, two heat pump experts were invited to individually annotate 226 visualisations of consumption data (a heat map covering one year of data, and a histogram) as either a variable or a fixed speed heat pump. In 212 cases, the experts were able to differentiate between these two classes. Because annotations by different experts may lead to discrepancies, the inter-coder reliability was assessed using Fleiss' Kappa, resulting in a moderate agreement level of 0.52 (Fleiss 1971; Viera et al. 2005). Resolving discrepancies between the two coders produced a final data set containing 171 labels.

Paper V uses two different questionnaires for users of a heat pump sales configurator and a photovoltaic system configurator to derive ground truth data on two instances of the *actual purchase* of a heat pump or a photovoltaic system. In the heat pump case, labels about the actual purchase were derived by asking users of the configurator whether they had ordered a heating system at any vendor since using the online configurator, and as a second question, which type of heating system they had chosen. If it was a 'heat pump', this was used as a positive example; otherwise as a negative example. For the second instance of actual purchase, users of the corresponding sales configurator were asked whether they had ordered a photovoltaics system at any vendor since using the online configurator. If they said 'yes', they served as positive example; if 'no', they served as a negative example.

4. Data analysis

The papers in this thesis utilise a wide variety of data analysis methods to address the research inquiries (Table 6). This section describes linear panel data regression, which allows researchers to analyse quantitative data from the conducted quasi experiment. It then outlines the typical process of applying supervised machine learning and relates these steps to the studies conducted. Finally, content analysis is described, which allows researchers to analyse qualitative data and to generate quantitative data.

Table 6: Data analysis methods used in this thesis

Data analysis method	Paper I	Paper II	Paper III	Paper IV	Paper V
Linear panel data regression	✓				
Supervised machine learning		✓	✓		✓
Content analysis				✓	✓

4.1. Linear panel data regression

While panel data describe a longitudinal data set that provides multiple observations on individuals (e.g. households) over time (Hsiao 2014, p.1), linear panel data regression makes use of such data to estimate a continuous dependent variable (e.g. energy consumption) based on several independent variables (e.g. policy measures such as treatments, external influences such as weather).

Panel data have several advantages over pure cross-sectional data sets. Due to the existence of many data points, they allow researchers to reduce the collinearity among explanatory variables and controlling the impact of omitted or non-observed variables such as individual or time heterogeneity (Hsiao 2014, pp.4–10). On the individual level, such heterogeneity can be, for example, unknown building characteristics or heating and showering behaviour of occupants, and on the time level, it can be changes in electricity prices or holidays that happen to all households. Unobserved heterogeneity is often given in data sets that do not stem from controlled experiments but from the field (Hsiao 2014, p.10). Such a situation is presented in Paper I, which uses a data set from multiple time series quasi-experiment (see section 3.2.1).

Three general model types of linear panel data regression exist: Pooled models, fixed effects (FE) models, and random effects (RE) models. While pooled models can be applied consistently only under the assumption that no time and individual effects exist, FE and RE models allow researchers to control for them. The main difference between the latter is that FE models assume the unobserved variables to be constant, while RE models assume them to be random variables (Hsiao 2014, p.10). The appropriate model can be determined with tests that analyse if the existence of FE can be rejected (F-Test) and if a random effects model is the better choice compared to a FE model (Hausman test) (Hausman 1978).

Paper I uses a FE model to estimate the treatment effect of an energy conservation campaign that can be generally formulated as the following

$$y_{it} = \beta_1 treatment_{it} + \beta_2 x_{it} + c_i + \lambda_t + u_{it} \quad (1)$$

where y_{it} is the dependent variable (i.e. electricity consumption) of a subject i (i.e. a household) in the given period t (i.e. a month); $treatment_{it}$ is an independent dummy variable indicating some sort of measure (i.e. a consultant inspected a heat pump); x_{it} corresponds to an example of further observed independent variable of a subject i in a given period t that influences the dependent variable (i.e. weather data); c_i is the unobserved individual FE for each subject; λ_t is the unobserved time FE in a respective period; u_{it} is the error term.

This formula can be extended to perform a subgroup analysis and test the effect of further independent variables that one assumes interact with the treatment, for example, a pre-selection criterion believed to explain the treatment effect.

$$y_{it} = \beta_1 treatment_{it} + \beta_2 treatment_{it} \times pre\_selection_i + \beta_3 x_{it} + c_i + \lambda_t + u_{it} \quad (2)$$

When estimating such models, one must also consider basic distribution assumptions on the standard errors. Two typical problems that can occur when using panel data are heteroscedastic standard errors and serial correlated (i.e. autocorrelated) standard errors (Hsiao 2014, pp.64–65). Both can lead to an invalid statistical test of significance. For example, t-statistics may appear more significant than they really are. One can address these issues by estimating a robust covariance matrix and cluster observations by subjects with the White-Arellano method (Arellano 1987; Wooldridge 2010).

4.2. Supervised machine learning

Studies that aim to assess the predictability of phenomena can give researchers guidance by providing benchmarks that show high level predictive accuracy as well as by showing low levels of predictability, since the latter can encourage researchers to improve existing or develop new approaches (Shmueli and Koppius 2011). To enable researchers to find possible starting points for such improvements, it is necessary to create transparency about how the predictive analytics study was applied in the specific context. For this purpose, this section uses the framework of Shmueli and Koppius (2011) to shed light on the steps taken and provides detailed information about how Papers II–III and V[9] conducted predictive analytics studies using supervised machine learning. The framework, shown in Figure 6, guides researchers and practitioners through an eight-step procedure to build and evaluate supervised machine learning models.

[9] Please note that also Paper IV conducts some steps necessary to conduct a predictive analytics study, by deriving labels for specific heat pump problems. However, the derived labels are then used to provide estimations on how many labels could be collected and do not serve as actual prediction problems. Moreover, the study provides hints on how smart meter patterns should look like, which may help to design features for specific heat pump problems, but it does not derive any features.

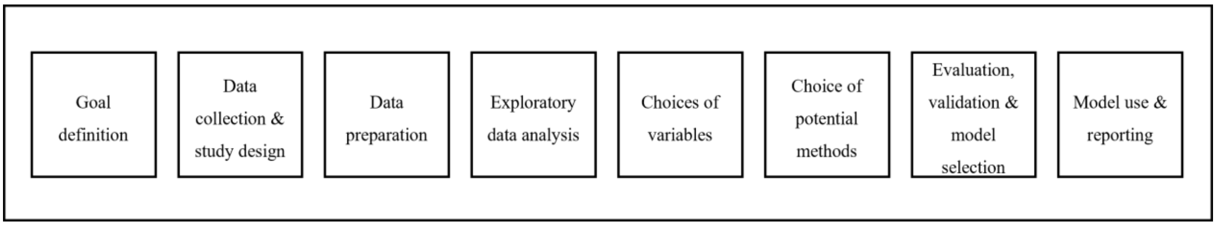

Figure 6: Process steps to build an empirical model (Shmueli and Koppius 2011)

In the first step, **goal definition**, one needs to specify the outcome variable, which is either numerical (one speaks in such cases from regression) or categorical (one speaks of classification or supervised machine learning). In case of categorical outcome variables, one could be interested in the class itself (e.g. certain heat pump characteristics) or in the probabilities that instances are in a certain class, which allows to find the 'top tier of a population' (Shmueli and Koppius 2011, p.562) such as potential customers of energy decentralisation and electrification solution that are interested in a sales talk. Papers II–III and V use classification or supervised machine learning to either predict a categorical outcome variable or its probability. Hence, the following descriptions note only aspects relevant for the prediction goal of supervised machine learning and omit aspects relevant for regression.

In the second step, **data collection and study design**, one can choose between clean experiment data or observational data from the field. Observational data may be preferred over experiment data as it allows to consider real-world aspects such as uncontrolled factors and noise (Shmueli and Koppius 2011). Since this thesis aims for showing utility companies the opportunities that arise from using data available for them to develop new businesses, the studies conducted focus on observational data from the field. For supervised machine learning two types of observational data must be collected: data that can be used to derive features and ground truth data (see section 3.3). Data collection involves multiple challenges regarding the measurement quality and the sample size (Shmueli and Koppius 2011), which are briefly summarised in the following.

Regarding the measurement quality, data available to utility companies can be considered noisy. For example, consider the case when a utility wants to use smart electricity meter to predict energy-efficiency relevant information about heat pumps (e.g. heat pump characteristics, heat pump problems). Meters in the field often do not exclusively measure the device of interest (i.e. the heat pump) but all devices together in a building (see Figure 3). Still, such noisy data are reflecting the reality better than laboratory data can.

Regarding the sample size, a sufficient number of examples is necessary for data-driven algorithms to infer rules (i.e. a model), to reduce model bias and sampling variance, and to evaluate the prediction performance of the model with before unseen examples (Shmueli and Koppius 2011). More specifically, one needs enough data of two kinds; data that can be used as features and data that serve as ground truth. If only one kind is scarce, the number of training examples will be limited. Utility companies often lack ground truth data they can assign to their available data sets, which was also the case for all studies in this thesis. However, even though the sample size is recommended to be 'large', it is difficult to determine the required sample sizes before conducting the analysis, since it depends on the nature of the data and the potential predictive power of the prediction problem (Shmueli and Koppius 2011). Table 7 shows the used dependent variables that stem from the ground truth data collection process (subsection 3.3.7).

Table 7: Generated ground truth data

Paper	Case	Dependent variable	Class	Class size	Relative
II	Basic heat pump characteristics	Heat pump existence	Heat pump	93	23%
			No heat pump	304	77%
		Heat pump type (reservoir)	Ground source	63	16%
			Air source	24	6%
			No heat pump	304	78%
		Heat pump age (binary)	< 10 years	49	54%
			≥ 10 years	41	46%
		Heat pump age (three classes)	< 10 years	49	54%
			10 ≤ X < 20	31	34%
			≥ 20 years	10	11%
III	Basic heat pump characteristics	Heat pump modulation type	Variable speed	130	76%
			Fixed speed	41	24%
V	Sales of electrification solutions	Heat pump sales talk initiation	Sales talk initiated	208	10%
			Sales talk not initiated	1,885	90%
		Heat pump purchase	Purchase	66	28%
			No purchase	172	72%
	Sales of decentralisation solutions	Photovoltaic sales talk initiation	Sales talk initiated	165	6%
			Sales talk not initiated	2,780	94%
		Photovoltaic purchase	Purchase	289	52%
			No purchase	271	48%

In the third step, **data preparation**, one addresses missing values and data partitioning (Shmueli and Koppius 2011). Missing data are often a problem, as many statistical models cannot cope with missing values (Kuhn and Johnson 2013, p.42). Typical strategies to cope with missing values are imputing and removing missing values (Kuhn and Johnson 2013, pp.41–45). The data sets used in this thesis frequently contain missing values. For example, the time-series data from electricity meters or weather data contain periods of missing measurements (i.e. due to connection problems) and the online sales configurators contain missing values because users did not fill out all values in the form or when the configurator could not calculate all numbers. Different strategies were applied to cope for missing values. For example, Paper II uses linear interpolation in case of time-series data such as weather or electricity meter data, but also removes predictors or parts of the time-series, and Paper V uses median-imputation.

Another crucial step in data preparation is data partitioning. Data are divided randomly into a training set (a set of instances used in the phase in which algorithms infer rules and build a model), and a test set (a set of instances unseen in the training phase before that is only used to evaluate the model). In case of having only a limited data set available, it is often necessary to use almost all examples available in the training phase; however, this has the drawback that testing the performance on only a tiny fraction will bias the evaluation of the model. Therefore, it is recommended to apply cross-validation (Shmueli and Koppius 2011; Kuhn and Johnson 2013, p.67ff). In k-fold cross-validation, available data are split repeatedly (k-times) into a training and a test-data set to build and evaluate a model. Given the limited data available to utility companies in all predictive studies in this thesis, k-fold cross-validation is employed (ten folds for Papers II and V, and five folds for Paper III) for model validation and evaluation.

The fourth and fifth step, **exploratory data analysis** and **choice of variables**, are closely connected since both aim to improve available data for the prediction task. While the former involves summarising data, handling outliers, and reducing dimensions, the latter involves the selection of features based on theory and domain knowledge (Shmueli and Koppius 2011). Reducing dimensions (i.e. with feature extraction) and feature selection allow researchers to improve the available data and are also often combined. Reducing data is often necessary since data sets that contain many possible features need even more training examples when applying predictive analytics (Hastie et al. 2009, p.22ff). Reduction is especially needed for time-series data (e.g. electricity consumption data, weather data), since in its raw format, each point of the time-series is a possible feature, which would lead to many features.

Feature extraction reduces the original data by engineering new features from original data, which is conducted with manual or automatic approaches. Manual feature engineering is noted to be one of the most challenging tasks in machine learning (Roh et al. 2021); however, constructing features using domain knowledge can often improve the outcome of machine learning (Hastie et al. 2009, p.151) and should be a starting point before applying more complex data reduction techniques such as feature selection (Guyon and Elisseeff 2003). In the context of predicting household characteristics, manual feature extraction based on smart electricity meter data and weather data has already been extensively studied and shown to be useful for predictions (e.g. Beckel et al. 2012; Beckel et al. 2014; Hopf et al. 2016b). For an overview, see (Hopf et al. 2018b; Hopf 2019), who suggest several feature categories, including consumption features, ratios of consumption figures, statistics, and time-series related figures, and correlations between weather electricity consumption data that result in more than 130 features. By contrast, automatic approaches are methods that allow the automatic extraction of features from time-series data (e.g. Christ et al. 2018; Barandas et al. 2020) or are embedded in some machine learning methods such as deep learning (Roh et al. 2021). However, deep learning requires tens of thousands labels for a task to perform well (Bach et al. 2017), which is contrasted by the fact that this thesis aims to cope with training examples in the hundreds (see Table 7). Hence, the paper in this thesis uses solely manual feature extraction techniques. After feature extraction, feature selection can follow to further reduce the number of available features. Feature selection methods can be divided into three classes: filter, wrapper, and embedded methods (Guyon 2006). While filter methods usually rank features based on some relevance index (e.g. correlation coefficients), both wrapper and embedded methods evaluate the feature value based on the prediction performance using an machine learning algorithm (Guyon 2006).

Papers II–III both extract features from time-series data. Paper II compares the prediction performance of three different combinations of feature sets: 91 features from a single week of 15-min electricity consumption data, 30 weather features, that are both extracted as described in (Hopf et al. 2018b), and adds three additional features from geographical energy efficiency data. Paper III extracts several feature categories, such as consumption features, ratios of consumption figures, and statistics for three different window sizes (one week, one month, and one year). Moreover, it tailors features to the prediction task, given the assumption that certain properties of the distribution of the values might be primary distinction criteria for the heat pump modulation type. Altogether, the study derives 78 features for a windows size of one year, and 53 each for the window sizes one week and one month. Furthermore, it tests the effect of a reduced set of features based on recursive feature elimination that iteratively retrains a model and removes the weakest feature (Guyon 2006). Paper V extracts features from two online configurators for energy decentralisation and electrification solutions, including building characteristics, socio-demographics, data on the configured system, monetary, and autarky figures. This results in 24 features for heat pump configurations and 29 for photovoltaic system configurations.

In the sixth step, **choice of potential methods**, one selects supervised machine learning algorithms that allow researchers to build a model for prediction. Classification methods can be generally categorised in linear classification models, nonlinear classification models, and classification trees and rule-based models (Kuhn and Johnson 2013). Well-known methods—and the ones used in this thesis—are, for example, in case of linear classification models, Logistic Regression (LR); in case of non-linear models, Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naïve Bayes (NB); and for classification trees and rule-based models, Decision Trees (DT) and random forests (RF) (Kuhn and Johnson 2013). While the methods used in this thesis belong to traditional approaches, there exists also a series of more recent deep learning methods (a special form of ANNs) that receive a great deal of attention: Deep learning can make use of sequential data and have shown good predictive power in various disciplines; for example, in speech recognition, object detection (LeCun et al. 2015), and business analytics (Kraus et al. 2020). However, deep learning methods are not useful for the cases investigated in this thesis since firms without extensive data sets (i.e. having only several hundred data points) cannot apply deep learning methods effectively (Kraus et al. 2020). Deep learning methods need tens of thousands of data points for a task to perform well (Bach et al. 2017). In short, Paper II applies RF, SVM, KNN, NB, ANN, all with default parameters[10], and Paper III applies RF, LR, SVM, KNN, DT, and NB with parameter optimisation in a grid search. Paper V applies RF, LR, and SVM, and uses default parameters of the algorithms but also tests parameter optimisation for RF and SVM in a grid search.

In the seventh step, **evaluation, validation and model selection,** one evaluates the predictive performance of the model using appropriate performance metrics, validates and selects the most appropriate models (Shmueli and Koppius 2011). All these steps require appropriate performance metrics that allow researchers to evaluate the predictive performance of a model and compare it with alternative models. Based on the calculated performance metrics, one selects a model from alternatives that stem either from testing different feature sets, classification models, sampling strategies, or combinations of them (compare the steps **choice of variables, choice of potential methods)** to build a final model. While it is common to report a number of different standard performance metrics (e.g. Accuracy, Recall, Precision, variants of the F-measure, ROC-AUC), not all performance metrics are equally strong when one faces well-known situations like class imbalances (i.e. having small classes) and different costs associated with mispredictions. For example, ROC-AUC and F-measure have been selected for Paper V due to their ability to cope with class imbalance (Fawcett 2006; He and Garcia 2009). Down-sampling has been used as a strategy to cope with class imbalance (Kuhn and Johnson 2013, p.427ff). Class imbalance is present for several prediction problems in this study (Table 7).

Metrics also vary in their ability to consider different costs of misclassification, which is exemplarily explained using the F-measure. It can be calculated for binary classification problems and is based on two other performance metrics, the Precision (the proportion of positive predicted instances which are actually correct) and the Recall (the proportion of actual positive instances which are correctly identified). The F-measure allows to mediate the importance of both measures by the factor β. Its basic formula is:

$$F_\beta(1+\beta^2) = \frac{Precision \times Recall}{(\beta^2 \times Precision) + Recall}$$

[10] The parameters selected for machine learning are described in detail in the original papers.

While the F_1 measure gives Precision and Recall the same weight, the F_2 measure lowers the importance of precision and increases the importance of the Recall, hence giving more weight to minimising the false negatives. For example, Paper V uses the F_2 measure to identify as many sales opportunities from the sales configurator data as possible (i.e. favouring the number of true positives) while at the same time avoiding a drastic increase in the number of the false positives to drastically since each sales talk is associated with costs for sales agents (i.e. time to prepare sales meetings and to drive on-site and collect additional data).

In the last step, **model use & reporting**, one reports performance measures and plots, explains the practical relevance, and interprets the results in the context of generating new knowledge (Shmueli and Koppius 2011). For example, Paper V, uses visualisations to show the impact of the proposed models for selecting the top tier of sales configurator users with a high potential for a sales talk or actual sales.

4.3. Content analysis

Content analysis is a data analysis technique that can be applied on qualitative data. It allows researchers 'making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use' (Krippendorff 2018, p.24). Content analysis is typically applied to text that stems from interviews or focus group discussions that have been recorded and transcribed. The method also qualifies to any material that 'may be considered as text' (Krippendorff 2018, pp. 24–25), such as emails, flipchart notes, or textual notes from energy efficiency reports. For this purpose, a coder uses rules to find codes (i.e. categories) in the text that are later on analysed (Krippendorff 2018, p.129). Reliably coding involves formulating observer-independent and detailed rules before coding is applied (Krippendorff 2018, p.129).

Content analysis not only enables the discovery of phenomena of interest (e.g. mechanisms in organisations) but has two characteristics important in supporting or evaluating predictive analytics tasks. First, and in comparison to other text analysis methods, content analysis enables the quantification of data through code frequency counting (Vaismoradi et al. 2013). Moreover, quantification enables the analysis of data in quantitative terms, e.g. using descriptive analysis, which allows 'describing, aggregating, and presenting the constructs of interests or the associations between the constructs to describe' (Recker 2013, p.85). Second, deriving codes can be seen as technique of human labelling aimed at generating ground truth data (Geiger et al. 2020). While the codes could serve as input (i.e. labels) for predictive analytics studies, the derived frequency of codes helps in pre-evaluating the feasibility of predictive analytics tasks (i.e. Is available material, such as energy efficiency reports, helpful to derive enough labels?).

Two papers used content analysis as a data analysis technique in this thesis. Paper IV applied content analysis to generate a list of overall problem classes and their occurrences from heat pump inspection reports. The coding is based on a set of detailed and observer-independent rules that have been formulated upfront, e.g. by defining the text field investigated (not all parts of the report are equally relevant to certain problem classes) and by providing examples that serve as inclusion criteria. The coding was carried out with the data analysis tool Excel to screen subsections and text fields of the report and code problems iteratively. The resulting pre-liminary list of problem classes and codes were validated during the interviews with heat pump experts and led to a final list of 47 problem classes and their frequencies. This list served as input to apply a classification scheme consisting of ten questions, each with several discrete choices. The result is like a survey which was analysed using descriptive analysis (e.g. contingency tables) and enriched with explanations from the experts to find candidates for heat pump problems that are suitable for utility-based digitalised energy efficiency consulting. In Paper V, several sources and types of qualitative data were investigated using content analysis, stemming from a data analytics case study. The data investigated included transcribed text from recorded interviews and focus group discussions, email conversations, flipchart notes, slide decks from presentations, and meeting notes. These sources were investigated using the data analysis tool MAXQDA to find resources and capabilities related to data analytics, value creation mechanisms, barriers hindering their functioning, and business value contributions.

5. Main results

This section summarises the results of this thesis. It first shows the results of the papers that focus on consultancy-intensive services, by using the example of energy-saving consultancy for heat pumps (Chapter 1). Subsequently, the section sheds light on use cases for predictive analytics for the sales of solutions for the decentralisation of energy supply, i.e. photovoltaic systems, and sales of solutions for the electrification of large consumers, i.e. heat pumps, and discusses data value creation with limited data for these cases (Chapter 2).

5.1. Paper I: Evaluation of a heat pump inspection campaign and targeted identification of high savers using smart meter data and heating system characteristics[11]

The expansion of smart metering (Tounquet and Alaton 2020; BFE 2021; EIA 2022) provides utility companies with valuable consumption data on heat pumps. Despite being effective for decarbonising building heat demand (IEA 2019), many heat pump systems consume more energy than expected (Puttagunta et al. 2010; Caird et al. 2012; Yin et al. 2019; Qiao et al. 2020; Chesser et al. 2021). Enhancing energy efficiency through monitoring and consulting could serve as a crucial step for utility companies to fulfil energy efficiency mandates (Taylor et al. 2014; Alberini and Towe 2015; Cho et al. 2019; EU 2021) and explore new business opportunities (Requejo et al. 2019; Colle 2020). However, recent research has not focused on the role of smart meter data for this purpose (Fischer and Madani 2017). Thus, Paper I aims to investigate whether smart meter data and simple criteria can enhance energy efficiency campaigns for heat pumps by targeting households with high saving potential.

Paper I conducts a quasi-experiment using four years of smart meter data from 297 households. Among these, 41 households received professional heat pump inspections and user training, while 256 households with heat pumps served as the control group. The analysis unfolds in three steps: first, assessing the overall impact of the inspection campaign using a two-way FEs panel data regression using ordinary least squares; second, identifying pre-selectors through subgroup analysis based on consumption data, heating system characteristics, and building features; and third, measuring the potential effect of these pre-selectors in a hypothetical campaign ex-ante.

Paper I finds that the overall campaign led to an average saving of 5.3%, amounting to 53.5 kWh per month or 642 kWh annually per treated household; however, the effect is not statistically significant (Table 8, Model 1a). While the campaign, where customers self-registered for inspections, did not show a significant impact overall, subgroup analysis revealed heterogeneity in savings. Groups like Savers, High-Savers, Low-Savers, and Non-Savers varied significantly in attributes such as consumption features from smart meter data and one heating system characteristic. Analysis suggests using these criteria as pre-selectors could enhance efficiency campaigns significantly. For instance, targeting

[11] Weigert, A., Hopf, K., Günther, S.A. and Staake, T. 2022. Heat pump inspections result in large energy savings when a pre-selection of households is performed: A promising use case of smart meter data. Energy Policy 169, p. 113156. doi: 10.1016/j.enpol.2022.113156.

households with above-median consumption through smart meter data could result in significant average savings of 15.2%, amounting to 152 kWh per month or 1,805 kWh annually (Table 8, Model 2–3). Similarly, focusing solely on households with ground source heat pumps could yield average savings of 23.5%, equating to 239 kWh or 2,158 kWh annually.

Table 8: Research results of Paper I: Overall treatment effect of a heat pump inspections campaign (Model 1a) and impact analysis of the identified criteria to pre-select high potential heat pumps (Model 2–3)

Independent variables	Consumption [kWh/month]					
	Model 1a		Model 2		Model 3	
	Estimate [CI]	S.E.	Estimate [CI]	S.E.	Estimate [CI]	S.E.
Inspected	-53.53 [-130.83; 23.78]	46.99	1.73 [-26.43; 29.89]	17.12	59.16 [-37.92; 156.24]	59.02
HDD	0.96 [0.75; 1.16]	0.12 ***	0.95 [0.75; 1.15]	0.12 ***	1.35 [0.33; 2.36]	0.62 *
Inspected × Control × $Median^{LC}$			12.68 [-14.94; 40.29]	16.79		
Inspected × Treatment × $Median^{LC}$			46.84 [-2.83; 96.52]	30.20		
Inspected × Treatment × $Median^{HC}$			-152.15 [-302.93; -1.37]	91.67 .		
Inspected × $HeatPump^{ground}$					-239.02 [-401.07; -76.98]	98.52 *
Observations						
Num. households analysed n	n = 297		n=297		n=41	
Range of months analysed T	T = 12-86		T=12-86		T=19-86	
Num. household months N	N = 14,815		N=14,815		N=2,353	
R^2 / R^2 adjusted	0.01 / -0.02		0.01 / -0.01		0.03 / -0.02	

Notes: ***, **, *, and . indicate statistical significance at 0.1%, 1%, 5%, and 10%. Robust standard errors clustered (S.E.) by households are estimated using the White-Arellano method (Arellano 1987); the 90% confidence interval is shown in square brackets.

In summary, Paper I reveals significant saving potential in many household-installed heat pumps, confirming previous studies highlighting efficiency gaps (Puttagunta et al. 2010; Caird et al. 2012; Yin et al. 2019; Qiao et al. 2020; Chesser et al. 2021). However, given the high costs of on-site visits for heat pump problems (CHF 400 per inspection at this utility company), the benefits in energy cost reduction must be considerable. Heterogeneous savings effects underscore the need for effective customer identification before costly on-site inspections. The proposed pre-selecting criteria demonstrate how utility companies can leverage smart meter data to target households with high saving potential more effectively than self-selection. The first suggested pre-selector, the above-median consumption, would even halve the number of visited households and thus reduce considerably the costs of such efficiency campaigns. This capability is crucial for utilities publicly mandated to promote efficient electricity use among customers (Taylor et al. 2014; Alberini and Towe 2015; Cho et al. 2019; EU 2021), potentially reducing costs and addressing the shortage of energy transition experts (HPA 2020; Ecoplan 2021; Nowak 2021; BMWK 2022; Branford and Roberts 2022; Hilpert 2022). Profit-oriented utilities can also benefit by identifying suitable customers and offering guarantees on inspection investment returns. Paper I demonstrates that even a little information known in advance can improve such campaigns. The subsequent papers will show that smart meter data and advanced analytics allow the derivation of basic information necessary for better pre-selection (Papers II–III) and that this data most likely holds further potential for identifying specific heat pump problems (Paper IV).

5.2. Paper II[12] and Paper III[13]: Detection of heat pumps and their characteristics with and without prior knowledge using limited data available to utility companies

As demonstrated in Paper I and noted for various energy inspection campaigns (Taylor et al. 2014), customer selection matters: Campaigns in which customers participate based on their own and often uninformed assessment of needing a heat pump inspection can yield heterogeneous savings, occasionally insufficient to offset costs. Leveraging smart meter data and detailed heat pump information can enhance campaign effectiveness. However, if utility companies want to move from customer-self-selection approaches to information-based approaches, knowing households' heat pump existence and further characteristics becomes crucial for tailored offerings. Papers II–III building on smart meter data analytics research (e.g. Fei et al. 2013; Beckel et al. 2014; Hopf et al. 2018b), replicate and extend this research field by exploring the dynamics of the limitedness of data available to utilities that may be helpful for a utility-company-initiated approach to heat pump inspection services.

Both papers use predictive analytics as a research method and apply supervised machine learning based on data sets limited in volume and data typically available to utility companies. They focus on different heat pump characteristics and explore various influences on prediction quality due to smart meter data characteristics and additional data sources (Table 9).

Paper II initially investigates whether a utility company can anticipate the existence of a heat pump in a household without prior knowledge. It also aims to determine how supplementary data sources, alongside smart electricity data, and the selection of time-series periods (e.g. heating vs. non-heating periods), impact prediction performance. Lastly, it tests the predictability of characteristics of a heat pump, including the reservoir type (ground or air source) and age (< 10 years, 10 ≤ X < 20, or ≥ 20 years) with and without prior knowledge of a heat pump's existence in a household. For this purpose, the study derives three feature sets using electricity consumption (91 features), weather (30 features), and geographical energy efficiency data (3 features). The study enriches smart meter metadata with a survey to generate labels as a foundation for training supervised machine learning models. This provides data for up to 397 households for heat pump prediction without prior knowledge, and up to 90 households with knowledge about a heat pump installation.

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[12] Weigert, A., Hopf, K., Weinig, N. and Staake, T. 2020. Detection of heat pumps from smart meter and open data. Energy Informatics 3(Supplement 1), p. 21. doi: 10.1186/s42162-020-00124-6.

[13] Brudermueller, T., Wirth, F., Weigert, A. and Staake, T. 2022. Automatic Differentiation of Variable and Fixed Speed Heat Pumps With Smart Meter Data. In: Proceedings on 2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm). Singapore, Singapore: IEEE, pp. 412–418. doi: 10.1109/SmartGridComm52983.2022.9961055.

In comparison, Paper III assumes that a utility company knows about a heat pump installation and strives to determine the modulation type of a heat pump (i.e. variable or fixed speed). Moreover, it aims to answer the question, of how the measurement concept of smart meter data available (separate meter for heat pump vs. aggregate) and the window size used to derive features (one week, one month, one year) affect the predictability of the heat pump modulation type. For this purpose, the study uses electricity consumption data from separately and aggregated measured heat pumps and derives 53, 53, and 78 features for weekly, monthly, and yearly windows, respectively. Moreover, it generates labels based on expert interviews for 171 households with a known heat pump installation.

Table 9: Investigated aspects in Papers II and III

Investigated aspects		Paper II	Paper III
Predicted heat pump characteristics		Existence Type (reservoir) Age	Modulation type
Smart meter data			
Measuring concept	aggregated consumption data	✓	✓
	separate heat pump data	-	✓
Window size	one week	✓	✓
	one month	-	✓
	one year	-	✓
Selection of a period		✓	-
Additional data sources	Weather data	✓	-
	Geographical energy eff. data	✓	-
Ground truth data collection method	Survey	✓	-
	Smart meter metadata	✓	-
	Expert interviews	-	✓

Paper II reveals that despite the data set's limited volume (397 households), utility companies' data allow to effectively predict two heat pump characteristics without any prior knowledge. Particularly, identifying a heat pump installation using the random forest classifier with aggregated smart meter data yields an average AUC value of 0.794, indicating adequate predictive capability. This prediction task benefits marginally from supplementation with geographical energy efficiency data (avg. AUC value of 0.797), and considerably from the inclusion of weather data (avg. AUC value of 0.822). However, combining all three data sources does not yield superior results (avg. AUC value of 0.807). Additionally, this prediction task demonstrates higher predictive power, when using data from heating periods, with an average AUC value of 0.774 compared to 0.667 for non-heating periods. This effect was stable over four consecutive years. Likewise, without prior knowledge, the heat pump type (reservoir) can be predicted well, with average AUC values of 0.859, 0.734, and 0.811 for 'air source heat pump', 'ground source heat pump,' and 'no heat pump' classes, respectively. However, models aiming to predict the heat pump type or age, assuming prior knowledge about the heat pump existence in a household, resulted in smaller data sets (fewer than 90 households) and showed limited predictive ability, as well as increased variance in the prediction score.

In contrast, Paper III finds that utility companies possessing limited data from only 171 households and have prior knowledge of heat pump installations can accurately detect the modulation type. Overall, one of the best models yields a mean AUC of 0.976 using solely aggregated smart electricity meter data based on a window size of a single week. This prediction task can benefit from better data. Using purer heat pump data, i.e., a measurement concept with a separate meter for the heat pump rather than a single meter, led in all cases to improvements ranging from 0.01 to 0.10 in terms of average AUC, dependent on the classifier. This trend remained consistent regardless of the window size used for feature derivation. However, increasing the amount of data used for feature derivation (window size) does not necessarily enhance the predictive power of the model: For random forest-based models, there was an 0.04 increase in average AUC using a yearly window compared to a monthly or weekly window, but no difference in terms of AUC was observed between monthly and weekly windows. Conversely, for the KNN classifier, models using weekly windows achieved the best results, with a slight decrease of 0.01 and 0.02 in average AUC when using monthly or yearly windows, respectively. Within the classifiers, these trends remained consistent regardless of the measurement concept (separate meter for heat pump vs. aggregate).

In sum, Papers II–III investigate the predictability of empirical phenomena aimed at assisting utility companies in identifying potential customers for energy efficiency and remote monitoring services for heat pumps. The studies demonstrate that utility companies can gain initial insights for efficiency consulting using supervised machine learning and typical smart meter data with 15-min readings and limited volume (i.e. number of households with labels). Accurate predictions about the existence and type of heat pumps (reservoir) from fewer than 400 households are feasible. In a second step, this knowledge about a heat pump installation combined with data from fewer than 200 households allow to derive the modulation type. Fewer than 100 households were not sufficient to accurately predict the age of a heat pump. The studies show that better data (i.e. consumption data from separately measured heat pumps rather than aggregating meters), larger window sizes (e.g. a yearly instead of monthly or weekly windows), as well as additional data (e.g. weather data) can help to enhance predictive accuracy but are not a must for starting such initiatives in companies. The findings suggest that even utility companies deploying a lone smart meter per household and just starting data collection can accurately predict basic heat pump characteristics. Still, when having only one or few weeks of data per household available, they must be careful to use consumption data from the heating rather than non-heating periods, most likely because not all heat pumps deliver hot water and run consistently throughout the year.

5.3. Paper IV: Identification and classification of heat pump problems in the field and their implication for a user-centric problem recognition[14]

As exhibited in Papers II–III, supervised machine learning with limited data enables utility companies to gain initial insights for heat pump efficiency consulting. However, the consultancy process typically relies on on-site experts recognising and solving problems. Having upfront information about specific problems could even enhance household pre-selection for consultancy in addition to the approaches suggested in Papers II–III. It may even lead to cost reduction, as parts of the manual problem recognition are omitted. With knowledge, simple problems might be solvable by the homeowner. But can the smart metering infrastructure also help in specific problem recognition? How many inspections are needed to gather sufficient ground truth data for specific problem classes? And are specialists always needed to solve problems? To learn more about the opportunities of information systems for utility companies to assist in problem recognition and solving, Paper IV aims to provide an overview of typical heat pump problems in the field.

To answer the questions raised above, Paper IV analyses reports from a heat pump inspections campaign conducted at a Swiss utility company and interviews with energy efficiency consultants. The study employs a holistic single-case study approach and utilises mixed methods, including content and descriptive analysis. The analysis proceeds in three steps: First, deriving problem incidents and problem classes from a content analysis of 228 reports from a heat pump inspection campaign spanning the years 2015 to 2021; Second, validating these problems and a classification scheme for heat pump problems with two experts in several interview sessions and applying the scheme to create a list of classified problem classes; And third, quantitatively analysing the classified list of problems to gain insights about problem detectability, solvability, and potential benefits of solving.

Paper IV has three main outcomes. First, the study describes 47 problem classes derived from heat pump inspection reports, of which 44 are pertinent for deriving efficiency measures. These problem classes exhibit diverse characteristics and frequencies, ranging from one-time occurrences to those appearing in 57% of cases. This emphasises the necessity for the second outcome of the study, a comprehensive classification scheme illustrated in Figure 7 that allows the analysis of heat pump problems based on ten questions from multiple dimensions related to recognition, problem solving, and potential benefits from resolution. The third outcome of the study is the descriptive analysis of problems applied to the classification scheme and synthesised with interview data and observations, which are briefly summarised along the three dimensions.

[14] Weigert, A. 2022. Identification and classification of heat pump problems in the field and their implication for a user-centric problem recognition. Energy Informatics 5(1), p. 70. doi: 10.1186/s42162-022-00250-3.

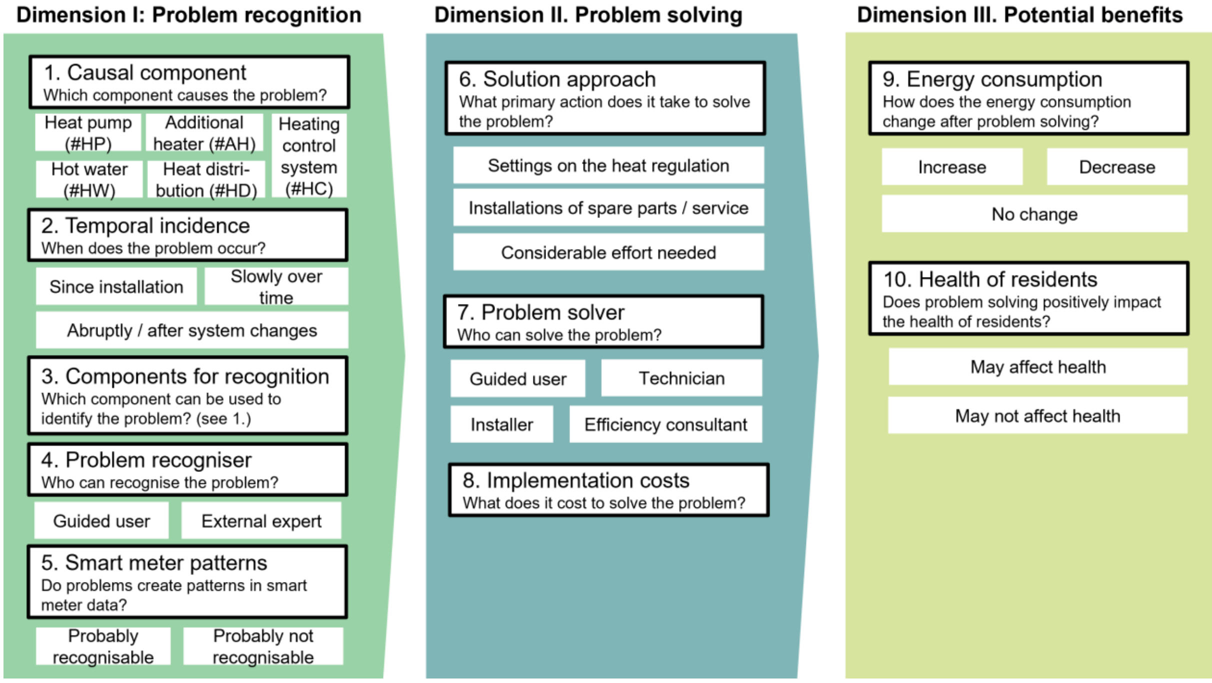

Figure 7: Research results of Paper IV—A classification scheme to analyse heat pump problems

Regarding problem recognisability, the analysis shows that thirteen problem classes (44% of the cases) are expected to exhibit recognisable patterns in smart meter data and are thus potential candidates for automated problem recognition. Moreover, the study describes various smart meter patterns for specific problems that could help in feature derivation and shows frequencies of the classes that help in planning training data collection. On average, each report revealed 1.6 issues likely to generate smart meter patterns, with the top 5 problems occurring in approximately 24% of cases. The results also shed light on the fact that a significant share of problems will still require humans for problem recognition. In a manual-only problem detection, experts are required for about half of the problems found (22 problem classes accounting for 55% of cases). The other half of the cases could potentially be detected by guided homeowners. The study provides further insights for developing user-assisted approaches, such as how guided users can identify problems themselves and what components and strategies are helpful for this.

Regarding solving recognised problems, the study reveals that 14 problem classes (47%) involve only the adjustment of settings on the heating control unit and need no spare parts. Moreover, energy consultants expect that a significant share of problems could be solved by guided users (11 problems, 42%); however, only if they are provided with necessary information. Especially setting problems seem to be good candidates for guided users.

Regarding potential benefits in problem solving, the analysis provides arguments for utility companies to offer and for households to enquire about energy efficiency services: Many problems found likely remained unnoticed since installation (68%), led to energy waste (65%) and thus to higher operating costs, while even 10% led to systems that may affect the health of occupants.

Figure 8 summarises the main results across all three dimensions. It shows the potential and frequency of problem classes for recognition approaches based on smart meter data analytics (orange rectangular) and/or involving guided heat pump owners (blue rectangular), as well as their potential for being solved by assisted heat pump owners.

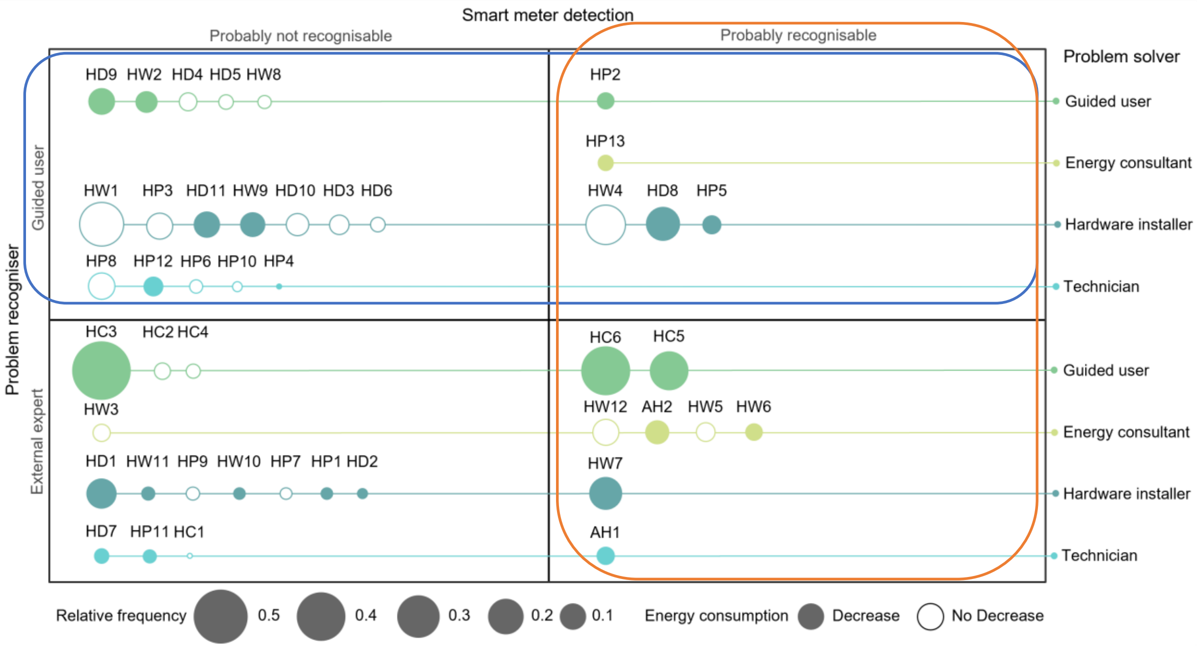

Figure 8: Research results of Paper IV—Problem matrix for automated and assisted detection and solving. The main axes show potential for automated recognition based on smart meter data, and for assisted recognition of humans. A bubble represents a problem class, which is described in detail in the original paper. Filled bubbles show problems with energy conservation potential. Bubble sizes indicate the relative frequency of problems reported during the inspection. Colours indicate actors who can typically solve problems.

In sum, Paper IV puts hope in the feasibility of information systems for heat pump energy efficiency consultancy services based on limited data assets available to utility companies. In particular, the study investigated heat pump problems for their suitability in automated recognition approaches (i.e. using smart meter data and supervised machine learning) and human-centred approaches for recognising and solving heat pump problems (i.e. assisting heat pump owners with information systems).

The results indicate that customer pre-selection (i.e. if an inspection is recommended for a specific system)—which has been demonstrated in Paper I and other efficiency campaigns (Taylor et al. 2014)—could be considerably improved using utility-company data: The experts surveyed expect that many typical problems create smart meter patterns and thus hold potential for automated recognition. Contextual information enriched with climate data will be key to designing features that help in distinguish patterns for a specific problem class. This aspect is particularly important for the many households that have only a single meter and in which heat pump patterns are confounded by other electricity consumers. The study also implies that historical data assets that emerge from energy efficiency consultancy (e.g. reports) hold value for collecting training data for supervised machine learning. For many important problem classes, only hundreds, not thousands, of inspections are necessary to establish a training database comparable to Papers II–III and related studies (e.g. Fei et al. 2013; Hopf et al. 2018b).

Despite the potential of automated problem recognition approaches, manual approaches involving humans will not be superseded by such technologies given the large share of problems that require manual recognition by experts. However, such technologies might enable non-professionals (i.e. homeowners) to recognise and solve a significant share of simpler problems themselves. Experts gain time since manual recognition on-site is reduced and can focus on complex cases. Thus, the suggested approaches could significantly improve economic viability and make such services available to more households than would be possible with solely on-site consultancy. Finally, the proposed information systems provide a research agenda in the field.

5.4. Paper V: A case study on predictive analytics for the sales of energy decentralisation and electrification solutions and value creation with limited data[15]

Motivated by the aspect that online configurators provide utility companies with novel data about planned projects early in the consultancy-intensive sales process of decentralisation and electrification solutions, this study focuses on opportunities in supporting sales agents using predictive analytics in an environment with limited data (i.e. few transactions) available. While several studies suggest that productivity gains resulting from data analytics investments are most evident in the IT industry (Müller et al. 2018) and in sectors characterised by heavy reliance on information processing (Wu et al. 2020) and substantial data volumes (Tambe 2014). Similar gains have not been consistently observed in other sectors (Tambe 2014; Müller et al. 2018; Wu et al. 2020). Aligning with these findings, research exploring value generation through data analytics often focuses on high volumes of data (Ghasemaghaei et al. 2018; Elia et al. 2020; Mikalef and Krogstie 2020) and thus operates under the field assumption that significant data volumes are essential for value creation, whereas limited data volumes although plentifully available (Wilson and Daugherty 2020), present a significant obstacle (Brodley et al. 2012; Baier et al. 2019; Someh et al. 2020).

Paper V contrasts this field assumption motivated by the observation that many utility companies gain access to new data sources in emerging business fields that are limited in volume (i.e. entries in databases in the order of hundreds, with attributes in the order of tens) and potentially of high value but remain mostly untouched. Building on the lens of the resource-based view (e.g. Barney 1991; Bharadwaj 2000; Sirmon et al. 2007), this study explores the occurrence of resources and capabilities related to (big) data analytics (Ghasemaghaei et al. 2018) and mechanisms for value creation through (big) data analytics (Grover et al. 2018; Zeng and Glaister 2018) in this context and formulates two propositions: 'Firms can form capabilities related to data analytics (i.e. analytics competency) already with limited data available.'

[15] Hopf, K., Weigert, A. and Staake, T. 2022. Value creation from analytics with limited data: a case study on the retailing of durable consumer goods. Journal of Decision Systems 32(2), pp. 289–325. doi: 10.1080/12460125.2022.2059172.

(proposition 1), and '(a) Democratising data, (b) Contextualising data, (c) Experimenting with data, and (d) Executing data insights are internal value creation mechanisms that can, each individually, help to achieve value targets even when only limited data are available in the company.'(proposition 2).

To test both propositions in the context of the utility sector, Paper V investigates a typical case for utility companies transitioning to online consumer retailing as new business field (Requejo et al. 2019). The selected Swiss utility company initially operated in offline sales of decentralisation and electrification solutions and was in the early stages of digital transformation toward using online sales configurators, resulting in limited data sources. The company sought to leverage analytics for better customer discrimination from the online configurator to reduce the effort of expensive sales agent consultations when creating binding offers. Methodologically, Paper V employs a single-case study design and embeds two predictive analytics cases—one focusing on photovoltaic systems and the other on heat pumps. The cases involve different data sources, mainly 5,038 heat pump and photovoltaic system configurations used to derive feature sets (up to 29 features), and ground truth data from CRM and surveys (up to 289 positive labels). Supervised machine learning models were built to predict two important phases of the sales process: sales talk initiation and the actual purchase. The study spans 17 months from 2018 to 2020, which led to seven single-person interviews and twelve focus group discussions mainly held with sales department members, along with additional material (emails, flipchart notes, dashboard web application, etc.) collected during and after the fieldwork, which were analysed using content analysis to explore the formulated propositions.

Paper V reveals that despite the data set's limited volume, utility companies can gain from predictive analytics in selling decentralisation and electrification solutions and finds support for both propositions. In the following, the results of both analytics cases along with results from the content analysis are briefly summarised. The two analytics projects embedded within the case study demonstrated that supervised machine learning models can help to better select potential customers in two phases of the sales process, the sales talk initiation and actual purchase of systems. In the case of selling photovoltaic systems, predicting the initiation of a sales talk achieves an average F_2 measure[16] of up to 0.32 (AUC=0.72) with only 165 positive labels, while forecasting an actual purchase reaches an average F_2 measure of up to 0.72 (AUC=0.77) with 289 positive labels. In the case of selling heat pumps, predicting the initiation of a sales talk achieves an average F_2 measure of up to 0.31 (AUC=0.56) with 208 positive labels, while forecasting an actual purchase reaches an average F_2 measure of up to 0.57 (AUC=0.67) with only 66 positive labels. An additional sensitivity analysis confirmed the stability of these models with even less data, but the performance dropped statistically significantly when using less than 80% of the data available.

[16] In this highly imbalanced setup (6–10% of the online configurations led to sales talks), the F_2 measure performance metric was selected as main evaluation criteria to balance between sensitive models (not losing high-stake sales opportunities) and precise models (having few false positives) but favour sensitive models in total. Furthermore, three prediction models have been treated with down-sampling to cope for imbalance.

The case analysis exposed four distinct ways in which predictive analytics, even with limited data, can support sales activities in the organisation. A key contribution is using the class probabilities of the models to prioritise customers. Figure 9 shows that when sale agents only handle 20% of the incoming leads from the photovoltaic online configurator, they reach 43.6% rather than 20% of the truly interested leads (an increase in chance by 118%). Building on this, handling only 20% of the most promising candidates after the initial sales talk would allow them to reach 33.6% rather than 20% of the actual purchasers. Moreover, the utility company found it beneficial to incorporate prediction scores into operational processes and into a dashboard together with additional information, and to visualise the drivers of the predictions (i.e. the most influential features that contributed to a prediction).

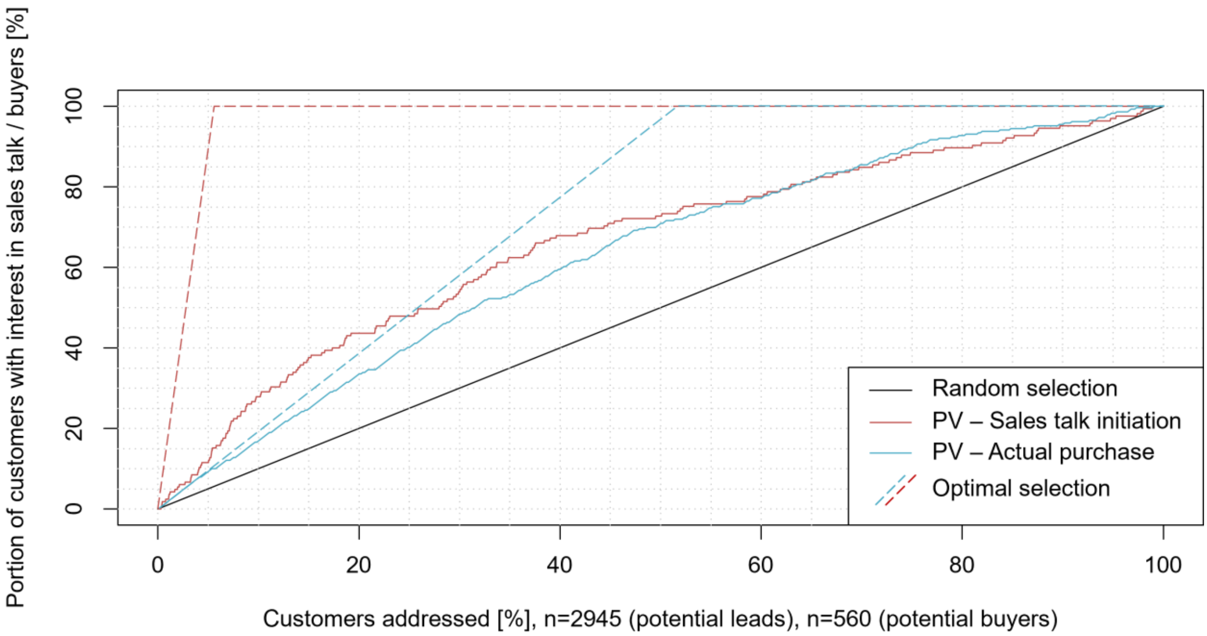

Figure 9: Research results of Paper V—Impact of prediction models in the photovoltaics' case for improved customer selection

With respect to proposition 1, the findings above show that limited data (i.e. having 66 to 289 positive labels) can serve as a sufficient resource for initiating analytics endeavours in the investigated case. Moreover, introducing initial analytics capabilities through external resources to the company raised awareness and understanding of the possibilities and limitations of data analytics. In a second step, the utility company hired two data scientists and thus created internal capabilities. With respect to proposition 2, the case study revealed that the four value creation mechanisms can be found also in a limited data environment in the investigated utility company case. Table 10 discusses them together with their realisable business value, value targets, and barriers to value creation in the case investigated.

Table 10: Research results of Paper V—Insights into value creation mechanisms and identified barriers at a utility company

Value creation mechanism	**Realisable business value through data analytics**	**Type of value**	**Barriers to value creation** *(as became apparent in our case)*
Democratise data	- Analytics uncover flaws in data and drive data literacy - Dashboard makes information available to different stakeholders (e.g. sales agents, marketeers, business developers)	Intangible	- Existing systems provide already access to much data - Data access may be restricted to selected roles (e.g. only some departments have access to systems)
Contextualise data	- Increase customer understanding in market niche (e.g. drivers of customers' purchase decisions) - Understand what data should be collected in the future	Intangible	- Model output not necessarily actionable for business (insights need to be transformed to prescriptions) - Contradictory findings and old convictions - Right balance between model performance and interpretability
Experiment with data	- Software (dashboard) guided decision making on data analytics investments - Continuous update of prediction models with new data	Intangible	- Definition of appropriate success criteria - Sufficient data and users available
Execute data insights	- Individual estimation of purchase probabilities (*prediction*) - Increase effectiveness of marketing efforts and allocate resources (*optimisation*) - Integrate results in business processes (*use*): Present predictions with simple visualisation (e.g. traffic light symbols), using them for targeting (e.g. marketing automation), and use detected pattern to define target groups	Tangible	- Integration of prediction in existing IT systems - Changes in business processes to act upon predictions - Real-time predictions (e.g. when new data comes in)

In sum, Paper V offers practical and theoretical insights from a case in which a utility company is in the transition to become an online retailer for electrification and decentralisation solutions, generating new data assets but fearing the limitedness of their data sets with transactions in the hundreds and attributes in the tens as obstacle to starting data analytical endeavours. From a practical perspective, the case shows that even data sources limited in volume (i.e. 66 to 289 positive labels describing instances of held sales talks and actual purchases of heat pumps and photovoltaic systems) hold potential for predictive analytic solutions that improve customer discrimination, i.e. prioritising potential customers that originate from online sales configurators. Such discrimination can save valuable expert time for sales employees, who are a scarce resource in the energy transition. From a theoretical perspective, the study challenges the field assumption that big data (i.e. high volumes) are essential for value creation through data analytics and contributes to existing research that suggests less emphasis should be placed on big data (e.g. Lycett 2013; George et al. 2014; Constantiou and Kallinikos 2015; Yoo 2015). The results indicate that the field assumption of needing big volumes of data should be considered as a flexible guideline rather than a strict constraint. In the investigated case, it is primarily the creation and execution of capabilities related to data analytics that matter, complemented by other contextual factors such as strategy and vision, leadership, openness to agile working methods, and employees' awareness of data. And yet, the case study showed that the field assumption is not completely abolished. There is a lower volume that restricts the application of analytics. In the case presented, fewer than 80% of the data (about 50–250 positive examples, depending on the prediction task) were not sufficient to build reliable models, however, this lower bound should be seen as case specific and emphasises the need to try to find this lower bound individually. In addition, executing value creation mechanisms such as 'experiment with data' (e.g. conducting A/B tests) might be difficult with only a few transactions available.

6. Contribution and implications

The aim of this cumulative thesis is to explore data analytics use cases relevant to utility business transformation and the energy transition. By investigating several use cases, the thesis provides contributions to different audiences, including overall implications for practice, policy, and theory. The contributions collectively provide actionable insights for developing data-driven energy efficiency consultancy services for heat pumps and sales processes for decentralisation and electrification solutions. Furthermore, they highlight the feasibility of using new but limited data assets available to utility companies for predictive analytics and challenge the common emphasis on big data in this area of application. Before naming limitations, future research endeavours, and concluding the Introductory Paper, this section provides a general discussion of all chapters of this thesis.

(1) Utility companies can benefit in new business fields from predictive analytics by allocating scarce experts primarily to customers with high potential business value

Key contributions
• ***Optimising the use of experts**:* The thesis demonstrates how predictive analytics can help utility companies to identify high-potential customers in two cases—namely, providing energy efficiency consultancy for installed heat pumps, and selling decentralisation (i.e. photovoltaic systems) and electrification solutions (i.e. heat pumps)—before engaging in costly sales and consultancy activities. This enables them to optimise the use of their scarce expert resources (e.g. sales agents and energy consultants).   • ***Leveraging new data sources**:* The thesis shows how data from smart meters, efficiency reports, online configurators, and additional data, can be used to build predictive models that allow customer prioritisation and streamline sales and consultancy processes, effectively using previously untapped data to focus efforts where they are likely to deliver the best value.   • ***Framework for analysing heat pump problems**:* The thesis proposes and applies a framework to analyse heat pump problems that provides insights into how expert resources could benefit from data analytics. Notably, it exposes first, a set of heat pump problems that could potentially allow automatic problem recognition based on smart meters, and second, differences between problems in terms of complexity for manual recognition and solving by end users, indicating that introducing service levels with different intensities of professional consultant involvement could further improve the efficient use of consultants.

Promising new businesses for utility companies include online consumer retailing of electricity-based renewable technologies (e.g. heat pumps, photovoltaic systems, battery storage) and a whole new chain of services around these products that, e.g., ensure their efficient operation (Requejo et al. 2019; Colle 2020). However, the provision of such products and services requires considerable sales and consultancy efforts, e.g., to satisfy information needs of customers and to perform manual work on site, which is challenged by the shortage of skilled labour in this area (HPA 2020; Ecoplan 2021; Nowak 2021; BMWK 2022; Branford and Roberts 2022; Hilpert 2022).

New sales channels, such as online configurators, give customers effortless access to preliminary offers, but also create a lot of potential work for suppliers, overwhelming sales teams and making traditional follow-up methods inadequate. However, configurators generate previously unavailable data before consultancy starts as part of the sales process which is a lever for predictive analysis. In the case of providing energy efficiency services, consultants often have little information before they start work on-site and have difficulties assessing whether a consultation will achieve the desired value, but new smart meter data could leverage such assessment.

A key concern of utility companies is therefore the efficient deployment of experts for which a promising approach, as this thesis shows, is the use of meaningful customer selection. This thesis contributes to this practical problem by providing evidence from two real-world cases, showing how high-potential customers can be identified before expensive sales or service provisioning activities begin, and suggesting ways to potentially reduce the effort required during consultancy activities, allowing for more effective use of valuable expert time.

In the case of heat pump energy efficiency consultancy, Paper I shows that knowledge on criteria such as heating system characteristics or simple criteria from smart meter data can significantly help to pre-select high-potential clients, allowing energy consultants to focus on cases with a better savings/cost ratio. If such criteria are not known, Papers II–III show that predictive analytics can infer several important characteristics with high accuracy based on a few hundred labels and smart electricity meter data. Finally, Paper IV highlights further strategies for optimising the use of expert resources by investigating smart-meter-based automated problem recognition. With knowledge about specific problems before consultancy activities start, experts could benefit from a more nuanced picture for pre-selection and reduce effort in manual problem recognition on-site of installations. The study contributes to these challenges by exposing a significant number of real-world heat pump problems that likely create detectable patterns in smart meter data and provides probabilities of their occurrences, making further analysis endeavours assessable (i.e. label generation for prediction tasks). Moreover, the study highlights significant differences among problems in terms of complexity for manual recognition and solving. While many comparatively simple problems could be potentially recognised and solved by end users themselves, given information and guidance, another significant share of complex problems requires the intervention of experts. This raises for utility companies the opportunity to design light-weight consultancy solutions, where they, for example, provide virtual or remote consultancy, and extensive variants, where they provide on-site consultancy.

In the case of selling decentralisation (i.e. photovoltaic systems) and electrification solutions (i.e. heat pumps), Paper V shows that data from online configurators are valuable for building predictive models that allow sales agents to score preliminary offers according to their probability of converting into successful sales talks and actual purchases of the solutions. The analysis shows that these scores can considerably increase the chances of identifying the high potentials. Moreover, it shows that integrating these scores into operational processes, enriching dashboards, and visualising the most influential features that led to the prediction, can support sales agents in their work.

In conclusion, the findings suggest that predictive analytics based on new data sets of utility companies from the new businesses (e.g. online configurator data, consultancy reports, smart electricity meter data) can reduce the amount of unnecessary consultancy work and thus alleviate the shortage of specialists by optimising their deployment, enhancing customer prioritisation, and enabling more efficient problem-solving.

(2) Sensor and data-related factors that influence the development of energy efficiency consultancy services for heat pumps

Key contributions
• ***Smart meter data:*** Papers II–III show that a wide variety of readily available 15-min smart meter data and only a few weeks from the heating period allow the prediction of a diverse set of heat pump characteristics. Purer consumption data (i.e. from separate meters) is helpful but not essential for reliable predictions, whereas selecting the right period (i.e. the heating period) is crucial. For more valuable insights, such as identifying specific problems in installations, separate meters and transitional period data are likely to become important. • ***Additional data:*** Papers II–III show that the prediction of basic heat pump characteristics based on smart meter data benefits from, but is not dependent on, weather data. Weather data are likely to become vital for the identification of efficiency-related problems. The gain from enrichment with geographical energy efficiency data is negligible in the investigated case.

Deriving information about the condition of heating systems that is useful for energy consultancy has been an option so far to heating system manufacturers and authorised vendors using proprietary multiple sensing approaches. With the advent of smart electricity meters in many buildings, utility companies are collecting large amounts of sensor data, including heat pump consumption patterns, which could enable energy efficiency information to be derived independently from manufacturers, including for the many older installations without their own sensors.

However, using smart meter data to derive energy efficiency-related characteristics of heat pumps poses several challenges for utility companies. These include aspects such as the suitability of consumption data when mixed with other appliances, the amount and selected period of the time series data required, and whether additional data sources are necessary or merely helpful in the prediction of important characteristics.

This thesis extends the field of smart meter data analytics by showing that a wide variety of smart meter data occurring in the field allow the prediction of a diverse set of heat pump characteristics. In particular, Paper III finds that even consumption data from a meter that records the heat pump consumption with all other electric appliances in a building can achieve a high predictive accuracy in deriving basic heat pump characteristics. However, models using data from separately measured heat pumps are superior overall. For more advanced information derivation, such as specific problem recognition, interviews with consultants in Paper IV revealed several cases where data from a separate meter, i.e. measuring only components of the heating system, could be advantageous in identifying relevant patterns. Consistent with previous research and now confirmed for a multi-year period, Paper II shows that period selection is important, as training data from non-heating periods led to significantly lower performance than models using data from heating periods. Regarding the previously in research neglected aspect of the necessary window size (e.g. a week, a month, or a year) for slicing the time series needed for feature derivation, Paper III presented mixed results. Different models either benefited from or were not hindered by larger or smaller window sizes yet, a week of data was typically sufficient. Although not fully comparable due to the different methods of analysis used, this finding contrasts somewhat with previous research, which found that using up to 15 weeks of data was superior to shorter periods (Hopf et al. 2018b).

Regarding the value of additional data for the derivation of basic heat pump information, Paper II revealed that weather data can help to improve the prediction results for basic heat pump characteristics, while Paper IV finds clues that some efficiency-relevant problems might be only interpretable when relating smart meter patterns to climate data. The effort of enriching smart meter data with geographical energy efficiency data does not seem to justify the marginal improvements in prediction quality found.

To sum up, a wide variety of readily available 15-min smart electricity consumption data allows utility companies reliably to predict heat pump characteristics. While better data (i.e. separately metered) and additional (i.e. weather) are helpful but not mandatory for a reliable prediction, selecting the right period of data (i.e. the heating period) is crucial. This means that most utility companies, even in early stages of smart meter rollouts, can start deriving heat pump energy efficiency information with just a few weeks of data from the heating period, without accumulating long periods of consumption data. The findings also indicate that the period selected, the kind of features derived, and the training size available might be more relevant factors than the window size chosen. Finally, the findings indicate that the derivation of more valuable information, such as such as efficiency relevant problems of heat pump, also requires more valuable data, namely separate meters for heat pumps, periods containing transition phases of heating and non-heating periods, and weather data will gain considerably in importance for reliable prediction.

(3) Implications for energy policy makers in designing energy efficiency programmes for heat pumps and the use of smart metering infrastructure for this purpose.

Key contributions
• ***Promotion of heat pump efficiency post-installation****:* The thesis highlights the need for energy policy to focus on improving the efficiency of heat pumps after they have been installed, addressing a gap in current energy policy and emphasising the importance of operational phase efficiency. • ***Variation in problems and saving potential****:* Papers II and IV demonstrate that the problems and savings potential of heat pumps vary greatly between households. This insight implies that current self-selection programmes for on-site inspections are inefficient and suggests a need for better upfront assessment methods. • ***Pre-selection criteria using smart meter data****:* The research introduces methods using smart meter data and heating system characteristics to better pre-select candidates for on-site inspections. This approach can enhance the efficiency of energy efficiency programmes by targeting households with higher savings potential. • ***Automated problem recognition****:* Paper IV lays the groundwork for developing automated systems to identify specific heat pump problems using smart meter data. This can reduce the costs and efforts associated with on-site consultancy, making energy efficiency improvements more accessible and cost-effective for households with varying savings potential.

Energy policy objectives include the promotion of renewable energy sources, for example, by massively subsidising the deployment of heat pump technology, and the improvement of energy efficiency, for example, by promoting energy audits for buildings and related equipment. Although heat pumps are often adequate to also replace old heating systems, this thesis provides evidence from the field that further action is needed to improve the energy efficiency of heat pumps.

The results of Papers I and IV emphasise that policymakers should concentrate on improving the efficiency of heat pumps after installation in the operation phase. Paper IV provides evidence that many installations face a diverse set of problems. While many of the problems found are very likely to have existed since installation and are negatively affecting energy efficiency, they could be solved with relatively simple settings optimisations on the heating control unit. Paper I also shows the actual savings potential in many of the homes inspected if they received professional on-site inspections focusing on easily solvable problems such as settings optimisation and user training.

However, both papers show, based on on-site consultancy data, that not only the problems identified (Paper IV) but also the saving potential (Paper I) vary greatly between households, which has implications for the design of energy efficiency programmes. If half of the customers did not reduce their consumption or only reduced it marginally with an on-site inspection, while another half could reduce their consumption considerably, this means that the typical heat pump owner may not be able to assess the actual need for an inspection. As a result, programmes that allow customers to self-select for on-site heat pump inspection do not translate into an efficient use of public funds for such programmes or a reasonable redistribution of taxpayers' expenditure. This implies the need for new approaches. On the one hand, it requires a better upfront assessment of those customers who are likely to have a high savings potential to justify the high costs associated with on-site consultancy. On the other hand, it requires approaches that reduce effort in problem recognition and solving and are less expensive in nature, if the aim is to induce energy savings cost-efficiently even for heat pumps with moderate to low savings potential.

For the former, Paper I suggests an approach that uses simple criteria from the smart meter infrastructure and heating system characteristics and shows their potential to better pre-select candidates for on-site inspections, resulting in average savings of 15.2%, amounting to 1,805 kWh annually. As consultants often lack basic information about an installation before starting an inspection, it is useful to enrich the picture with additional heat pump characteristics. For this, and beyond the derivation of simple consumption criteria, the smart meter infrastructure can help. Papers II–III significantly extend existing prediction approaches to derive a set of heat pump characteristics that are associated with less efficient systems and thus might have potential to serve as additional pre-selection criteria.

For the latter, Paper IV lays the ground for automated recognition approaches that can potentially identify specific problems (and thus indicate potential savings) based on the smart meter infrastructure. It shows two important aspects crucial for developing analytical solutions. First, half of the problems found in field installations are likely to create consumption patterns in smart meter data. Second, field label generation is possible with moderate effort, as many problem classes (the five most common occur in about a quarter of the installations) occur so frequently that labels in the quantities comparable to Papers II–III and other works (e.g. Fei et al. 2013; Hopf et al. 2018b) that allowed basic heat pump characteristics prediction, could be generated using documentation about conducted field inspections. Finally, Paper IV contributes to the field of energy conservation by showing that end users could be involved by manually identifying and solving of problems. The proposed approaches could significantly reduce the costs associated with energy consultancy for heat pumps.

In sum, the results suggest that on-site inspection can enable significant savings for many heat pumps, but mandatory follow-up checkups for heat pumps after installation or open-access programmes are not necessarily a cost-effective solution overall. Energy policy makers should prioritise data-driven and targeted promotion of energy efficiency consultancy services for heat pumps. The results confirm the usefulness of smart metering infrastructure to identify high-savers and relevant information about installations before expensive consultancy activities start and may even help to achieve further cost reductions through detailed problem recognition, which would allow to also address heat pumps with moderate to low savings potential in a cost-effective way.

(4) The predictability of phenomena and value creation through data analytics in limited data environments

Key contributions
• ***Overvaluing big (volumes of) data***: In the field of energy transition activities of utility companies, this thesis challenges the assumption that big volumes of data are necessary for value creation through data analytics. It shows directly that even in limited data environments, capabilities related to data analytics can be formed and value creation mechanisms can be executed, and indirectly, the predictability of many phenomena that are valuable for energy efficiency consulting. • ***Size of limited data:*** In two different application areas, the case of selling decentralisation and electrification solutions and the derivation of heat pump characteristics for energy efficiency consulting, only a few hundred positive labels were sufficient for many prediction tasks.

Inspired by the controversy that productivity improvements from data analytics have largely been observed in IT, data-heavy, and competitive industries (Tambe 2014; Müller et al. 2018; Wu et al. 2020), and despite the fact that many organisations, especially utility companies, have numerous small and untapped datasets that are described as potentially high value (Wilson and Daugherty 2020; BDEW 2021), but at the same time are seen as insufficient for data analytics initiatives (BDEW 2020), this thesis emphasises the value of limited datasets. Hence, it challenges the belief that large amounts of data are essential for extracting value from data analytics.

Directly, and validated in a case study, Paper V contributes to the body of knowledge by corroborating the formation of capabilities related to data analytics (i.e. analytics competency) and the existence of four different value creation mechanisms in a utility company undertaking a data analytics project with limited data. For the case of improving the sales process for decentralisation (i.e. photovoltaic systems) and electrification solutions (i.e. heat pumps), it shows that the belief that large volumes of data are needed should be seen more as a flexible guideline rather than a strict rule, in line with existing research that emphasises other factors over the sheer volume of data (Constantiou and Kallinikos, 2015; George et al., 2014; Lycett, 2013; Yoo, 2015). In the case studied, data sources with 66 to 289 positive labels describing instances of successful sales talks and actual purchases of heat pumps and photovoltaic systems were sufficient for the application of predictive analytic solutions that allow prioritisation of potential customers that originating from online sales configurators. The immateriality of large volumes of data suggests that other factors could be more relevant, such as the creation and execution of capabilities related to data analytics, and contextual factors such as strategy and vision, leadership, openness to agile working methods, and employee awareness of data.

Indirectly, and as a precursor to data analytics activities in utility companies, Papers II–III find further support for the findings of Paper V by demonstrating the predictability of a number of phenomena (i.e.

heat pump characteristics) that are valuable for developing data-driven energy efficiency consulting. Using their own limited data sources, utility companies can gain insights through data analytics. For example, accurate predictions about the existence and type of heat pumps (reservoir) can be made from fewer than 400 households. If the existence of a heat pump is known, the modulation type can be inferred from fewer than 200 households. However, fewer than 100 households were not sufficient to accurately predict the age of a heat pump. Finally, Paper IV demonstrated the value of energy efficiency reports produced as a by-product of energy consulting. This source is valuable for further analytical work, as the study shows that this data source allows the collection of a training database comparable to the number of labels used in Papers II–III and related studies (e.g. Fei et al. 2013; Hopf et al. 2018b), for many important problem classes found in the field.

In sum, the studies implicate that limited data sets can be a rich source. In the cases investigated, it showed that it allows enabling the use of predictive analytics to derive information of value of utility companies. Overall, the examples from the utility sector raises the question, to what extent large volumes of data are essential for value creation in organisations, which should be further explored in other contexts and industries.

7. Limitations and future research

Despite thorough efforts in this research, the contributions presented have some notable limitations that warrant careful consideration. This section details the primary limitations of this thesis, emphasising aspects related to self-selection bias, regional aspects, and the temporal nature of data analytics, before suggesting directions for future research.

In Chapter 1, Papers I and IV use field data from a real-life energy efficiency campaign conducted by a utility company in central Switzerland. One aspect of the conducted field studies is the self-selection bias of participants. It is unclear what motivated heat pump owners to participate on the energy efficiency campaign, which may introduce bias. Factors such as an assumed large savings potential, environmental attitudes, sensitivity to heating costs, experience with heat pumps, and dissatisfaction with the installer may have played a role. In addition, self-selection may play a role in the overestimation of treatment effects in Paper I due to over-motivated study participants, which has been observed in previous studies with energy consumption feedback (e.g. Davis et al. 2013). Although this cannot be completely ruled out, it can be considered minor given the nature of the treatment studied, which combines quick fixes to the heating system from consultants for immediate improvements, with recommendations for future improvements (e.g. installation of a more efficient circulation pump by installers) and user training. It is unclear whether the inspection resulted solely in immediate technical adjustments by the consultant, where over-motivation from end users is negligible, or also prompted residents to make future changes, such as further modifications to the heating system and altering their behaviour with heat pump use or other electricity-consuming appliances. Furthermore, one of the aims of the studies was precisely to examine the status quo approach of energy consultancy, which often relies on self-selection by customers, and analyse the value of data-driven approaches as an alternative to self-selection. However, future work should control for such factors.

In Chapter 1, Papers I and IV are confronted with regional aspects such as climate conditions, the influence of vendors and installers, and regulatory aspects. First of all, the savings identified for many heat pumps in Paper I also depend on the climate conditions in central Switzerland, which corresponds approximately to the average climate zone in the EU or slightly colder according to the often used standard EN 14825 (Grünenwald 2019). Cautiously estimated, the heat pump inspections and user training effects analysed in Paper I would lead to a correspondingly higher savings potential in the cold climate zone and a correspondingly lower savings potential in the warm climate zone. Secondly, while the inspections in Papers I and IV covered various heat pump types and vendors, they were limited to those active in the central Switzerland market. Installation and post-installation practices often depend on national regulations, manufacturers' specifications, and training materials, which means the saving potential from different installers and manufacturers might vary. Although this thesis did not explicitly analyse the effect of installers and vendors, which would be an interesting research endeavour, overall, the main finding of significant saving potential in many installations across different vendors and system types is in line with previous research (Puttagunta et al. 2010; Caird et al. 2012; Gleeson and Lowe 2013; Yin et al. 2019; Qiao et al. 2020; Chesser et al. 2021; Gao et al. 2021; O'Hegarty et al. 2022). Finally, regulatory aspects may play a role in the assessment of problems, as the diverse set of problems described in Paper IV also includes some issues that depend on national regulations and may be different or irrelevant in other countries. Future research could replicate the approaches shown for different climate zones and regions.

Another limitation, which affects Chapters 1–2, is the evolving nature of data, data analytics, and consequently the resulting value contributions over time. This longitudinal perspective implies that the models proposed in Papers II–III and V are likely subject to changes and must be adapted in the future. For example, the smart meter data analysed in Papers II–III are likely to change. This is due to the ongoing societal activities towards electrification (e.g. battery-electric vehicles) and decentralisation of energy generation (e.g. battery storage, photovoltaic systems) which will very likely change load patterns of aggregated smart meters. However, none of the smart meter data analytics studies in this thesis (Papers I–III) have investigated cases where photovoltaic systems, battery systems, or electric vehicles were installed together with a heat pump, which should be the subject of future research. Similarly, in Paper V, a company was studied that had just begun to invest in data analytics. As the data analytics environment matures, the nature and extent of value contributions will undoubtedly evolve. Moreover, subsidies associated with the sale of electrification and decentralisation technologies are often subject to change, and end-customers' perceptions of these technologies can also fluctuate greatly. Models will need to incorporate such changes to be able to continue to add value.

There are numerous promising paths for future research that go beyond these limitations. For Chapter 1, two promising paths involve smart meter data analytics for heat pump problem recognition, and activities in utilising information in energy consultancy. Paper IV identified several heat pump problems likely predictable due to their relatively frequent occurrence and smart meter patterns. However, it remains uncertain if smart meter data analytics beyond basic heat pump characteristics allows problem prediction. Studies should also examine the necessary smart meter data characteristics, such as aggregated vs. separately measured heat pump data and the value of weather data. Until now, the working hypothesis is that a few hundred labels, such as for the prediction of heat pump characteristics, are sufficient. A key question is, therefore, how many labels are required for specific problem identification, as the generation of labels is an essential and probably the most expensive part of such projects. Another important question is how utility companies should utilise the newly acquired information about likely heat pump problems to improve energy efficiency consultancy services. One alternative is improving business operations, such as better pre-selection of potential high-savers or saving time during manual inspections. Another potentially valuable alternative involves integrating end users in the problem recognition and solving process, as suggested by interviews in Paper V. Possible end-user roles include confirming potential problems found before professional support takes over, or even a light version of problem solving. It remains unclear how information systems should be designed to best assist end users in manual problem recognition and solving. Such an investigation should also include a comparison between status quo approaches (i.e. manual on-site problem recognition and solving through energy consultants) and newly developed end-user assistance solutions. Chapter 2 shows, for exemplary use cases centring around the sales of decentralisation and electrification solutions, that limited data are not an exclusion criterion for value creation through data analytics in this context. Two aspects should be addressed by future research. First, the results indicate that there is a need for a better understanding the underlying factors that provide the basis for value creation. One important aspect that should be explored by future research is in line with the suggestion of Grover et al. (2018), who point to moderating factors (i.e. strategy, culture, governance, leadership, competition) that influence the process of building and realising capabilities. Second, even though the value of data analytics with limited data has been demonstrated in selected cases of the utilities industry, more studies are needed that replicate the findings in other industries or contexts that also have an abundance of limited data sets with high potential value and that have not benefited, or have benefited only marginally, from data analytics efforts to date.

8. Conclusion

The objective of this dissertation was to explore how utility companies can leverage data analytics in emerging business areas that are crucial for their business transformation and the societal energy transition. By analysing small yet high-potential field data from energy efficiency consultancy and the sales of decentralisation and electrification solutions, this thesis provides data analytics use cases for consultancy-intensive products and services and showcases the opportunities and challenges of analytics with limited data.

Field studies on energy efficiency services for heat pumps found both a heterogeneous range of efficiency problems and savings effects on installations through on-site inspections, pointing to the crucial role of information-based customer selection. Importantly, the studies demonstrate the adequacy of a wide variety of typical smart meter data for this purpose; enriched with limited data (only a few hundred labels), heat pump characteristics prediction allows consultants to get a more nuanced picture of an installation. Moreover, a proposed framework for analysing heat pump problems has highlighted promising prospects for information-centred and digitalised energy efficiency consultancy based on smart electricity meter data and limited data. In addition, a case study accompanying a utility company's initial data analytics efforts in selling decentralisation and electrification solutions demonstrated that limited data could yield valuable predictive insights for sales agents and optimise sales processes. Finally, the work contributes to the discussion on value creation through data analytics with one exemplary case that challenges the prevailing assumption that large data volumes are necessary.

Overall, the findings imply the potential of data analytics for the development of new business opportunities in the energy transition for utility companies and the achievement of societal environmental goals in a cost-effective manner. It showcases how previously untapped, yet valuable limited data sets held by utility companies can be harnessed through data analytics.

While this thesis has advanced the understanding of the opportunities presented by data analytics with limited data in the utility sector, there are still a number of future paths to explore for smart meter data analytics and digital energy efficiency for heat pumps. Moreover, there remains a significant need to further understand the role of data volume, contexts, and moderating factors that influence value creation through data analytics.

Ultimately, this thesis informs practitioners and policymakers about the next steps in harnessing the full potential of data treasures available in many utility companies for the energy transition.

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Chapter 1: Data analytics for the provision of energy efficiency services with limited data

Paper I

Heat pump inspections result in large energy savings when a pre-selection of households is performed: A promising use case of smart meter data

Andreas Weigert
University of Bamberg

Konstantin Hopf
University of Bamberg

Sebastian A. Günther
University of Bamberg

Thorsten Staake
University of Bamberg, ETH Zurich

Weigert, A., Hopf, K., Günther, S.A. and Staake, T. 2022. Heat pump inspections result in large energy savings when a pre-selection of households is performed: A promising use case of smart meter data. Energy Policy 169, p. 113156. doi: 10.1016/j.enpol.2022.113156.

Paper II

Detection of heat pumps from smart meter and open data

Andreas Weigert
University of Bamberg

Konstantin Hopf
University of Bamberg

Nicolai Weinig
University of Bamberg

Thorsten Staake
University of Bamberg, ETH Zurich

Weigert, A., Hopf, K., Weinig, N. and Staake, T. 2020. Detection of heat pumps from smart meter and open data. Energy Informatics 3(Supplement 1), p. 21. doi: 10.1186/s42162-020-00124-6.

Paper III

Automatic differentiation of variable and fixed speed heat pumps with smart meter data

Tobias Brudermüller
University of Bamberg

Florian Wirth
University of St. Gallen

Andreas Weigert
University of Bamberg

Thorsten Staake
University of Bamberg, ETH Zurich

Brudermueller, T., Wirth, F., Weigert, A. and Staake, T. 2022. Automatic Differentiation of Variable and Fixed Speed Heat Pumps With Smart Meter Data. In: Proceedings on 2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm). Singapore, Singapore: IEEE, pp. 412–418. doi: 10.1109/SmartGridComm52983.2022.9961055.

Paper IV

Identification and classification of heat pump problems in the field and their implication for a user-centric problem recognition

Andreas Weigert
University of Bamberg

Weigert, A. 2022. Identification and classification of heat pump problems in the field and their implication for a user-centric problem recognition. Energy Informatics 5(1), p. 70. doi: 10.1186/s42162-022-00250-3.

Chapter 2: Data analytics for the sales of energy decentralisation and electrification solutions with limited data

Paper V

Value creation from analytics with limited data: A case study on the retailing of durable consumer goods

Konstantin Hopf
University of Bamberg

Andreas Weigert
University of Bamberg

Thorsten Staake
University of Bamberg, ETH Zurich

Hopf, K., Weigert, A. and Staake, T. 2022. Value creation from analytics with limited data: a case study on the retailing of durable consumer goods. Journal of Decision Systems 32(2), pp. 289–325. doi: 10.1080/12460125.2022.2059172.

Appendix

Publications

Weigert, A., Hopf, K., Günther, S.A. and Staake, T. 2022. Heat pump inspections result in large energy savings when a pre-selection of households is performed: A promising use case of smart meter data. Energy Policy 169, p. 113156. doi: 10.1016/j.enpol.2022.113156.

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