Advancing energy-efficient retrofits in the residential building sector: Financial challenges and technological developments

Dissertation

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Copyright Statement

The following sections are partly comprised of content taken from the research articles included in this doctoral thesis. To improve the readability of the text, I omit the standard labeling of these citations.

Abstract

Climate change poses an ever-increasing existential threat to humanity, heading towards a point of irreversible damage to our livelihoods. The Paris Climate Agreement intended to unite governments in the fight against this global challenge. However, research shows it is already too late to keep global warming below some of the limits set out in the Paris Climate Agreement. Nevertheless, there is hope, as many industrialized nations, such as Germany, propose even more ambitious targets to replace fossil fuels and increase their energy efficiency, whereby the carbon footprint of residential buildings plays a significant role. Extensively reducing greenhouse gas emissions within the building sector requires high annual retrofit rates, which currently stagnate at 1% in Germany. Consequently, this cumulative doctoral thesis investigates several approaches to intensify energy-efficient retrofits in the residential building sector. First, it identifies the most significant barriers to energy-efficient retrofits and develops tailored policy measures. Financial and regulatory barriers are perceived as the most critical, calling for grant-based subsidies, improved tax incentives, legally binding funding terms, and reduced bureaucracy, especially for historic buildings. Besides that, experts advocated a single official source for information to support homeowners' decision-making. Second, it thoroughly investigates financial challenges as they were identified as the most relevant barrier. Utilizing a novel cluster-based XAI methodology, the financial impacts of energy-efficient building features in the UK are analyzed, indicating that transaction prices are positively influenced by improved energy efficiency and negatively correlated with high operating costs. The results of a study on German residential buildings indicate that glazing retrofits offer the most significant financial saving potential, followed by better roof and wall insulation. Furthermore, they indicate the necessity for a well-working subsidy system regarding heating system changes for lower budgets. Third, it identifies the potential of recent developments of digital technologies. The results show that ensemble models considerably outperform stand-alone AI models when predicting the building energy performance. This is complemented by a taxonomy on generative artificial intelligence applications for building energy efficiency, which offers valuable insights for researchers and practitioners on leveraging this new technology. In summary, this thesis offers policy recommendations, financial perspectives, and an overview of technological developments aimed at increasing the retrofit rate in the residential building sector.

Keywords: *Building Energy Performance*, *Energy Efficient Retrofits*, *Policy Recommendations*, *Generative Artificial Intelligence*, *Machine Learning*, *Energy Informatics*

Table of Contents

List of Figures

Abbreviations

ABR:	AdaBoost regressor
AI:	Artificial Intelligence
ANN:	Artificial neural network
AVR:	Averaging regressor
BEE:	Building energy efficiency
BEP:	Building energy performance
BGR:	Bagging regressor
C2E:	Conceptual-to-empirical
DisAI:	Discriminative artificial intelligence
DTR:	Decision tree regressor
E2C:	Empirical-to-conceptual
EER	Energy-efficient retrofit
ETR:	Extra trees regressor
FI:	Feature importance
GenAI:	Generative artificial intelligence
KNN:	K-Nearest-Neighbor
MAE:	Mean absolute error
MAPE:	Mean absolute percentage error
ME:	Mutually exclusive
MLP:	Multilayer perceptron
MSE:	Mean squared error
NE:	None mutually exclusive
PDP:	Partial dependence plots
PFI:	Permutation feature importance
PR:	Policy recommendation
RCV:	Ridge cross-validation
RFR:	Random forest regressor
RMSE:	Root mean squared error
SHAP:	Shapley additive explanations
STR:	Stacking regressor
SVR:	Support vector regression
XAI:	Explainable Artificial Intelligence
XGB:	Extreme gradient boosting

I Introduction

I.1. Motivation

The history of our planet is marked by a wide variety of climatic conditions, with alternating periods of cold and warm temperatures that ultimately made life on Earth possible. Exogenous or endogenous events are responsible for such alternations and the formation of the climate as we know it (Crowley, 2000). However, it is by no means the case that all climatic changes represented an improved starting point for the emergence or preservation of life on Earth (Bengtson, 1994). The Cretaceous period ended 66 million years ago when the Chicxulub asteroid impact caused a sudden change in climatic conditions, leading to the extinction of the dinosaurs that had populated Earth's surface for millions of years (Chiarenza et al., 2020; Schulte et al., 2010). More recently, during the Paleolithic period, volcanic activity in the Phlegraean Fields caused temperatures to drop by two to four degrees Celsius for several years, contributing to the extinction of the Homo neanderthalensis (Wolf et al., 2018). Just as the extinction of the dinosaurs and the extinction of the neanderthals gave mammals and humans the necessary space to thrive, some living beings will adapt and survive the current climatic changes. The most decisive question, however, is whether humans will be among these living beings or whether the Anthropocene will go down in Earth's history as one of the shortest but most impactful eras. Never in the history of Earth has any species increased carbon emissions so dramatically in such a short time (Ripple et al., 2024). While temperatures changed slowly over millennia, recent atmospheric proportions over the last decades increased dramatically for carbon dioxide (+49%), methane (+165%), and nitrous oxide (+24%), resulting in anthropogenic climate change (Intergovernmental Panel on Climate Change, 2023; Marvel et al., 2023). These greenhouse gases alter the composition of our atmosphere and increasingly reflect solar radiation onto the Earth's surface, leading to an average temperature increase of 1.39°C over the last 65 years compared to pre-industrial levels, which are set to cross the 1.5°C threshold in 2028 (Kirchengast & Pichler, 2025). Our current situation is comparable to a greenhouse on a hot summer morning, where one already feels the effects of the solar radiation trapped within it as temperatures start rising. As beneficial as this concept may be in agriculture, as negative is its impact on global ecosystems, when they do not have enough time to adapt to the new climatic conditions (Carleton & Hsiang, 2016). The ubiquitous climate change is already threatening the livelihoods of rural and smallholder communities in the Global South, causing secondary crises such as mass migration and famines, ultimately leading to social instability (Abbass et al., 2022;

Otto et al., 2017). Most of humanity has understood and accepted the threat that climate change poses to our existence, and nations worldwide have begun to decrease their carbon emissions, as there remains only a limited window of opportunity to counteract its negative effects.

A milestone in the fight against climate change was the 2015 Paris Climate Agreement. Overall, 195 countries, foremost the industrialized nations, committed to limiting global warming to 1.5°C in the best-case scenario, but holding the increase in the global average temperature to well below 2°C (Paris Agreement, 2016). In 2021, the European Union adopted the *Fit for 55* package as part of the European Green Deal, which aims to reduce greenhouse gas emissions in Europe by 55% by 2030 compared to 1990 (Fit for 55, 2021). Germany, having one of the highest greenhouse gas emissions within the EU, proposed even more demanding climate goals, aiming to achieve carbon emission neutrality for buildings by 2045 (Bundes-Klimaschutzgesetz, 2021). These ambitious decarbonization goals require considerable long-term investments and political commitment (Kotz et al., 2024). Yet Roelfsema et al. (2020) estimate the gap between the current path of the G20 nations and the optimal pathways to limit temperature rises at 1.5°C to 2°C to be between 22.4 and 28.2 billion tons of CO2eq by 2030. Addressing this tremendous challenge requires a two-step approach: transforming our primary energy sources from fossil fuel dependencies to renewable energies while simultaneously reducing the overall energy demand (Holechek et al., 2022).

According to Cao et al. (2016), the building and construction sector plays a crucial role as it accounts for 36% of global greenhouse gas emissions and 40% of the total energy consumption in Europe, thereby offering significant savings potential. In 2022, residential buildings in Germany accounted for approximately 27% of its total carbon emissions, with similar figures for many other industrialized nations (German Environment Agency, 2023). Bürger et al. (2017) forecast that most likely as much as 80% of the current (residential) building stock will also exist in 2050. Therefore, it will persistently contribute to global greenhouse gas emissions over the following decades without any retrofit measures (Fylan et al., 2016). Consequently, the European Union has required all member states to establish a revised National Building Renovation Plan by the end of 2025 that combines regulatory policies, monitoring instruments, and financial support to convert the existing building stock into zero-emission buildings by 2050 (Energy Performance of Buildings Directive, 2025; Zangheri et al., 2018). Despite the need for greater energy efficiency to reduce energy demand, Germany's share of annually retrofitted buildings remains stagnant at around 1% (Behr et al., 2023). However, it would require a rate of up to 4% to meet the EU’s climate neutrality target by 2050 (Energy performance of buildings: climate neutrality by 2050, 2023). To combat these challenges, it is imperative to identify the financial challenges and technological developments that help advance energy-efficient retrofits (EERs) in the residential building sector. Only by identifying such challenges and technological possibilities can appropriate measures be derived.

I.2. Research Aim

Over the past few years, international bodies, governments, municipalities, and cities have adopted many policy measures to address the causes and effects of climate change (Alabid et al., 2022; G. Liu et al., 2020; Miu & Hawkes, 2020). Many of these policy initiatives have focused on EERs of residential buildings to increase the retrofit rate and thus reduce energy consumption (Achtnicht & Madlener, 2014; Lai et al., 2022). However, political decision-makers do not implement the measures themselves but rather formulate regulations and framework conditions for achieving specific targets, which do not necessarily lead to the practical implementation of the necessary EERs (Chen & Lin, 2021; Lyulyov et al., 2021). Even when EERs are financially viable in the long term, homeowners do not necessarily implement them, resulting in what is known as the energy efficiency gap (Gerarden et al., 2017; Jaffe et al., 2004). Consequently, the literature has extensively dealt with the causes of financial barriers (Häckel et al., 2017; Tovar Reaños et al., 2023). Despite early political efforts to address financial pitfalls, many additional barriers persist (Casquero-Modrego et al., 2025). Accordingly, academia has begun to research the multitude of individual barriers to EERs, as it is essential to understand the associated decision-making process to develop tailored political measures (Camarasa et al., 2021; Lang et al., 2021). These diverse dimensions can be summarized in five overarching thematic areas: financial, regulatory, informational, technical, and behavioral barriers (Ambrose & McCarthy, 2019; Hrovatin & Zorić, 2018; G. Liu et al., 2020). From a financial perspective, homeowners frequently face high upfront investment costs or split incentive problems, where landlords finance retrofit projects, but their tenants benefit from lower energy costs (Achtnicht & Madlener, 2014; Miu & Hawkes, 2020; Trotta, 2018). This is often accompanied by the absence of long-term regulatory objectives and unreliable political guidelines (G. Liu et al., 2020). In this context, Tovar Reaños et al. (2023) and März et al. (2020) found that many homeowners lack sufficient information about EERs and possess limited technological expertise. Even if homeowners decide on an EER, it is intricate to find trusted and reliable experts for the technical implementation (Casquero-Modrego et al., 2025; Panakaduwa et al., 2024). In addition, many professionals do not leverage technological developments, where, for example, sophisticated machine learning models considerably outperform energy experts when predicting a building's energy performance (BEP) (Calì et al., 2016). Moreover, retrofit projects are often influenced by behavioral barriers such as social influences, personal preferences, or individual risk perception (Ahlrichs & Rockstuhl, 2022; Allcott, 2011). To effectively mitigate behavioral barriers, policymakers should formulate clear policies that incentivize homeowners to undertake retrofit projects (Zhou et al., 2016).

This doctoral thesis aims to narrow the energy efficiency gap by investigating the impact of financial, regulatory, informational, and technical barriers on retrofit behavior as an indispensable step towards achieving climate goals within the residential building sector. As a wide range of policy instruments, decision-making support, and literature identifying barriers already exist, this doctoral thesis has three main research objectives:

> **Research Objective #1**: *Assessing the most relevant barriers regarding EERs to derive tailored policy measures.*
>
> **Research Objective #2**: *Investigating financial challenges of EERs to close the information gap between expected and achievable returns.*
>
> **Research Objective #3**: *Identifying technological developments for BEP prediction improvements and novel approaches to EERs.*

Although the German government has issued several policy instruments aimed at incentivizing homeowners to implement EERs, their success has been limited to date, as indicated by low retrofit rates (Achtnicht & Madlener, 2014; Behr et al., 2023). Consequently, Gerarden et al. (2017) emphasize the importance of prioritizing the effectiveness of academic assessments of energy-efficiency policies to identify and target remaining barriers. Research Objective #1 guides policymakers by identifying the most pronounced barriers for practitioners and researchers, thereby bridging the gap between theoretical knowledge and practical implementation. Building on these results, Research Objective #2 evaluates the financial challenges of EERs to simultaneously address financial, regulatory, and informational barriers. For this, it investigates green price premiums and carbon emission savings achieved through EERs by leveraging data-driven BEP approaches. Research Objective #3 examines the methodological approaches employed to address Research Objective #2 and provides a broader evaluation of the potential of recent technological developments for BEP predictions, particularly in relation to artificial intelligence (AI). This is especially important, as accurate predictions provide the empirical foundation for reducing informational and financial uncertainty. In this context, the primary objective of this doctoral thesis is to evaluate and assist in overcoming the diverse barriers to increase EER rates. It offers a valuable contribution to reducing carbon emissions in the residential building sector.

I.3. Structure of the Thesis and Overview of Embedded Research Articles

As this doctoral thesis is cumulative, the following section provides an overview of the five research articles that constitute the basis of this work. Figure 1 particularly illustrates the embedding of each research article within it.

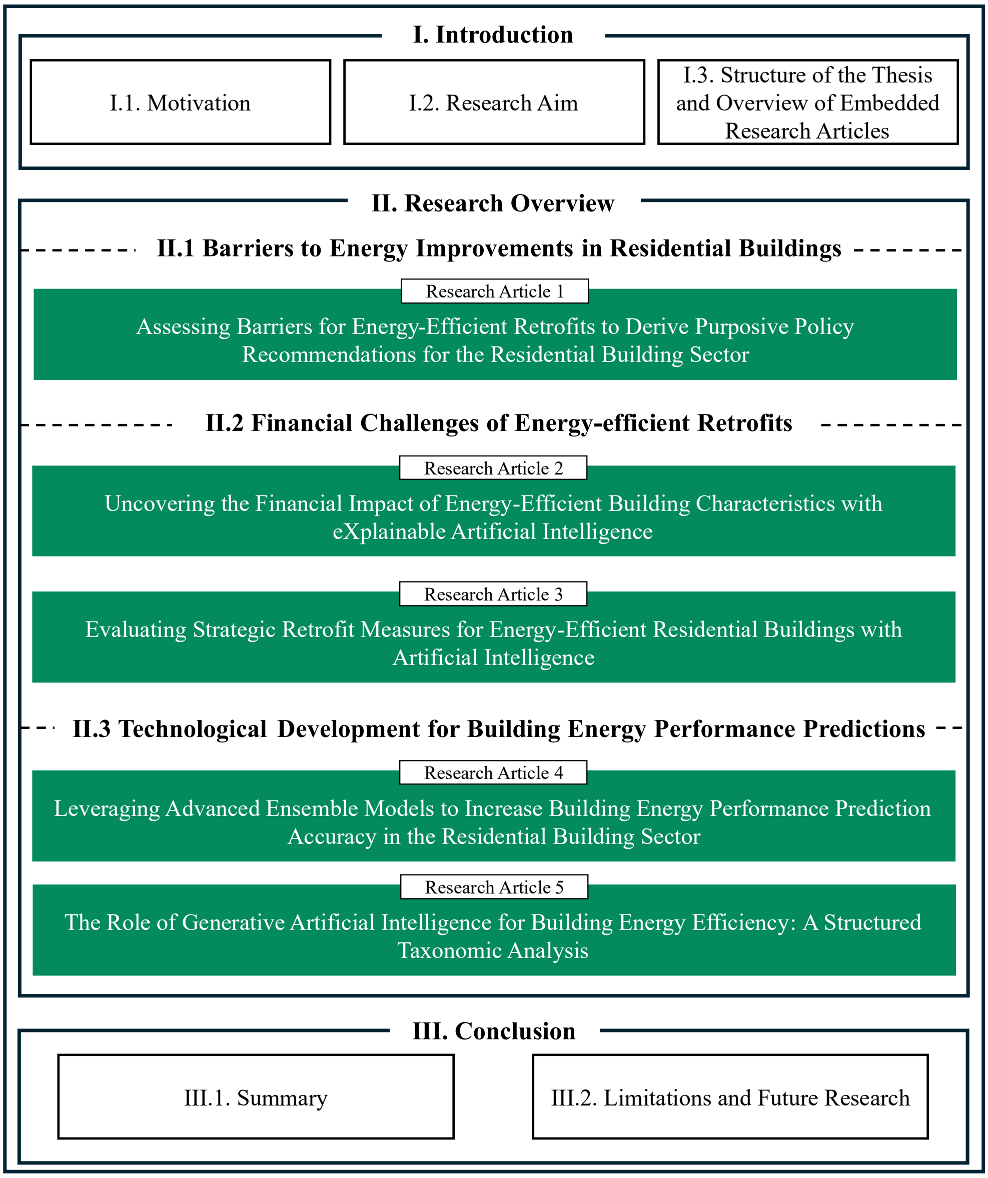


Figure 1: Structure of this doctoral thesis. Own illustration.

This doctoral thesis has three primary research objectives: first, to assess the most relevant barriers for EERs and derive actionable policy solutions; second, to investigate the financial challenges and benefits of EERs; and third, to evaluate how technological developments can positively impact EERs. Despite the urgency of reducing greenhouse gas emissions, annual retrofit rates in Germany stagnated at around 1% (Behr et al., 2023). The literature has intensively investigated and identified several barriers hindering homeowners from taking action (Amoah & Smith, 2024; Stieß & Dunkelberg, 2013). However, it remains unclear how relevant they perceive specific barriers, and there are only limited evaluations of policy measures that potentially address them (Research Objective #1). Research Article #1 addresses this research gap by combining an extensive literature review with a survey of 64 domain experts, who evaluated financial, regulatory, informational, and technical barriers to identify 25 actionable policy measures.

Research Object #2 is directly derived from the results of Research Article #1, which identifies financial barriers as most relevant for retrofit projects, which is in line with similar research results in the literature (Bagaini et al., 2020; Camarasa et al., 2021). Consequently, Research Article #2 focuses on the financial challenges of EERs and investigates green price premiums for energy-efficient building features by utilizing explainable artificial intelligence (XAI). The study's findings illuminate the financial benefits of low carbon emissions and a tendency for high energy running costs to be well reflected in transaction prices. Research Article #3 employs three machine learning models and a novel feature value substitution methodology that integrates homeowners' investment budgets, expected local governmental subsidies, and potential ecological benefits. This directly addresses the informational barrier identified in Research Article #2, as it provides a single informative yet comprehensible retrofit index that assists homeowners in identifying the best EER option for a specific property. This approach simultaneously addresses financial, technical, and informational barriers and helps to overcome the regulatory uncertainty regarding EERs (Rockstuhl et al., 2022).

Research Object #3 particularly focuses on advancements in digital technologies, specifically those related to AI, that may impact EERs. Generally, accurate predictions of a building's energy performance are essential for retrofit investment decisions (Wenninger & Wiethe, 2021). Therefore, Research Article #4 benchmarks the prediction performance of ensemble models against stand-alone models to assess their applicability for energy performance predictions of residential buildings. Indeed, the study shows that ensemble models are advantageous and mostly outperform stand-alone models. Research Article #5 investigates the impact of Generative Artificial Intelligence (GenAI) on EERs through a structured taxonomic analysis. It identifies essential characteristics of GenAI applications used for EERs and divides them into four distinct archetypes. This creates a structured knowledge base for decision-makers, entrepreneurs, and researchers who want to foster EERs in the residential building sector.

Section II provides a detailed description of each research article, highlighting its methodological approach and main contributions. Section III summarizes the results of this doctoral thesis, discusses its limitations, and provides an outlook for further research. Section IV lists the referenced publications, while Section V provides a detailed description of and supplementary information on all research articles (V.1), followed by a comprehensive summary of my individual contributions to each research article in this doctoral thesis (V.2). The subsequent Sections (V.3 – V.7) provide information on the research articles themselves.

II Research Overview

II.1. Barriers to Energy Improvements in Residential Buildings

Answering Research Objective #1 is the starting point for this doctoral thesis. Research Article #1 explores the most relevant barriers to EERs, ultimately enabling more tailored policy initiatives to increase the stagnating retrofit rate in Germany (Behr et al., 2023). Recent literature has extensively investigated the diverse barriers from a theoretical perspective, whereby the focus on practical feasibility was often of secondary importance (Ricci et al., 2025; Tian et al., 2024). However, various methodological approaches exist to assess barriers for EER, ranging from data analysis of publicly available household data to surveys and structured literature reviews, all possessing the potential to narrow the chasm between theoretical insights and practical implementation, thereby directly addressing the energy efficiency gap (Blomqvist et al., 2022; Casquero-Modrego et al., 2025). Research Article #1 employs a two-step approach to identify the primary barriers influencing EER decision-making for residential buildings in Germany and to determine how policymakers can effectively address them.

To achieve this, the article first employs a systematic literature review grounded in the theory of Wolfswinkel et al. (2013) to develop an in-depth understanding and categorization of current barriers in the literature. Second, applying this categorization, the study utilizes an online survey following the approach of van Selm and Jankowski (2006) and Dillman et al. (2014) to rank the perceived relevance of the barriers based on both quantitative and qualitative questions. The structured literature review was based on an extensive pre-search to build the search string used across five scientific libraries, resulting in 1.117 potentially relevant articles. After the Examination, Analysis, and Inclusion phase, the 31 remaining articles were used to categorize existing barriers thematically. The online survey was sent to 701 German-speaking experts from eight different domains, divided into six cohorts. Following Emerson (2017), participants used both open-ended questions and a 10-point Likert Scale, ranging from strongly disagree (1) to strongly agree (10), to rank EER solutions and barriers, leading to a total of 130 responses, of which 64 were entirely and 66 partially completed. The methodological approach of Research Article #1 is illustrated in Figure 2.

Figure 2: Methodological approach of Research Article #1.

The findings of this article underscore financial considerations as the most decisive barriers in the literature, where 67% of the investigated studies identify financial barriers as highly relevant to both the decision-making process and practitioners. Among these, the split incentive problem and uncertainty about the return on investment, combined with high upfront costs, pose considerable barriers for EERs, regardless of proven long-term energy savings (G. Liu et al., 2020; Miu & Hawkes, 2020; Tovar Reaños et al., 2023). While the literature intensively explores the free rider problem – incentivizing homeowners who would also retrofit without such subsidies – practitioners are primarily concerned by short-term political strategies and poor regulatory conditions, particularly regarding monumental protection laws (Dolšak et al., 2020; Panakaduwa et al., 2024). The survey results indicate that regulatory and political requirements are considered the second most important barrier, confirming the need for continuity and stability in long-term political strategies that are well-coordinated (R. Zhang & Wang, 2022). In line with Rodriguez et al. (2024) and Tian et al. (2024), experts assigned the highest regulatory relevance to reducing subsidy bureaucracy. They expressed a strong interest in targeted subsidy programs for existing buildings with a long-term planning capability. Stakeholders often face informational barriers given the intransparency and knowledge gap regarding their retrofit project (Broers et al., 2019). In combination with regulatory requirements, multiple administrative contact points, diverse communication channels, and even misinformation, often spread through informal networks such as friends, family, or social media, EERs require a complex mental effort (G. Liu et al., 2024; Stieß & Dunkelberg, 2013). This complexity is further exacerbated by stakeholders' difficulties in interpreting technical specifications, such as performance indicators, or selecting the appropriate retrofit technology, particularly pronounced among older residents and individuals with limited technical knowledge (Stieß & Dunkelberg, 2013). Besides this G. Liu et al. (2020) have identified the persistent shortage of skilled workers and qualified professionals (e.g., energy experts) as a continuous technical barrier to EER. Recent developments in digital technologies, such as smart-metering systems or digital assistants for consumer education, can help overcome these technical limitations as experts increasingly turn to digital information systems.

By combining theoretical and practical perspectives, Research Article #1 provides 25 policy recommendations (PR) to derive tailored policy measures that address the identified financial, regulatory, informational, and technical barriers. Financial barriers are mainly caused by high upfront costs, uncertainty regarding interest rates, a lack of liquidity, calculation risks, and price increases (Antonopoulos et al., 2024; Dolšak et al., 2020). To counteract these barriers, *limited interest rates for EERs (PR1)* have proven to be successful in the Netherlands, whereas *increasing rents to pass EER costs from landlords to tenants (PR2)* already mitigates the split incentive problem in Germany (Handford, 2022; März et al., 2020). Furthermore, experts advocated *targeted and socially graded subsidies (PR3)* and *municipal funds for purchasing residential buildings (PR4)*. Policymakers should ensure that EERs are *economically viable rather than pushing technological limits (PR5)* and *reduce potential windfall effects (PR7)* of subsidies. In addition, *simplified condominium borrowing for owners' associations (PR6)* can ease access to debt capital for multi-family residential buildings, accompanied by *legally fixed terms for funding conditions (PR8)* (Behr et al., 2023). Similar to Rodriguez et al. (2024), the results indicate the *need to reduce bureaucracy in subsidy application (PR9)*. As EERs often trigger multiple other regulations, *adjusting monument protection regulations (PR10)* and *decoupling EER measures from other regulatory requirements (PR11)* offer significant potential to reduce the bureaucratic burden for homeowners. Moreover, policymakers could *facilitate retrofits by repurposing existing buildings (PR12)* and issuing *CO2 certificates for completed retrofit projects (PR13)*, thereby continuing to reduce carbon emissions in the building sector. Regarding informational barriers, experts and academia strongly call for a *central coordination office at the state or municipal level (PR14)* that offers *expert advice on current regulatory policies (PR15)* through a *combination of trade fairs and online information services (PR16)*. In addition, *mandatory disclosure of energy efficiency ratings (PR17)*, such as the EU's energy performance certificates, is well received. At the same time, some experts consider a *ban on advertising fossil fuels (PR18)* or *recommendations from the immediate personal environment (PR19)* as even more beneficial for EERs (März, 2018). Regarding technical barriers, a *clear time schedule for EER projects (PR20)* helps to reduce uncertainty (Casquero-Modrego et al., 2025). Following Rodriguez et al. (2024), this can be reinforced by *educating contractors and professionals to explain technical changes in simple terms (PR21)*. Experts suggest that policymakers should *promote capital investments to accelerate innovation (PR22)* and tap into opportunities such as *smart metering systems in combination with data-driven AI models (PR23)*, *digital assistants for consumer education (PR24)*, or *building information modeling systems that standardize the intake of building information (PR25)*.

II.2. Financial Challenges of Energy-efficient Retrofits

High upfront costs and uncertain returns were perceived as the most significant barriers in the literature and the online survey, with long amortization periods being the most prominent financial reason against EERs. Interestingly, experts rated the increase in building value as the most relevant financial objective for EERs, yet Min et al. (2014) found that homeowners initially assume disproportionately high internal rates of return for EERs, which are unrealistic in most cases. This discrepancy negatively affects EER projects and directly leads to Research Objective #2, which involves investigating the financial opportunities of EERs and presenting them in a comprehensive manner to close the information gap between expected and actually achievable returns.

Research Article #2 focuses on green price premiums for energy-efficient building characteristics. It examines whether cluster-based XAI enhances the interpretability of data-driven models, enabling the identification of the financial impact of energy-related building characteristics on property valuation. Previous studies indicate that properties with higher energy efficiency also achieve higher market prices (Fuerst et al., 2015; Stanley et al., 2016; Taruttis & Weber, 2022). Therefore, the value increase of residential buildings can serve as a considerable incentive for minimizing carbon emissions if the financial uncertainty of required EERs is adequately addressed (Rockstuhl et al., 2022). According to Evangelista et al. (2020), novel data-driven approaches can help to mitigate this uncertainty. Consequently, multiple studies leveraged large datasets and AI to investigate the correlation between building properties, energy consumption, and value increases of residential buildings (Karasu & Altan, 2022; Wenninger & Wiethe, 2021). However, accurate predictions require large amounts of data, and interpretability is limited by the black-box nature of AI, which contradicts informational transparency and ultimately leads to trust issues (Ribeiro et al., 2016). According to Barredo Arrieta et al. (2020), interpretable and explainable AI has gained significant momentum in addressing interpretability concerns over the past decade. Following Golizadeh Akhlaghi et al. (2021), Research Article #2 combines SHapley Additive exPlanations (SHAP), an explanatory method derived from game theory by Lundber and Lee (2017), with a novel clustering approach to investigate the effects of energy-related building properties on financial valuation.

For this purpose, a case study is conducted, encompassing 530,718 building transactions in England and Wales from January to December 2019, along with their associated energy performance certificates, to train two sophisticated machine learning models, namely XGB and CatBoost. To further account for the effects of market volatility during the reference period, the UK House Price Index (UK HPI) from the HM Land Registry was utilized as an indicator of market dynamics. Permutation Feature Importance (PFI) and SHAP are utilized to calculate Feature Importance (FI). Then, based on a μσ-threshold, overproportionally high FIs are isolated. Following Czétány et al. (2021), the optimal number of clusters is determined by evaluating the maximum silhouette score and verifying the results with the elbow method. Based on the BIRCH algorithm, developed by T. Zhang et al. (1996), the resulting hierarchical tree structure allows SHAP to be applied for an in-depth analysis of more intricate dependencies without being overshadowed by the most prominent features. The results from the UK dataset show that

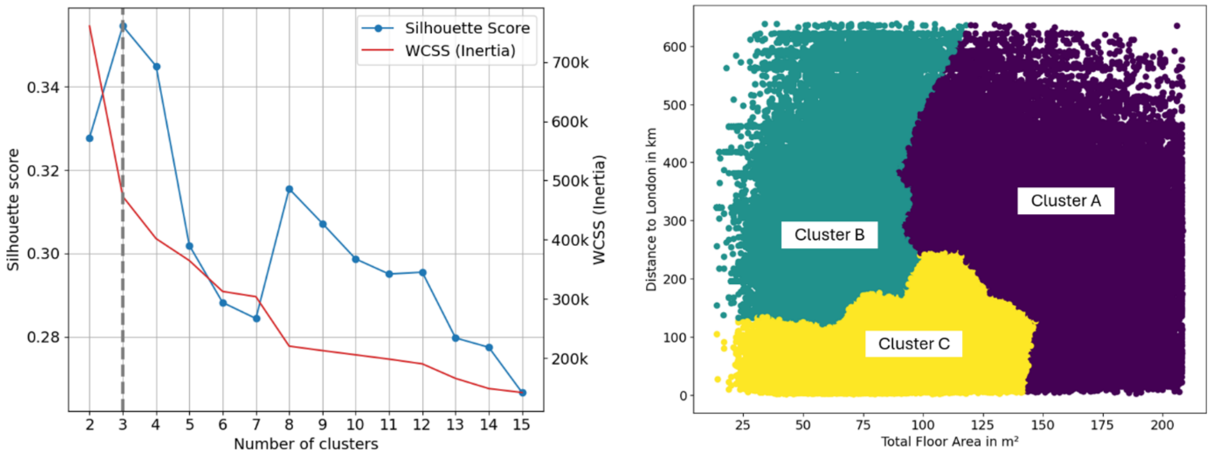


Figure 3: Silhouette and elbow method (left) and BIRCH clustering (right).

distance to London and total floor area have the highest PFI, both exceeding the μσ-threshold, and are consequently used as variables in the hierarchical BIRCH clustering. Figure 3 (left) illustrates the optimal number of clusters, and Figure 3 (right) depicts the three resulting clusters: large buildings mostly outside of London (Cluster A), smaller-sized buildings outside of London (Cluster B), and small to medium-sized buildings close to London (Cluster C).

First, and foremost, at one-tenth of the standard deviation, the presented clustering approach halves the Mean Absolute Percentage Error (MAPE) of the best-performing AI model compared to training on the entire dataset, showcasing the high potential of cluster-based AI to dissect complex datasets. Furthermore, this approach reveals that the distance to London is significant for buildings closer to the Metropolitan center, yet considerably less relevant for medium-sized buildings further away. Overall, higher energy efficiency is most positively correlated with increasing transaction prices in rural areas. Figure 4 leverages Partial Dependency Plots (PDPs) to quantify the financial effect on transaction prices for energy consumption, greenhouse gas emissions, and heating costs. The results indicate higher property valuations for lower energy consumption and reduced carbon emissions, whereas the latter has a notably higher impact, especially for low-energy buildings. This means that lower carbon emissions are well reflected in transaction prices and are likely perceived as important by homebuyers. Considering all three metrics, the effect is most pronounced for Cluster A. Lower heating costs per square meter increase property valuation, most notably for larger buildings and those located at greater distances from London. Naturally, the larger the living space, the greater the long-term effect of heating costs, which indicates that home buyers factor this into transaction prices. For houses in London, this effect is often overshadowed by the property's location. Lightning costs, in turn, have a considerably less pronounced effect as their share of total annual costs is low.

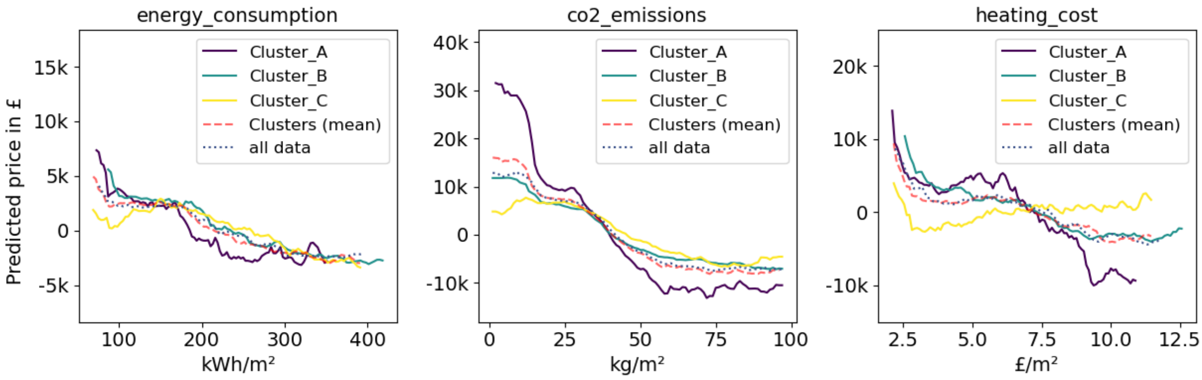


Figure 4: PDPs of energy consumption, greenhouse gas emission, and heating cost.

Research Article #2 has several theoretical and practical implications. Its key methodological novelty lies in introducing a cluster-based XAI approach to the building energy and AI research community, with its comprehensible procedure enabling additional applications in this area and beyond. It identifies the financial impact of energy-related building properties on transaction prices by applying XAI in a real-world case study. Thereby addressing the uncertainty regarding the financial returns of EERs by specifically linking energy-specific building characteristics to property valuations. In doing so, it utilizes XAI approaches to illustrate a pathway towards a low-carbon society, enabling stakeholders to make informed decisions that align environmental sustainability with economic benefits.

Research Article #3 builds on the results of Research Articles #1 and #2 as it simultaneously addresses financial and informational barriers by linking subsidy programs for EERs, the highest-rated solution for financial barriers of Research Article #1, with retrofit budgets and energy consumption savings. It combines all three perspectives into a single yet informative retrofit index. Various studies use single standardized buildings to investigate the diverse impact of individual retrofit measures (Ali et al., 2020; Lu et al., 2021; Mejjaouli & Alzahrani, 2020). Moreover, sophisticated AI models have proven to be a well-suited method for predicting the annual energy performance of residential buildings (J. Guo et al., 2023; Wenninger & Wiethe, 2021). Although focusing on standardized buildings and higher model accuracy forms an indispensable starting point for research, it does not directly lead to greater energy efficiency, as it does not offer generalizable or, in the case of higher accuracies, broadly applicable recommendations for EERs (Ali et al., 2020; Wei et al., 2018). Consequently, this article addresses multiple calls for further research and investigates retrofit-related economic constraints, energy consumption reductions, and ecological gains at a larger scale (H. Liu et al., 2023; Sun et al., 2020). To achieve this, it introduces a novel feature value substitution method, illustrated in Figure 5, to simulate the effect of isolated retrofit measures (e.g., changing windows from double to triple

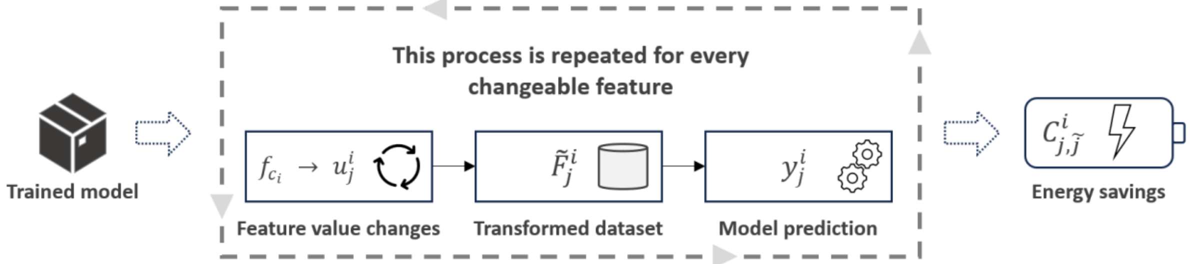


Figure 5: Feature value substitution steps.

glazing) by evaluating the predicted energy consumption for each possible configuration. For this, the study utilizes a real-world dataset containing information on 20,588 German single and two-family buildings constructed from the early 20th century to 2012. Each building is characterized by 23 categorical or numerical values that specify building information and energy-efficient building properties, normalized to a geographic location based on climatic conditions. Building on this dataset, three state-of-the-art AI algorithms, namely XGB, CatBoost, and LightGBM, are trained to predict the annual BEP. To simulate and determine the energy saving potential for each retrofit option (c.f. Figure 5), all feature values f_{c_i} are systematically modified to generate a transformed dataset $\tilde{F}_j^i$ that is used to calculate the probability distribution, ultimately indicating the energy saving $C^i_{j,\tilde{j}}$ for the specific retrofit option u^i_j. Then, following Maia et al. (2024), the three main criteria for decision-making, namely energy and carbon emission saving, financial incentives, and investment budgets, are combined in a single retrofit index.

The performed analysis evaluates retrofits of outer wall insulation, glazing, roofing, roof insulation, energy source, and facade condition to investigate their impact on BEP measured as annual energy consumption per square meter. Figure 6 illustrates the results, showing a generally increasing energy efficiency for retrofit measures. This trend is specifically evident for changes from the least to the most energy-efficient retrofit option. Changes from single glazing to triple-thermal glazing offer the most significant potential for reducing energy consumption, whereas wall insulation taps into substantial yet less profound saving potentials. Both roof insulation and roofing retrofits have a positive correlation with annual energy savings, while façade conditions can be considered irrelevant. Furthermore, the results suggest that modifications to the heating system result in considerable greenhouse gas savings. Figure 7 indicates

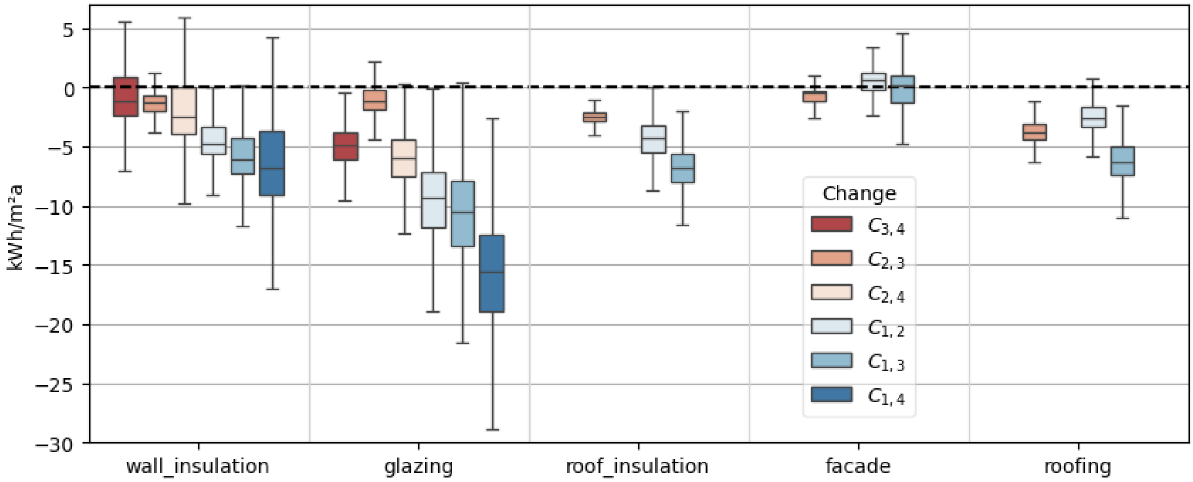


Figure 6: Distributions of predicted energy consumption changes of retrofit measures.

that the primary energy source plays an even more pronounced role when considering financial, ecological, and economic perspectives simultaneously. This indicates that socially adapted subsidies, such as those introduced by the German Government for electric heating systems (e.g., electric heat pumps), can significantly influence retrofit projects, as they directly address the financial barrier for homeowners prone to tighter budget restrictions.

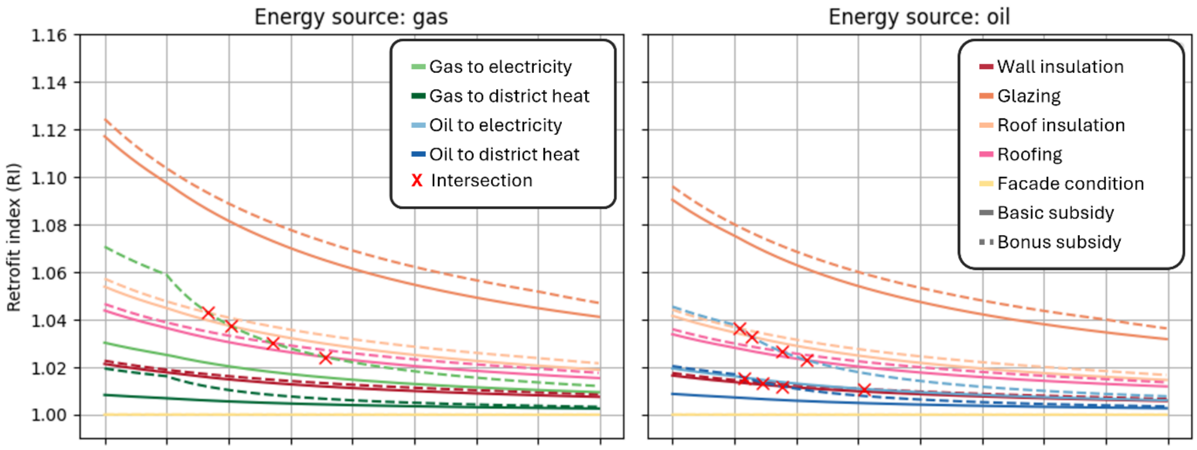


Figure 7: Retrofit index for retrofit measures within different energy sources.

Research Article #3 answers multiple calls for further research and contributes to the ongoing discussion regarding EERs by conducting a large-scale case study to quantify energy savings for specific retrofit options. In this vein, it introduces a novel feature value substitution methodology to address data scarcity and provides a comprehensible retrofit index to the research community, combining financial incentives, energy and greenhouse gas savings, and individual retrofit budgets. Therefore, it directly contributes to mitigating uncertainty in the decision-making process and identifying the most suitable EERs in the residential building sector.

II.3. Technological Developments for Building Energy Performance Predictions

While the previous section of this doctoral thesis explored solutions to financial and partially informational barriers for EERs, this section focuses on developments in digital technologies that potentially help to overcome technical barriers. Therefore, it directly addresses Research Objective #3 by leveraging technological developments for improvements in BEP prediction and novel approaches to EERs. Given the rapid development and high applicability of AI tools in the energy building sector, this section primarily focuses on prediction improvements and recent developments in GenAI.

Sutherland (2020) found that data-driven energy quantification methods offer better BEP predictions than legally prescribed engineering or physical heat flow methods. According to Calì et al. (2016), performance gaps between predicted and actual BEP of traditional methods reach up to 287%. Consequently, academia started to benchmark individual energy quantification methods to identify the approaches offering the most promising prediction results (Deng et al., 2018; Wenninger & Wiethe, 2021). Although the results of individual models, such as support vector regression (SVR), extreme gradient boosting (XGB), or artificial neural networks (ANN), are promising, more advanced AI techniques may even surpass these results for high-dimensional building data (Dong et al., 2021). As more advanced techniques are insufficiently addressed in the literature, Research Article #4 investigates prediction gains of ensemble techniques that combine multiple AI models into a singular prediction (Sagi & Rokach, 2018). To this end, it explores the extent to which advanced ensemble models can increase BEP predictions compared to traditional AI models after reasonable training efforts. Consequently, several stand-alone models and heterogeneous and homogeneous ensemble models are trained to benchmark their performance.

With slight modifications, the real-world case study builds upon the same dataset as Research Article #3. After rigorous preprocessing, the dataset was used to train five stand-alone models, five homogenous models, and two heterogeneous models to predict the annual BEP of residential buildings in Germany. After a meticulous hyperparameter tuning, the models were evaluated based on four error metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and MAPE. The results in Figure 8 show that, on average,

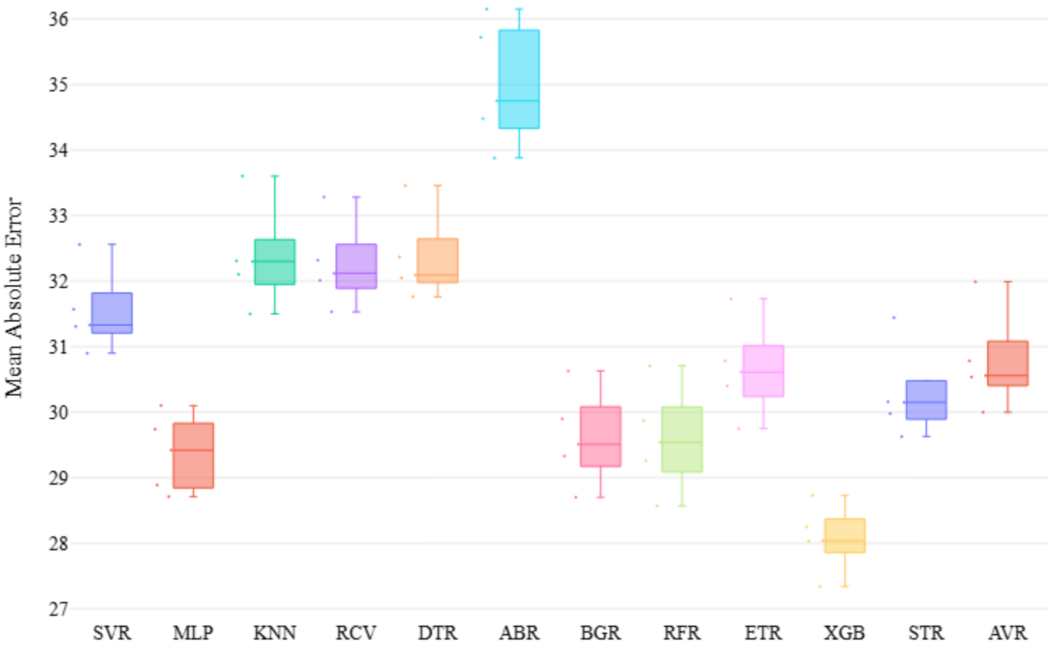


Figure 8: Five-fold cross-validation of different AI models for BEP predictions.

all stand-alone models have a higher MAE than ensemble models, except for the Multilayer Perceptron (MLP), which significantly outperforms all other stand-alone models. The standard deviation is similar for all models, except for the AdaBoost regressor (ABR), which also shows the largest MAE in total. Except for ABR, ensemble models are more accurate than the investigated stand-alone models. The homogeneous ensemble model XGB significantly outperforms all other models in each iteration. Based on this insight, Research Article #2 and Research Article #3 also include XGB as a primary prediction model. To effectively benchmark the prediction quality of ensemble models, all models are tested on equal data subsets for specific living size and building age bins. Figure 9 illustrates that larger living spaces, up to 200 square meters, generally correlate with higher prediction accuracy, whereas most ensemble models constantly outperform stand-alone models. Regarding building age, all models tend to perform better for newer buildings, where the majority of data points are available. In line with the previous findings, ensemble models outperform stand-alone models on average across all building age classes. However, the decision tree regressor (DTR) performs similarly for older buildings, with the highest error rates. That can mainly be attributed to more lenient energy efficiency regulations for older buildings (Crawley et al., 2019). The results strongly suggest that advanced ensemble models can significantly increase BEP predictions compared to traditional AI models after reasonable training efforts.

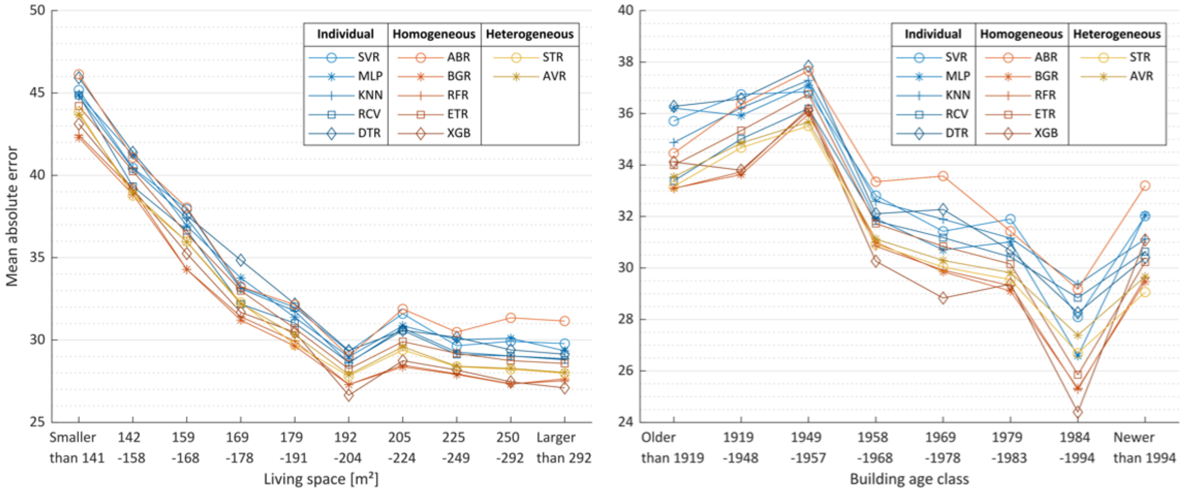


Figure 9: Model-specific MAE for different living spaces and building age classes.

Research Article #4 contributes to existing research by evaluating the prediction accuracy of advanced ensemble methods against stand-alone models, offering valuable insights for BEP predictions and EER decision-making. This article presents the first rigorous real-world benchmarking case study to evaluate the applicability of ensemble models in the residential building sector. Broadening the knowledge of energy quantification models and improving BEP prediction performance enables stakeholders to better estimate savings, minimize associated risks, and ultimately increase their willingness to invest (Ali et al., 2024; Wiethe & Wenninger, 2023).

Regarding BEP prediction models Ma and Yeung (2024) distinguish between two variations of AI: discriminative artificial intelligence (DisAI) and GenAI. Whereas DisAI models were previously considered to be state-of-the-art when dealing with large amounts of data, transformer models and GenAI have increasingly gained momentum over the past years in a wide variety of research fields (Roitero et al., 2024; Sengar et al., 2025). GenAI is a special form of deep learning that follows probabilistic patterns to generate multimodal output data, e.g., text, images, or videos guided by user prompts (descriptions of the desired output) (Banh & Strobel, 2023). Its main advantage over DisAI is that GenAI models can offer a broader and more intuitive applicability, enable creative processes, and cope well with unlabeled data such as natural speech (Roitero et al., 2024). Consequently, Research Article #5 examines potential applications of GenAI to enhance building energy efficiency (BEE). It investigates how they can be systematically structured to address the open field of research regarding the effect of GenAI on BEE (Aydin, 2024; Bandi et al., 2023). GenAI enables a comprehensive approach to increasing BEE rates through (1) its ability to process multimodal building information, (2) higher transparency by providing tailored explanations, and (3) an agent-centric approach that integrates multiple DisAI models (Aydin, 2024; Ma & Yeung, 2024; Roitero et al., 2024). Despite these potentials, academia lacks a holistic overview of its essential characteristics and possible configurations due to its novelty, especially regarding BEE use cases.

Following Nickerson et al. (2013) and Kundisch et al. (2022), the taxonomy development process starts by specifying applications of GenAI in the context of BEE as the observed phenomenon and defining a suitable target user group. Following this, the meta-characteristic is derived, and objective and subjective ending conditions for the taxonomy development process are determined. Figure 10 depicts the complete methodological approach of this article. In the first conceptual-to-empirical (C2E) step, the structured literature review identifies 71 relevant articles (Wolfswinkel et al., 2013). In the second C2E step, the discussion with a taxonomy expert leads to refining the dimensions. The presentation of the results to a focus group of AI and IS

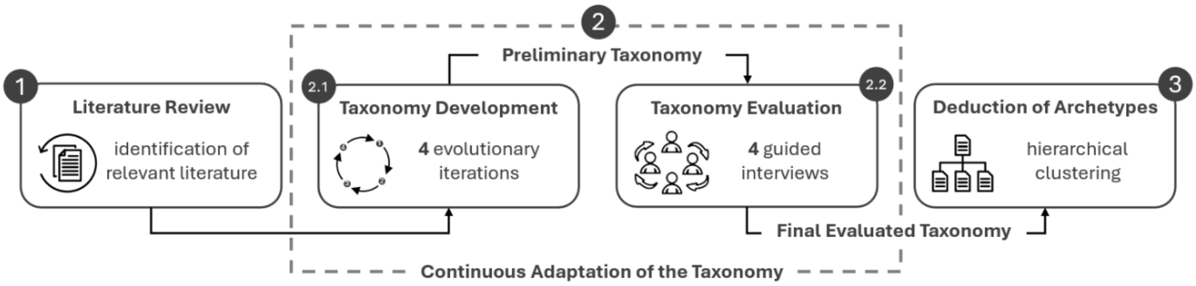
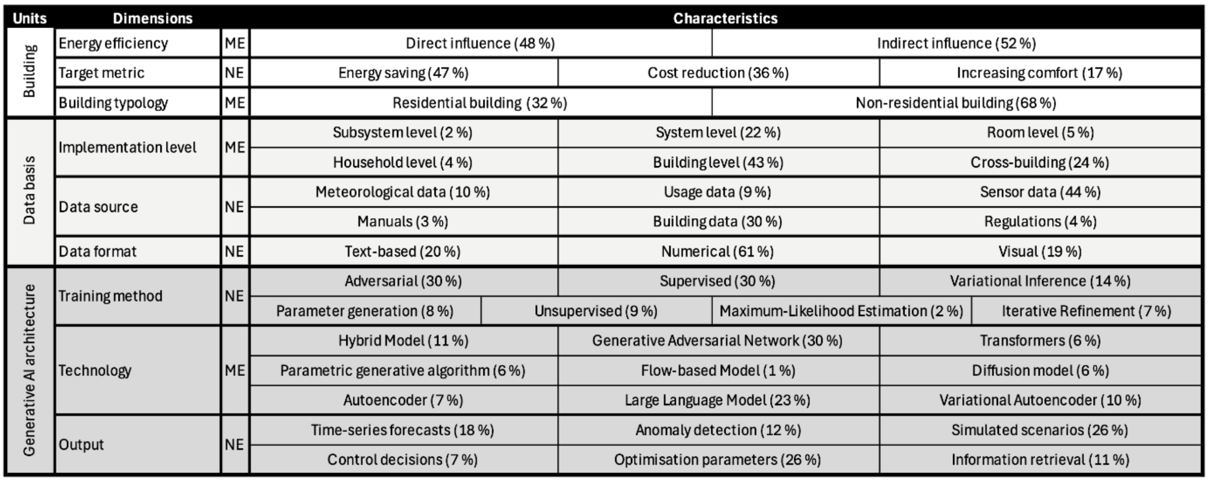


Figure 10: Methodological approach for the taxonomy development.

researchers, the third C2E iteration, resulted in removing one dimension, adding two new dimensions, and condensing characteristics within another. In the fourth step (empirical-to-conceptual), the robustness of the taxonomy was tested by analyzing and categorizing 15 examples of GenAI applications. The final taxonomy in Figure 11 comprises three units, nine dimensions of which four are mutually exclusive (ME) and five non-exclusive (NE), and 44 characteristics.



Units	Dimensions		Characteristics			
Building	Energy efficiency	ME	Direct influence (48 %)	Indirect influence (52 %)		
	Target metric	NE	Energy saving (47 %)	Cost reduction (36 %)	Increasing comfort (17 %)	
	Building typology	ME	Residential building (32 %)	Non-residential building (68 %)		
Data basis	Implementation level	ME	Subsystem level (2 %)	System level (22 %)	Room level (5 %)	
			Household level (4 %)	Building level (43 %)	Cross-building (24 %)	
	Data source	NE	Meteorological data (10 %)	Usage data (9 %)	Sensor data (44 %)	
			Manuals (3 %)	Building data (30 %)	Regulations (4 %)	
	Data format	NE	Text-based (20 %)	Numerical (61 %)	Visual (19 %)	
Generative AI architecture	Training method	NE	Adversarial (30 %)	Supervised (30 %)	Variational Inference (14 %)	
			Parameter generation (8 %)	Unsupervised (9 %)	Maximum-Likelihood Estimation (2 %)	Iterative Refinement (7 %)
	Technology	ME	Hybrid Model (11 %)	Generative Adversarial Network (30 %)	Transformers (6 %)	
			Parametric generative algorithm (6 %)	Flow-based Model (1 %)	Diffusion model (6 %)	
			Autoencoder (7 %)	Large Language Model (23 %)	Variational Autoencoder (10 %)	
	Output	NE	Time-series forecasts (18 %)	Anomaly detection (12 %)	Simulated scenarios (26 %)	
			Control decisions (7 %)	Optimisation parameters (26 %)	Information retrieval (11 %)	

Figure 11: Taxonomy of GenAI applications for BEP.

Building on the 86 research articles for the taxonomy development, Figure 12 illustrates the results of the hierarchical clustering approach performed to derive thematic patterns based on the Calinski-Harabasz Index (Calinski & Harabasz, 1974). Additionally, it presents the clustering results and the literature distribution within each of the four clusters, serving as an analytical basis for deducing archetypes. The archetypes help to categorize GenAI applications for BEE improvements and differ in terms of the pursued objective (e.g., increasing comfort vs. cost reduction), utilized data types (e.g., sensor, building, vs. usage data), their focus (e.g., residential vs. non-residential), and the technical foundation (e.g., transformer vs. generative adversarial network).

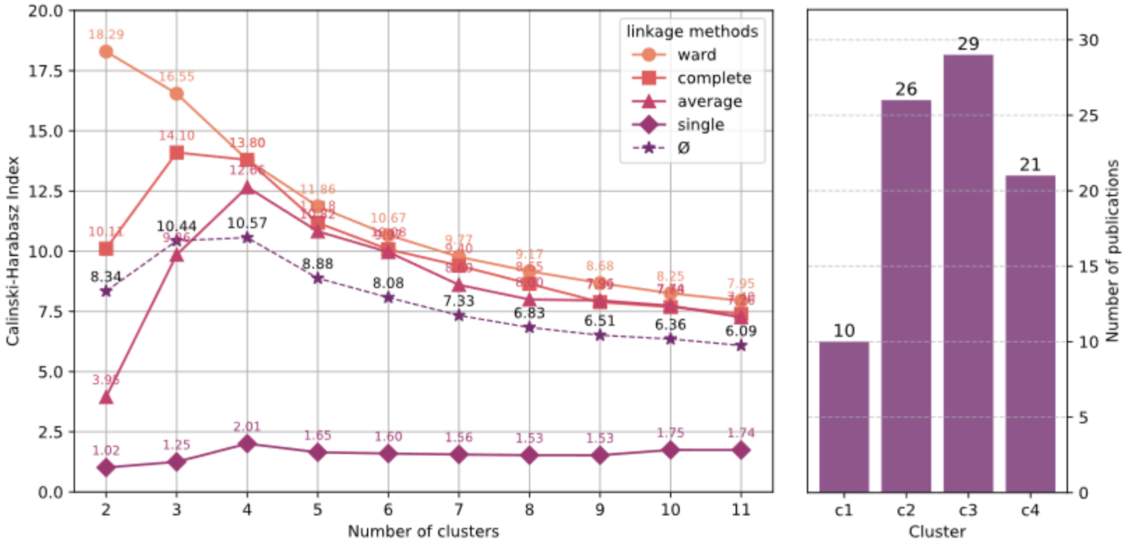


Figure 12: Optimal cluster number (left) and cluster distribution (right).

Research Article #5 presents a structured classification of GenAI applications for BEE improvements, defining the design space for novel solutions within this domain. The article has four main theoretical implications: (1) pointing to a principle of complementarity between GenAI and DisAI for BEE improvements, (2) linking optimization goals (e.g., cost reduction) to specific GenAI applications, (3) aligning specific architectures with optimization goals and data requirements, and (4) highlighting model types that increase the transparency for decision making. From a practitioner's perspective, the taxonomy provides the necessary tools to select the best-fitting functionalities, models, and technologies to leverage GenAI for more energy-efficient buildings.

All research articles directly contribute to the research aim of this doctoral thesis as they foster the identification and mitigation of EER barriers. To this end, Research Article #1 extensively investigates the literature to provide an overview of relevant barriers, whereas Research Article #5 presents a robust theoretical foundation for future applications of recent technological developments. The remaining three articles leverage extensive real-world datasets to derive actionable recommendations that enable practitioners, homeowners, and researchers alike to address the identified barriers. In doing so, this doctoral thesis contributes to reducing the energy efficiency gap in the residential building sector.

III Conclusion

III.1. Summary

Climate change poses an ever-increasing existential threat to humanity through droughts, floods, and other extreme weather events, already causing secondary crises such as mass migration that deprive humans of their livelihood, especially in the Global South (Abbass et al., 2022). In 2015, governments worldwide committed to the two paths defined in the Paris Agreement, effectively limiting the average global temperature increase compared to pre-industrial levels to either 1.5°C or 2 °C. While writing this thesis in 2025, the average global temperature increase is currently at 1.39°C, set to cross the 1.5°C threshold in 2028, meaning that the 2°C path is the only viable option left (Kirchengast & Pichler, 2025). According to Mercure et al. (2021), governments worldwide have taken active measures and issued environmental policies over the past decades to address climate change. Nevertheless, despite their effort, they have been insufficient. This is well reflected in the low retrofit rate in the German residential building sector, lagging far behind its climate targets, still accounting for more than one quarter of total greenhouse gas emissions in Germany (Behr et al., 2023; German Environment Agency, 2023). Consequently, this doctoral thesis leverages several data-driven approaches to investigate financial challenges of EERs in the residential building sector. To achieve this objective, it investigates technological developments for BEP prediction improvements and novel approaches to address EER barriers that cause the energy efficiency gap. For this, it first assesses the perceived relevance of multiple barriers. Second, it addresses the most relevant barrier, economic expenditures, by identifying the financial challenges of EERs. Third, it demonstrates how recent technological developments can significantly contribute to bridging the energy efficiency gap.

Research Article #1 directly addresses the first research objective by identifying the most relevant barriers for stakeholders regarding EERs and deriving tailored policy measures. By combining a structured literature review with an online expert survey, Research Article #1 links practical perspectives and theoretical insights to assess the relevance of financial, regulatory, informational, and technical barriers for EERs. This integrated approach assesses barriers and potential solutions, resulting in 25 actionable policy recommendations. Experts consider financial and regulatory barriers the most relevant, which can be addressed through grant-based subsidies, improved tax incentives, legally binding funding terms, and reduced bureaucracy, particularly for monumental buildings. Central coordination offices and improved knowledge sharing can mitigate informational barriers, whereas adopting smart metering, AI-based analytics, and digital assistants can potentially remove technical barriers.

Research Article #2 and Research Article #3 address the second research objective by examining the financial challenges associated with EERs. Research Article #2 introduces a novel cluster-based XAI methodology to the research community, aiming to uncover the financial impacts of energy-related building features on property valuation in a case study of the UK's building stock. The results suggest that energy efficiency leads to financial benefits, especially outside London. Information on carbon emissions is primarily relevant for medium to large buildings outside of London. Furthermore, high running costs are well reflected in transaction prices for larger buildings. Research Article #3 presents a real-world case study that utilizes residential buildings in Germany to quantify the expected energy savings for specific EER measures. The study combines these results with local subsidies and retrofit budgets to provide a comprehensible retrofit index. For this, it devises a novel feature value substitution method and identifies glazing as the EER measure with the highest potential energy savings for residential buildings, offering a potential saving of up to 16 kWh in annual energy consumption per square meter. Similarly, improvements to roof and wall insulation lead to significantly lower energy consumption, whereas the impact of better facade conditions is negligible. The retrofit index empirically indicates a well-working subsidy system for lower budgets regarding heating system changes from oil or gas to electric heating pumps.

Research Article #4 and Research Article #5 address the third research objective by leveraging technological developments to improve BEP prediction and exploring novel technological approaches to EERs. For this, Research Article #4 benchmarks the performance of homogeneous and heterogeneous ensemble models against traditional stand-alone models to evaluate performance gains regarding BEPs. Ensemble techniques substantially outperform stand-alone techniques both in terms of the best-performing model and the average performance of each model type. Four error metrics were applied to scrutinize the robustness of the results, while living space and building age bins were examined to rule out systematic biases. The ensemble model XGB considerably outperformed all other models. Research Article #5 structures novel GenAI applications for EERs based on 86 research articles in a newly developed taxonomy. The resulting taxonomy comprises three units, nine dimensions, and 44 characteristics. Subsequently, a hierarchical clustering approach is employed to identify four distinct archetypes. The taxonomy and the archetypes have multiple theoretical and managerial implications as they define the design space for GenAI applications in the domain of energy-efficient buildings, align data requirements and specific architectures with optimization goals, and highlight model types that increase decision-making transparency.

From a broader perspective, all individual findings from the aforementioned research articles directly contribute to the three research objectives outlined in the introduction to this work. As the retrofit rate in Germany currently falls short of its potential, it is of utmost importance to create suitable conditions that incentivize EER projects to meet the EU's climate targets and minimize the effects of climate change. Understanding the barriers that hinder EER projects and evaluating their relevance to stakeholders is a crucial step in creating suitable conditions through tailored policy measures. Overcoming financial uncertainties regarding EERs, identified as the most serious barrier, plays a key role in this regard. To this end, two of the research articles thoroughly investigate the financial challenges of EER projects, aiming to close the information gap regarding the viability of certain retrofit measures. This is achieved by leveraging novel technological developments to enhance BEP predictions and provide new informational and regulatory insights. However, most central to this work is its aim to provide actionable findings that can be translated into policies and utilized by decision-makers to reduce greenhouse gas emissions in the residential building sector, one of the largest carbon emitters in industrialized nations.

III.2. Limitations and Future Research

The results of this doctoral thesis are restricted by certain limitations that provide several opportunities to spur further research, building upon this work. This section summarizes the overarching limitations, refraining from delving into article-specific limitations; instead, it provides the reader with a more general and comprehensible overview.

(1) **Data-driven simulations and case studies** are inherently limited regarding their data selection and the quality of datasets. This is particularly relevant for Research Article #2, Research Article #3, and Research Article #4, which derive their results from real-world data, naturally prone to error. All three research articles rely on accurate data collection by energy experts and homeowners, meticulous preprocessing, and the availability of sufficient high-quality data. However, even high-quality datasets cannot always accurately reflect real-world scenarios, which can affect the results of this work. To make them more robust, Research Article #2 and Research Article #3 intentionally use datasets from different countries.

However, future studies could build on this and verify the results of this doctoral thesis in other countries. Furthermore, it could inspire additional initiatives for open-source datasets, following the example of the UK Ministry of Housing, Communities & Local Government (Department for Levelling Up, Housing & Communities, 2025). Moreover, future research could enhance the survey design of Research Article #1 to increase the number of participants and make it accessible across different countries, thereby achieving a higher response rate and even more robust survey results.

(2) **Technical constraints** are especially relevant for the Research Articles #1 - #4 as they acquire new data or process existing datasets with diverse methodological approaches. The black box character of AI, in particular, still poses a significant barrier to adoption that needs to be adequately addressed. Research Articles #2 and #3 consequently leverage explainability approaches by applying clustering and XAI methods to increase the transparency of results. Further research could apply these novel methodological approaches to other research domains and investigate additional methods to enhance the explainability of both DisAI and GenAI.

(3) **Temporal validity** is a grand challenge as the regulatory landscape adjusts to new scientific findings, external circumstances, and prevailing political opinions. Foremost, Research Article #1 and Research Article #5 are susceptible to such changes as their results only reflect a snapshot of time, and the relevance of EER barriers might change, which became apparent, for example, during the first years of Russia's invasion of Ukraine. The taxonomy of Research Article #5 is limited by its methodological approach, as it can only consider studies published before or during the development period. Therefore, further research must reevaluate the results regularly to account for technical or political changes.

(4) **Rational decision-making** cannot always be encountered in human behavior, which also applies to EERs. All research articles assume a rational cause-and-effect relationship, meaning that the results of this doctoral thesis, if known and proven beneficial, will ultimately narrow the energy efficiency gap. According to Kahneman and Tversky (1979), this may not always be the case, as irrational behavior, often caused by a lack of knowledge or shortsightedness, hinders joint efforts to reduce the energy efficiency gap. Therefore, academia should further investigate behavioral incentives and barriers related to EERs to understand how promising scientific results can be translated into practical implementations as quickly as possible. This can be achieved through tailored policies that are easy to understand.

(5) **Focusing on residential buildings** enables an in-depth analysis of potential barriers within this domain. However, it comes at the price of neglecting a significant part of the energy and building sector. Consequently, the findings of all research articles are limited to residential buildings and may not be transferable to other areas of the building sector, which hampers their generalizability if not extended by future studies. This includes other domains such as manufacturing, healthcare, office, public facilities, and even the construction of new buildings. Broadening the research scope could potentially reveal intersections and yield insightful results for reducing greenhouse gas emissions across the entire building sector.

(6) **Reliance on policymakers** exists for all research contributions that provide new regulatory proposals, as researchers themselves do not implement new political initiatives but rather formulate scientific recommendations for elected decision-makers. Recommendations regarding the imminent threat of climate change existed well before governments issued the first laws (Bonneuil et al., 2021). Therefore, it is imperative for the research community to not only provide a scientific foundation for tailored policy measures but also actively promote them to society and political actors to generate the necessary social pressure for their implementation, as only the interplay between scientific, political, social actors, and industry representatives can ensure tailored policies to target climate change.

Despite the limitations of this doctoral thesis, its methodological approaches, diverse findings, and actionable policy recommendations provide a valuable contribution to academia and practitioners. Therefore, let us unitedly continue to walk the path we defined in the 2015 Paris Agreement, so that future generations will have even better opportunities to thrive as we do today.

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V Appendix

V.1. Index of Research Articles for this Doctoral Thesis

Research Article #1: Assessing Barriers for Energy-Efficient Retrofits to Derive Purposive Policy Recommendations for the Residential Building Sector

Koray Konhäuser, Constantin Rothdach, Nina Schwarz, Tim Werner. Assessing Barriers for Energy-Efficient Retrofits to Derive Purposive Policy Recommendations for the Residential Building Sector. *Energy Policy (2026).*

(VHB-Jourqual 3 equivalent: Category B | Impact Factor (2025): 9.2)

Research Article #2: Uncovering the financial impact of energy-efficient building characteristics with eXplainable artificial intelligence

Koray Konhäuser, Tim Werner. Uncovering the financial impact of energy-efficient building characteristics with eXplainable artificial intelligence. *Applied Energy (2024).*

(VHB-Jourqual 3: Category B | Impact Factor (2025): 11.0)

Research Article #3: Evaluating strategic retrofit measures for energy-efficient residential buildings with artificial intelligence

Koray Konhäuser, Nina, Schwarz, Tim Werner. Evaluating strategic retrofit measures for energy-efficient residential buildings with artificial intelligence. *Energy & Buildings (2026).*

(VHB-Jourqual 3 equivalent: Category B | Impact Factor (2025): 7.1)

Research Article #4: Leveraging advanced ensemble models to increase building energy performance prediction accuracy in the residential building sector

Koray Konhäuser, Simon Wenninger, Tim Werner, Christian Wiethe. Leveraging advanced ensemble models to increase building energy performance prediction accuracy in the residential building sector. *Energy & Buildings (2022).*

(VHB-Jourqual 3 equivalent: Category B | Impact Factor (2025): 7.1)

Research Article #5: The Role of Generative Artificial Intelligence for Building Energy Efficiency: A Structured Taxonomic Analysis

Koray Konhäuser, Maximilian Schmid, Nina Schwarz, Tim Werner, Björn Häckel. The Role of Generative Artificial Intelligence for Building Energy Efficiency: A Structured Taxonomic Analysis. *Working paper submitted to Applied Energy.*

(VHB-Jourqual 3: Category B | Impact Factor (2025): 11.0)

Over the course of my dissertation, I also co-authored the following research papers. These papers are not part of this doctoral thesis.

- Häckel, B; Meierhöfer, S; Müller, M; Oberländer, A. M.; Süzeroğlu, S; Werner, T; Wiedemann S. (2025). Unlocking Sustainability Potentials Through Artificial Intelligence: Insights from a Consortium Research Project in the Printing Industry. In: HMD Praxis der Wirtschaftsinformatik. *(VHB-Jourqual 3: Category C)*
- Meyer-Hollatz, T; Schwarz, N; Werner, T. (2023). Punctuality Predictions in Public Transportation: Quantifying the Effect of External Factors. In: Wirtschaftsinformatik 2023 Proceedings. *(VHB-Jourqual 3: Category C)*
- Konhäuser, K.; Mais, L.; Schwarz, N.; Werner, T.; (2025). Communicative Constitution of Organizations in the Digital Age: Leveraging Network Analysis for the Identification of Communication Roles. In: Proceedings of the 32nd International Conference on Information Systems (ICIS). *(VHB-Jourqual 3: Category A)*
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  (Working paper)

V.2. Individual Contribution to the Research Articles of this Doctoral Thesis

This cumulative dissertation comprises five research articles representing the main body of work. All articles were developed in teams with multiple co-authors listed in alphabetical order, except in the case of primary authorship. This section details the respective research settings and highlights my individual contributions to each article following the CRediT (Contributor Roles Taxonomy) author statement.

Research Article #1: This research article was developed by a team of four co-authors, including Koray Konhäuser, Constantin Rothdach, and Nina Schwarz. I was responsible for *Project administration*, *Supervision,* and the initial *Conceptualization*, formulating the research objectives. Furthermore, I co-developed the *Methodology* for our extensive literature review approach along with the online survey, handled the *Data Curation* activities, and performed the *Formal Analysis*. I was responsible for the *Writing – original draft* as well as providing critical commentary and revisions during the *Writing – review & editing*.

Research Article #2: This research article was developed by Koray Konhäuser and me. Due to my *Supervision* role during the project, I was responsible for the *Project Administration*. We jointly formulated initial ideas and research objectives during *Conceptualization* and designed the research *Methodology*. I guided and assisted the *Formal Analysis* of the study data and was responsible for the *Validation* to ensure their reproducibility. We were equally involved in *Writing – original draft* and *Writing – review & editing*.

Research Article #3: This research article was primarily developed by me, supported by my two co-authors, Koray Konhäuser and Nina Schwarz. Consequently, I was predominantly responsible for the *Project administration*, *Writing – original draft*, and *Formal Analysis*. Together with my two co-authors, we applied several data preparation steps during the Data Curation to enable the Formal Analysis, combining potential ecological gains, household investment budgets, and expected local governmental subsidies. We jointly addressed critical commentary and revisions during the *Writing – review & editing*.

Research Article #4: This research article was developed by a team of four co-authors, including Koray Konhäuser, Simon Wenninger, and Christian Wiethe. I conducted a *Formal Analysis*, leveraging ensemble and stand-alone models alongside other statistical and computational techniques to analyze the study data. I was also responsible for *Software* development and jointly handled *Data Curation* and *Visualization*. Over the course of this research project, I contributed alongside my co-authors to *Writing – original draft* and *Writing – review & editing*.

Research Article #5: This research article was developed by a team of five co-authors, including Koray Konhäuser, Maximilian Schmid, Nina Schwarz, and Björn Häckel. I was responsible for the overall *Project administration* and provided *Supervision* by co-leading our research activity and providing mentoring for less experienced authors. My further contributions included the *Conceptualization* of our research objectives and approach, *Writing - original draft*, as well as the critical review and revision of the work in *Writing - review & editing*.

V.3. Research Article #1

Assessing Barriers for Energy-Efficient Retrofits to Derive Purposive Policy Recommendations for the Residential Building Sector

Authors: Koray Konhäuser, Constantin Rothdach, Nina Schwarz, Tim Werner

Published in: Energy Policy

Abstract:

The European Union aims to reduce its carbon emissions by 55% by 2030, with the building sector accounting for more than one third of its total energy consumption. Therefore, it is imperative that countries with large populations, such as Germany, identify the most relevant barriers for energy-efficient retrofits (EER) to accelerate building retrofit activities. However, policymakers still lack evidence on which barriers are most important in practice, making systematic identification and prioritization necessary to avoid misdirected interventions. Consequently, this study combines a structured literature review with an online survey to derive financial, regulatory, informational and technical barriers empirically assessing their real-world relevance in a survey of 64 building experts from eight different professions using eight quantitative and 14 qualitative questions. This analysis leads to 25 policy implications that provide policymakers with actionable guidelines. Our findings show that experts perceive financial and regulatory barriers as most critical, calling for grant-based subsidies, better tax incentives, legally fixed funding terms, and less bureaucracy, particularly for retrofits of recently inherited buildings. Informational and technical challenges remain significant, with demands for a central coordination office, improved knowledge sharing, and the adoption of smart metering, AI-based analytics, and digital assistants to support decision-making. By aligning academic synthesis with stakeholders' priorities, this study offers a structured approach to overcoming EER barriers in Germany and presents transferable insights for other countries.

Keywords: Retrofit Barriers, Residential Buildings, Building Energy Efficiency, Policy Implications

V.4. Research Article #2

Uncovering the Financial Impact of Energy-Efficient Building Characteristics with eXplainable Artificial Intelligence

Authors: Koray Konhäuser, Tim Werner

Published in: Applied Energy

Abstract:

The urgency to combat climate change through decarbonization efforts is more crucial than ever. The global building sector is one of the primary contributors to carbon emissions, yet the economic implications of energetic building characteristics of residential buildings remain elusive. This study addresses the intersection of building energy performance, market valuation, and carbon emissions reduction by introducing a novel cluster-based eXplainable Artificial Intelligence (XAI) methodology to uncover the financial impact of energetic building features on property valuation. We combine Energy Performance Certificates (EPC) and property transaction data within the UK and apply two sophisticated machine learning models: XGB and CatBoost. To this end, we use hierarchical BIRCH clustering to identify subgroups within our comprehensive dataset and leverage SHapley Additive exPlanations (SHAP), Permutation Feature Importance (PFI), and Partial Dependency Plots (PDP) to reveal nuanced insights into the financial contribution of energetic building characteristics to property valuation. This research contributes to the academic discourse by introducing a cluster-based XAI approach for analyzing energy-related financial incentives in the building sector. Our results suggest that energy-efficient building features lead to significant financial benefits outside of London. The cluster-based approach reveals that carbon emissions are predominantly relevant for medium to large buildings outside of London but have a reversed financial effect within the capital. For larger residential buildings, we find a tendency for high running costs for energy (e.g., lighting costs) to be well reflected in transaction prices. The presented findings underscore the potential economic benefits for targeted energy efficiency improvements and illuminate the pathway towards a low-carbon society by addressing inherent uncertainties surrounding the economic viability of energetic investments, thus fostering informed decision-making and sustainable development.

Keywords: Building energy efficiency, Explainable artificial intelligence, Energy performance certificates, Energy efficient investments, Hierarchical Clustering

V.5. Research Article #3

Evaluating Strategic Retrofit Measures for Energy-Efficient Residential Buildings with Artificial Intelligence

Authors: Koray Konhäuser, Nina Schwarz, Tim Werner

Published in: Energy & Buildings

Abstract:

The global building sector is one of the main contributors to annual global greenhouse gas emissions, yet homeowners remain hesitant regarding specific retrofit measures to reduce carbon emissions. This is unsurprising as the link between retrofits that reduce energy consumption and corresponding economic and ecological benefits remains elusive. Therefore, this study addresses the intersection of building energy performance, carbon emission reduction, and financial subsidies by quantifying expected energy savings based on specific energy-related retrofits with a real-world dataset containing 25,000 German residential buildings. The simulated energy savings for specific retrofit measures are based on a novel feature value substitution methodology and three sophisticated machine learning models, namely XGBoost, CatBoost, and LightGBM. This study then combines potential ecological gains, household investment budgets, and expected local governmental subsidies into a single informative yet comprehensible retrofit index to overcome the uncertainty regarding retrofits. The results show that glazing is the most impactful feature for potential energy savings of residential buildings, followed by heating system changes from oil to electric heating pumps. In contrast to the neglectable impact of better facade conditions on building energy performance, roof and wall insulation improvements lead to significantly lower energy consumption. This study underscores potential ecological savings of targeted retrofit measures and enables practitioners to cut expenses and reduce the associated financial risks.

Keywords: Building energy efficiency; Building energy savings; Artificial intelligence; Energy retrofits; Energy performance simulation; Retrofit subsidies

V.6. Research Article #4

Leveraging Advanced Ensemble Models to Increase Building Energy Performance Prediction Accuracy in the Residential Building Sector

Authors: Koray Konhäuser, Simon Wenninger, Tim Werner, Christian Wiethe

Published in: Energy and Buildings

Abstract:

Accurate predictions for buildings' energy performance (BEP) are crucial for retrofitting investment decisions and building benchmarking. With the increasing data availability and popularity of machine learning across disciplines, research started investigating machine learning for BEP predictions. While stand-alone machine learning models showed first promising results, a comprehensive analysis of advanced ensemble models to increase prediction accuracy is missing for annual BEP predictions. We implement and thoroughly tune twelve machine learning models to bridge this research gap, ranging from stand-alone to homogeneous and heterogeneous ensemble learning models. We benchmark their prediction accuracy based on an extensive real-world dataset of over 25,000 German residential buildings. The results provide strong evidence that ensemble models substantially outperform stand-alone machine learning models both on average and in the case of the best-performing model. All models are tested for robustness and systematic bias by evaluating their prediction performance along different building age classes, living space bins, and several error measures. Extreme gradient boosting as an ensemble model exhibits the highest prediction accuracy, followed by a multilayer perceptron ahead of further ensemble models. We conclude that ensemble models for annual BEP prediction are advantageous compared to stand-alone models and outperform their results in most cases.

Keywords:

Building energy performance, Energy quantification methods, Machine learning, Ensemble learning, Artificial intelligence, Building energy consumption, Supervised learning, Energy efficiency

V.7. Research Article #5

The Role of Generative Artificial Intelligence for Building Energy Efficiency: A Structured Taxonomic Analysis

Authors: Koray Konhäuser, Maximilian Schmid, Nina Schwarz, Tim Werner, Björn Häckel

Submitted to: Applied Energy

Extended Abstract:

Achieving climate goals requires an increasing focus on reducing energy consumption, which, among other things, involves higher energy efficiency (EE) standards. As one of the largest energy consumers, the building sector offers considerable potential for energy and emissions savings, as it accounts for 38% of global greenhouse gas emissions and 39% of global energy consumption (Royston et al., 2018). Unlocking that potential demands advanced analytical approaches capable of navigating the building sector's vast, heterogeneous data landscape to uncover EE potentials on a large scale. Although artificial intelligence already plays a fundamental role within the building energy sector, the focus is increasingly shifting to applications that leverage generative artificial intelligence (GenAI) to achieve higher EE standards (Suphavarophas et al., 2024). GenAI is uniquely suited for this task because it can synthesize new insights and simulations. Moreover, research suggests that GenAI applications may be able to address outstanding problems, such as poor data quality, by incorporating and structuring multimodal data streams, as well as addressing the lack of democratization in conversational interactions and providing individual explanations of model results. To this end, discriminative and generative artificial intelligence jointly promise powerful benefits in overcoming current challenges in this domain by efficiently processing large amounts of energy data, addressing complex stakeholder demands, and improving the accuracy of energy consumption forecasts. However, research lacks a comprehensive understanding of its possible configurations and essential characteristics due to its novelty and diversity. Yet, such a classification is imperative for researchers, practitioners, and innovators as they face several challenges when identifying, developing, and deploying value-adding applications based on generative artificial intelligence within the building energy sector. Consequently, this study investigates potential applications of generative artificial intelligence to enhance building energy efficiency and systematically structures use cases. To address this research question, we develop a taxonomy following the approach of Nickerson et al. (2013) and extend the proposed seven-step approach with the methodological steps introduced by Kundisch et al. (2022) to take greater account of the purpose of applying the taxonomy in their development process. Consequently, this study identifies essential characteristics of building-related generative artificial intelligence applications by reviewing scientific literature, incorporating practitioner experience, and summarizing them in a comprehensive taxonomy. comprising three units, nine dimensions, and 44 characteristics. We then utilize a hierarchical clustering approach to derive four distinct archetypes based on the developed taxonomy. We conclude our study by elaborating on the theoretical and managerial implications, namely, how each archetype can lower development costs, reduce performance gaps, and accelerate the adoption of low-emission solutions, to support researchers and practitioners in designing and implementing concepts for generative artificial intelligence applications that stimulate innovations and increase ER within the building sector.

Keywords:

Generative Artificial Intelligence, Energy Efficiency, Building Sector, Taxonomic Analysis