Data-driven support and risk modeling for a successful heat transition in the building sector

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Copyright Statement

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

Abstract

Growing international interest in climate change and the ambitious climate goals of the Paris Climate Agreement requires policy decisions and actions to curb the adverse effects of human-made climate change. The buildings sector accounts for more than one-third of global greenhouse gas emissions and energy consumption, with space heating and water heating accounting for most of these, and offers great potential for progress toward climate goal achievement. Moreover, most of today's existing buildings were built before introducing more strict building codes than today and are therefore not sufficiently energy efficient. Due to the low number of new buildings compared to the existing building stock, extensive retrofitting is necessary, as the current building stock will continue to account for the largest share of energy consumption in buildings in the future. However, retrofits of these buildings are sparse, and the retrofit rate - the percentage of buildings that undergo retrofits in a year - is too low to meet climate goals. Therefore, this cumulative doctoral thesis examines two aspects for a successful heat transition in the building sector. The first aspect deals with the identification of general factors influencing energy efficiency and retrofitting practices on a regional level. It is not yet fully understood which local differences exist in building performance, energy efficiency, and retrofitting practices and how socio-economic factors influence these. Thus, this doctoral thesis follows the call to use the opportunities of advancing digitalization and data availability to examine this aspect. The findings indicate strong evidence for regional differences in building energy efficiency, confirm existing qualitative and small-scale studies regarding the influence of socio-economic factors and classify retrofitting-related CO_2 taxes as reasonable and easy to implement. The second aspect shifts the focus from a regional level to individual retrofit decisions. It examines risk in general and inaccurate predictions of building energy performance in particular as barriers to individual retrofit decisions. The results show that promoting energy efficiency reduces the variance – and thus the risk - of future energy bills and opens up opportunities for more sustainable investment behavior. In addition, policy instruments such as energy efficiency insurance are more effective and cost-efficient than subsidies in mitigating the risk of environmentally friendlier investments. Regarding building energy performance prediction, data-driven approaches exceed the currently prescribed engineering method (in Germany) by almost 50% in prediction accuracy and provide insights into influencing factors. In summary, this doctoral thesis provides insights using data-driven and risk-modeling approaches for a better understanding of factors influencing energy efficiency and retrofitting on a regional level and risk in retrofit decisions and contributes managerial and policy implications that support a successful heat transition in the building sector.

Keywords: *Energy Efficiency, Risk, Building Sector, Energy Performance Certificates, Energy Informatics, Data Analytics, Building Energy Performance*

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I. Introduction

I.1. Motivation

Human-induced climate change is showing its first adverse effects and rapidly increases society's interest and eagerness for discussion (Dziminska et al., 2021). Concerns about other harmful effects on ecosystems and people caused by the rise in global temperatures associated with climate change are fueling societal demands for greater sustainability in all sectors (Magnan et al., 2021). With the Paris Agreement concluded in 2015 at the international climate conference, also known as the "United Nations Framework Convention on Climate Change, 21st Conference of the Parties (COP 21)", almost all the countries worldwide committed themselves to shape the global economy in a more climate-friendly way, thus setting important impulses (Falkner, 2016). Unlike the Kyoto Protocol, where only a few industrialized countries were involved, almost all participating countries have defined national climate protection targets (Savaresi, 2016). By ratifying the Paris Agreement, the countries have committed themselves under international law to take appropriate measures to achieve the targets set (Savaresi, 2016). As a common goal of the Paris Agreement, the countries agreed to limit global warming to well below two degrees Celsius compared to pre-industrial levels, ideally to 1.5 degrees (Glanemann et al., 2020). Despite the set targets, the implemented policies seem insufficient and lead to an average emission gap of 22.4 to 28.2 $GtCO_2eq$ by 2030 (Roelfsema et al., 2020). Even though the COVID-19 pandemic has led to a short-term global decrease in energy consumption and reduction of Greenhouse Gas (GHG) emissions as well as air pollutants, measures and long-term system-wide investments in decarbonization of economies need to be intensified to reduce global warming (Forster et al., 2020; Shan et al., 2021).

To achieve the climate goals, a reduction in energy consumption across all sectors and an increase in the share of renewable energies are crucial (Da Graça Carvalho, 2012). The building sector, including residential and commercial buildings, is the largest energy consumer, accounting for 38% and 39% of global GHG emissions and energy consumption, respectively, and therefore offers great potential for progress toward climate goals (Somu et al., 2020). Thereby, space heating accounts on average for 32% of total energy consumption in residential buildings and 33% in commercial buildings worldwide, giving energy efficiency in the building sector an important role (Ürge-Vorsatz et al., 2015). The share of energy consumption for space heating can vary significantly due to climatic conditions. In particular, there is a high potential for energy savings in more northerly countries, where space heating can account for 60-80% of total energy consumption in buildings (European Commission, 2013). For instance, space heating and hot water production account for 84% of the overall final energy consumption in German residential single- and two-family buildings (Cao et al., 2016; Federal Ministry for Economic Affairs and Energy, 2018). In addition, the current building stock will continue to be responsible for the largest share of energy consumption in buildings in the future due to a low number of new buildings compared to the existing building stock (Deutsche Energie-Agentur GmbH, 2016; Fylan et al., 2016). The German building stock, where more than 64% of residential buildings were constructed before 1979, suffers from less stringent building codes than today and poor insulation (Federal Statistical Office of Germany, 2011). Thus, a successful heat transition, defined as "expanding renewable energy sources and energy efficiency in heat generation and demand" (Töppel, 2020, p. 7), and extensive retrofitting are necessary to meet climate goals (Stanica et al., 2021).

Although the targets and potential are ubiquitously known, and policies and subsidies such as those for replacing oil-fired heating systems in Germany are made available, the achievements fall far short of the necessary targets to curb global warming (Häckel et al., 2017; Michelsen and Madlener, 2016). In Germany, the retrofit rate - the percentage of buildings that undergo retrofits in a year - has stagnated at around 1% for about a decade. However, a doubling of at least 2% would be necessary (Deutsche Energie-Agentur GmbH, 2021). Nevertheless, it is essential to overcome the failure of current incentives and policy instruments to successfully master the heat transition (Achtnicht and Madlener, 2014). Policy instruments to increase the retrofit rate must be effective and efficient against the background of limited financial resources (Csutora and Zsóka, 2011). Therefore, maximizing GHG reductions per unit of money invested in retrofit and energy efficiency projects must be sought.

I.2. Research Aim

In order to increase the retrofit rate and energy efficiency in the building sector, a broad mix of different policy instruments is already available today, which can vary both nationally and locally (Weiss et al., 2012). These instruments range from legal requirements for energy efficiency levels in new buildings to information campaigns or financial support through subsidies or tax incentives (Tan et al., 2018). They can be categorized as direction-based policies, regulation-based, organization & professional training, evaluation-based, knowledge & information, and financial support instruments (Liu et al., 2020; Tan et al., 2018). Table 1 provides an overview and understanding of the wide range of possible retrofitting policy instruments. Even though the instruments can be distinguished in terms of objective and functionality, in practice, the combination and close interaction of different instruments are shown to be more effective and efficient (Iwaro and Mwasha, 2010).

Researchers are intensively investigating various aspects of retrofitting and the heat transition in qualitative and quantitative studies to efficiently design policy instruments and specific measures. Most of this research can be summarized under the term energy efficiency gap (Ahlrichs et al., 2020). The energy efficiency gap, also referred to as the energy efficiency paradox, describes the phenomenon that although energy efficiency investments "seem to present clear economic and environmental advantages, the level of investment in them does not reach the levels which would correspond to such benefits" (Linares and Labandeira, 2010).

Policy instrument	Description	Example
Direction-based	Provide and outline future directions and roadmaps for retrofitting and energy efficiency, setting the foundation for other policy instruments.	EU’s directive on the energy performance of buildings and energy efficiency 2018/844 (EU Parliament, 2018)
Regulation-based	Enforcing a government's retrofitting/energy efficiency goals through laws, standards, and regulations.	Building Energy Law (Gebäudeenergiegesetz (GEG) (Federal Ministry of Justice and Consumer Protection, 2020)
Financial support	Subsidies or other incentives to minimize residents’ resistance to regulation measures and to increase the willingness to implement retrofits.	Replacement premium for oil heating systems in Germany (Federal Office for Economic Affairs and Export Control, 2020)
Evaluation-based	Tools and measures that assist and inform stakeholders in making decisions for or against retrofits, as well as tools that assist in evaluating the energy performance of buildings and allow for the derivation or evaluation of retrofit strategies.	Energy Performance certificates available through Europe (Arcipowska et al., 2014b)
Knowledge & information	Increase stakeholders' knowledge and awareness by providing easily accessible information on successful retrofit experiences, benefits, measures, subsidies, loans, or qualified experts.	Online accessible overview of possible funding programs (in Germany) (Federal Office for Economic Affairs and Export Control, 2020)
Organization & professional training	Establishment of relevant professional associations and the training of competent experts for a professional implementation of retrofits.	Training programs for qualified auditors/energy consultants (Arcipowska et al., 2014b)

Table 1. Categorization of retrofitting policy instruments (according to Liu et al., 2020 and Tan et al., 2018)

Literature identified multitudes of energy efficiency barriers classified as behavioral barriers and structural barriers preventing higher and more investments in energy efficiency and retrofits (Brown, 2001; Shogren and Taylor, 2008; Weber, 1997). Behavioral barriers include social influences, emotional and moral motivations, or decision heuristics caused by bounded rationality. Structural barriers instead can be divided into non-market failures and market failures addressing barriers such as institutional barriers, organizational barriers, the riskiness of energy efficiency investments, or the effects of imperfect capital markets and imperfect information (Brown, 2001; Hilbert, 2012; Shogren and Taylor, 2008; Weber, 1997). Understanding these energy efficiency barriers and their impact on retrofitting behavior is of significant relevance for closing the energy efficiency gap and achieving the climate goals set.

Therefore, the overall aim of this doctoral thesis is to contribute to a successful heat transition and provide the basis for deriving managerial and policy implications by addressing two aspects of energy efficiency barriers and their impact. Specifically: (1) analysis of general factors influencing retrofitting practices at the regional level, (2) investigation of risk in general and inaccurate predictions of building energy performance (BEP) in particular as barriers to individual retrofit decisions.

The need to explore aspect (1) results from limitations of existing studies and is methodologically motivated by numerous studies calling for leveraging the potentials of data-driven approaches. Existent research on circumstances of and barriers against retrofitting is diverse (Ben and Steemers, 2018; Bertoldi and Mosconi, 2020). For instance, Tziogas et al. (2021) identify regional differences in the number and costs of retrofits in Greece. Magnani et al. (2020) find that tax incentives for retrofits are ineffective and local intermediaries strongly influence the local retrofit level in Italy using a mixed-methods approach. Further, Gómez-Navarro et al. (2021) analyze survey-based energy poverty in Valencia, Spain. However, research to date is often limited to qualitative studies. It is not yet fully understood which local differences exist in building performance, energy efficiency, and retrofitting practices and how socio-economic factors influence these. From the methodological perspective, research does not fully exploit the opportunities created by advancing digitization and data availability. Recently published papers highlighted two different needs for future research. First, Pasichnyi et al. (2019) proposed using the (openly accessible) databases of building Energy Performance Certificates (EPC) for data-enabled energy policy instruments. They conclude that EPC data might have a broader spectrum of applications than initially intended and are suitable to design policy instruments for energy efficiency. Second, literature suggests using explainable artificial intelligence (XAI) in the building sector to derive insights about the relations of different parameters and variables (Golizadeh Akhlaghi et al., 2021). In this context, prior research such as Athey (2017) also encouraged using artificial intelligence (AI) beyond plain predictions to derive data-driven policy implications. Therefore, this doctoral thesis aims to contribute to the existing research gap using data-driven approaches as highlighted in literature.

Investigating aspect (2) goes back to Mills' (2003) findings. He found that the financial risk of energy savings is a central barrier for investments in energy efficiency, and therefore, a significant inhibitor of the allure of retrofits. Future energy prices, among other sources of risk, are uncertain and typically result in volatile energy (cost) savings as financial risk. Risk in retrofit investment decisions is driven by extrinsic factors such as energy prices or weather conditions and intrinsic factors such as occupants' behavior or insufficient calculations (Wilde, 2014). Thus, this doctoral thesis aims to analyze risk in retrofitting decisions and the impact of different policy instruments on these decisions. Further, since BEP predictions prior and after retrofitting, such as depicted in EPCs, are central for deciding whether retrofitting is economical or not, BEP prediction accuracy as a barrier to individual retrofit decisions should be investigated in more detail. EPCs and BEP prediction are hotly debated in the research community, as they exhibit low prediction accuracy – thus representing high risk (Hardy and Glew, 2019). Research sees potential in using data-driven methods to predict BEP instead of using the legally prescribed engineering methods typically applied by qualified auditors, e.g., energy consultants (Arcipowska et al., 2014b; Foucquier et al., 2013). This risk-reducing potential of data-driven methods will be investigated additionally within aspect (2) of this doctoral thesis.

I.3. Structure of the Thesis and Embedding of the Research Papers

This doctoral thesis is cumulative and consists of six research articles contributing to the elaborated research aim. Using data-driven methods and risk modeling approaches, it discusses aspects for a successful heat transition in the building sector. Accordingly – and as illustrated in Figure 1 – the research articles in this doctoral thesis are structured in terms of two overarching topics: Identifying influencing factors on energy efficiency and retrofitting practices and risk and inaccurate BEP predictions as barriers for retrofitting.

Following the research aim, the first aspect (Section II) deals with the identification of general factors influencing energy efficiency and retrofitting practices on a regional level, for the example of the residential building stock of the UK. On the one hand, the residential building stock of the UK is well suited as it represents the oldest building stock in Western Europe and is responsible for more than a quarter of the total energy consumption of the UK consumption (Dowson et al., 2012; Filippini et al., 2014; Fylan et al., 2016; Piddington et al., 2020). On the other hand, much data is publicly available in the UK, allowing for large-scale analyses compared to other countries. Research Articles #1 and #2 apply data-driven methods to publicly available EPC data, additional house price data, and sociodemographic data. Research Article #1 uses unsupervised methods to fundamentally examine regional differences in the UK housing stock and the influence of socio-economic factors on building energy efficiency. Building on this, Research Article #2 changes the focus from factors influencing regional building energy efficiency in general to factors influencing retrofitting practices. Data availability issues for retrofitting measures conducted require a combination of supervised machine learning (ML) and XAI methods to identify socio-economic factors influencing retrofitting practices. Both research articles allow deriving policy implications on regional and local levels to increase energy efficiency in the residential building stock through targeted incentives and programs.

The second aspect (Section III) examines risk in general and inaccurate predictions of BEP in particular as barriers to individual retrofit decisions. The focus is shifted from regional factors discussed in Section II to individual retrofit decisions and thus also investment decisions in energy efficiency. Research Article #3 lays the theoretical foundation for the influence of (financial) risk and its perception on individual retrofit decisions. Two perspectives on risk are identified in literature and subsequently compared by developing a theoretical model and a case study to analyze their influence on retrofit decisions. Research Article #4 builds on this by examining the impact of policy instruments on risk and return of investment in retrofit measures using a risk-integrated thermal energy hub approach. Given that prediction of BEP, especially its accuracy plays a central role in retrofit decisions, Research Articles #5 and #6 analyze the potential of data-driven approaches (especially ML) for BEP predictions. With the help of accurate BEP predictions, the financial risk in retrofit decisions can be significantly reduced, which positively impacts retrofit rates and investment levels. Therefore, Research Article #5 compares the currently by law required Energy Quantification Methods (EQM) with state-of-the-art data-driven EQMs in terms of BEP prediction accuracy. Upon this, Research Article #6 compares different data-driven EQMs with the novel algorithm QLattice regarding BEP prediction accuracy, computational times, and explainability in a case study. Exploring aspects of explainability allows deriving further insights from data-driven EQMs often referred to as black-box models. Summing up, Research Articles #3 through #6 thus contribute to individual retrofit decisions and enable more efficient policy design using digital and data-driven technologies.

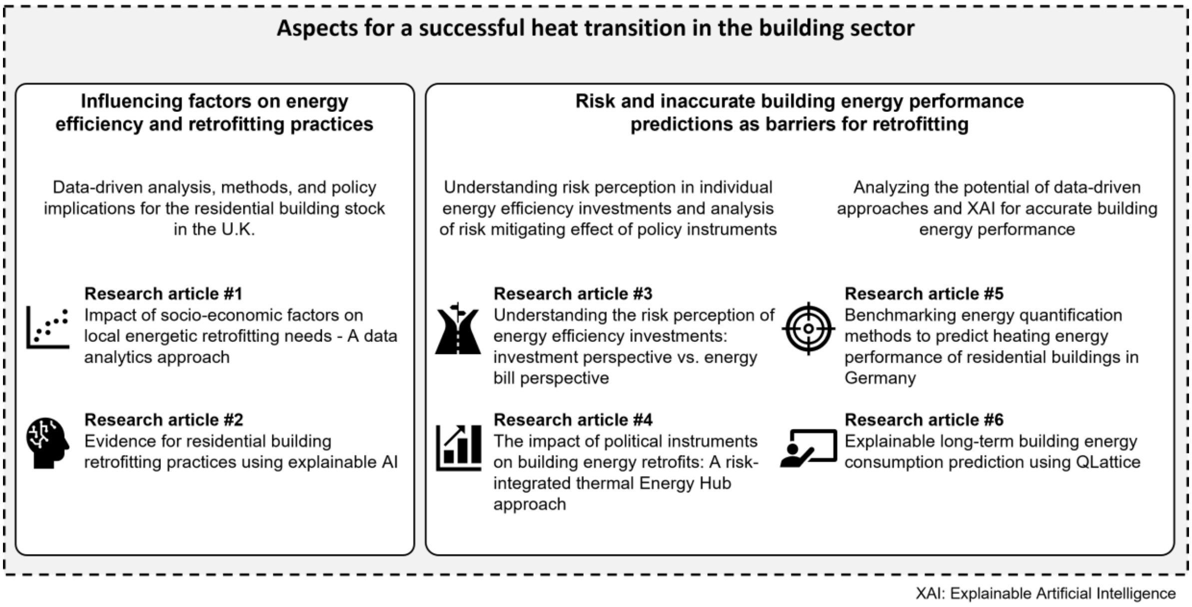

Figure 1. Structure of the Doctoral Thesis and Classification of the research articles

This doctoral thesis then concludes in Section IV with a summary of all key findings (cf. subsection IV.1) and provides pertinent limitations as well as prospects for further research (cf. subsection IV.2) before discussing earlier, related and work published during the time this thesis was written (cf. subsection IV.3).

Section V contains the thesis references. The appendix in Section VI provides additional information on the six research articles included in this thesis (cf. Subsection VI.1). Subsection VI.2 details the contributions of the author of this thesis to each of the research articles. All research articles' (extended) abstracts are depicted in subsection VI.3. The supplementary material not intended for publication contains the full texts of all research articles.

II. Factors Influencing Energy Efficiency and Retrofitting Practices

II.1. Impact of Socio-Economic Factors on Local Energetic Retrofitting Needs

The current policy instruments in England, Scotland, and Wales fail in increasing the energetic retrofit rate for residential buildings and thus do not sufficiently counteract climate change (Brown, 2018; CCC, 2019; Rosenow and Eyre, 2016). Possible explanations are local differences in building properties and socio-economic factors that might influence the effectiveness of policy instruments incentivizing retrofitting (Jones et al., 2009; Kastner and Stern, 2015). Thus, understanding the interdependencies between building energy efficiency and these factors are required to enable locally tailored policy for an effective and efficient resource allocation (Fylan et al., 2016; Gerarden et al., 2017; Rosenow and Eyre, 2016). Local authorities already provide a range of energy services, are committed to reducing GHG emissions (Comodi et al., 2012; Wade et al., 2020), and are responsible for coordinating policies and measures to reduce residential energy use (Morris et al., 2017). Thus, examining the influence of socio-economic factors on building energy efficiency at a local level is essential. Despite growing empirical research on energy efficiency in general (Ben and Steemers, 2018; Bertoldi and Mosconi, 2020; Zhang et al., 2012) and enhanced application of data mining methodologies, it is not fully understood yet which local differences regarding building characteristics and buildings' energy efficiency exist and how socio-economic factors influence them.

Therefore, Research Article #1 sets out to analyze if there are local differences in the energetic retrofitting needs of the residential building stock in England, Scotland, and Wales, and which socio-economic factors might explain these local differences. Using a data-driven approach on an extensive real-world dataset of more than 10.5 million EPCs in England, Scotland, and Wales local differences of residential buildings energy efficiency on local authority level by using a χ^2 independence test are derived in a first step. Finding significant differences already at such an aggregated level reinforces the importance of locally tailored policies. Second, local differences in the building stock retrofitting needs are determined by deriving the most important building parameters influencing the energy efficiency by applying a Random Forest Classifier prior to using a K-means cluster analysis to obtain building archetypes with their different retrofitting needs. A second χ^2 independence test on the distributions of the resulting archetypes per local authority confirms small but significant differences in the building stock and their retrofitting needs for a 5% significance level. Moreover, the effect strength might increase with more granular data (e.g., district level), such that even bigger local differences become apparent.

To identify socio-economic factors influencing local authority energy efficiency, several Random Forest Regressions of socio-economic factors obtained from the last census 2011 are applied on different quantiles of the local authorities' energy efficiency. Findings reveal that the correlation of socio-economic factors with building energy efficiency varies with the energy efficiency level. Figure 2 illustrates the overall weighted importance of the superordinate domains (of socio-economic factors) Demographic, Economic, Employment, Household Composition, Housing, and Socio-Economic for each quantile[1]. Leaving out the extreme 1 and 99% quantiles, there are pronounced trends in the domain importance. The importance of the domains "Employment" and "Housing" decreases with increasing energy efficiency of the buildings from 22% to 14% and 26% to 12%, respectively. Further, there is a slight decrease in importance of "Demographics". In contrast, the "Socio-Economic" and "Economic" domains gain importance with increasing energy efficiency. The overall importance of "Household Composition" is almost constant.

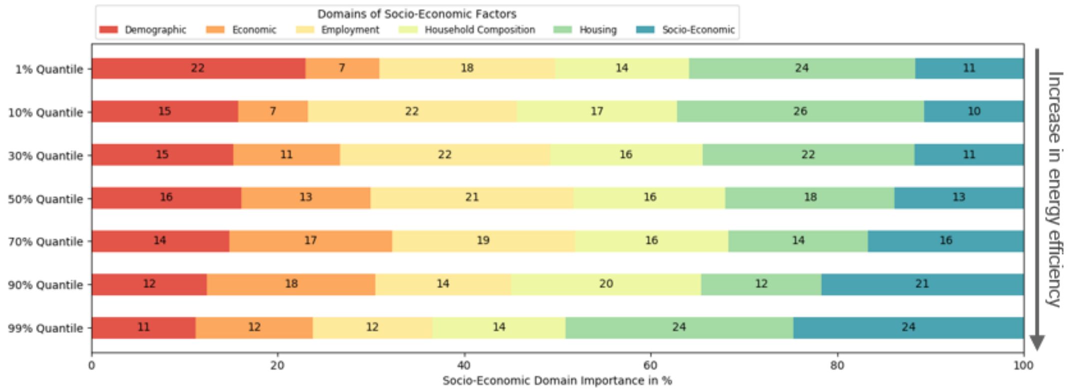

Figure 2. Comparison of the importance of the different socio-economic domains shows how the influence of the domains shifts with different levels of local energy efficiency

On the level of individual socio-economic factors, some more important factors impact regressions, e.g., the rurality of a region. Generally, factors from the domain "Employment" appear to be highly important. Further major influences are "share of vacancy", "living rent-free", "residents age above 60", and "travel to work". These findings allowed deriving policy implications to effectively increase the energy efficiency of residential buildings: First, there is strong evidence for local differences in energy efficiency and the residential building stock across England, Scotland, and Wales. Thus, policy instruments should be locally tailored to be most effective and might be even more effective on a more detailed, less aggregated level. Second, deriving archetypes of buildings support the prioritization of necessary retrofits for the residential building stock in a local authority and thus gives guidance on which instruments to implement. Third, policymakers should consider the local population with their respective socio-economic factors and the intended target in terms of current and future levels of energy efficiency when implementing policy measures to maximize the effect of resource allocation. Even for the same energetic retrofitting need in two areas, influencing socio-economic factors might differ. For instance, the Scottish rural local authority "South Ayrshire" and the London local authority "Islington"

[1] Note, that "socio-economic" is both an individual superordinate domain and the generic term for all factors. The naming of these superordinate domains and the assignment of each socio-economic factor originate from the census 2011. Consider that each superordinate domain includes a different number of factors.

require roof retrofitting. However, differences may arise from the availability of local skilled labor or the share of professionals working from home, in addition to material availability and constraints in the construction process. Fourth, for instance, a specific policy could aim to reduce the construction time in areas where many people work from home since disruption of life is an obstacle, which can be mitigated by shorter construction times (Caird et al., 2008). To this end, initiatives such as "Energiesprong" using prefabricated building facades, roof elements, and building services modules might help to increase the retrofit rate (Brown et al., 2019). Further, as travel time is longer and skilled labor is less available in rural areas, local policymakers should support traffic and accommodation for workers. In addition, education and training programs for craftsmen should be redesigned to meet local retrofitting needs with specific upgrade courses alongside basic nationwide training (Gram-Hanssen et al., 2018).

II.2. Identifying Residential Building Retrofitting Practices Using Explainable Artificial Intelligence

After Research Article #1 examined the impact of socio-economic factors on local energetic retrofitting needs - the building stocks' energy efficiency - the influence of various factors on the implementation of retrofits also needs to be analyzed. This can provide further essential insights for the design of policy instruments. However, a challenge in large-scale analyses of this kind is data availability. Either information on retrofitting measures carried out or time-series data (from EPCs) must be available to derive conducted retrofits. The low data availability, the high effort to extract the necessary information, and the necessary methodological procedures are possible reasons for the lack of such studies. Research Article #2, motivated by the suggestions in literature for the use of XAI in the building sector to derive insights about the relations of different parameters and variables (Golizadeh Akhlaghi et al., 2021), is dedicated to this topic. Building on Research Article #1, Research Article #2 investigates to what extent XAI approaches based on EPC, house price, and socio-economic data contribute to the derivation of policy implications for retrofitting behavior in residential buildings. Therefore, the data prepared in Research Article #1 is enriched with additional house price data of the residential building stock in England and Wales. Then, whether a building has been retrofitted and which measures have been carried out are extracted from the EPC data using a self-developed method. Supervised ML is applied to the datasets using an XGBoost (eXtreme Gradient Boosting) model to classify whether a building has been retrofitted or not before using SHapley Additive exPlanations values (SHAP) as an XAI technique to identify the key factors and relationships that influence this classification.

Figure 3 reports on the SHAP values of the top influencing factors on retrofitting with higher values indicating a more substantial influence. Positive SHAP values indicate that a retrofit has been carried out, while negative SHAP values indicate the opposite effect. Further information on SHAP values, their detailed analysis, and factor abbreviations can be found in the supplementary material. The most important factors represent a mixture of building properties (e.g., current heating costs, glazing proportion or wall and roof energy efficiency), economic properties (median and mean houses prices) and sociodemographic properties (e.g., a population from age 0 to 15, employment rate, Gross Disposable Household Income (GDHI)).

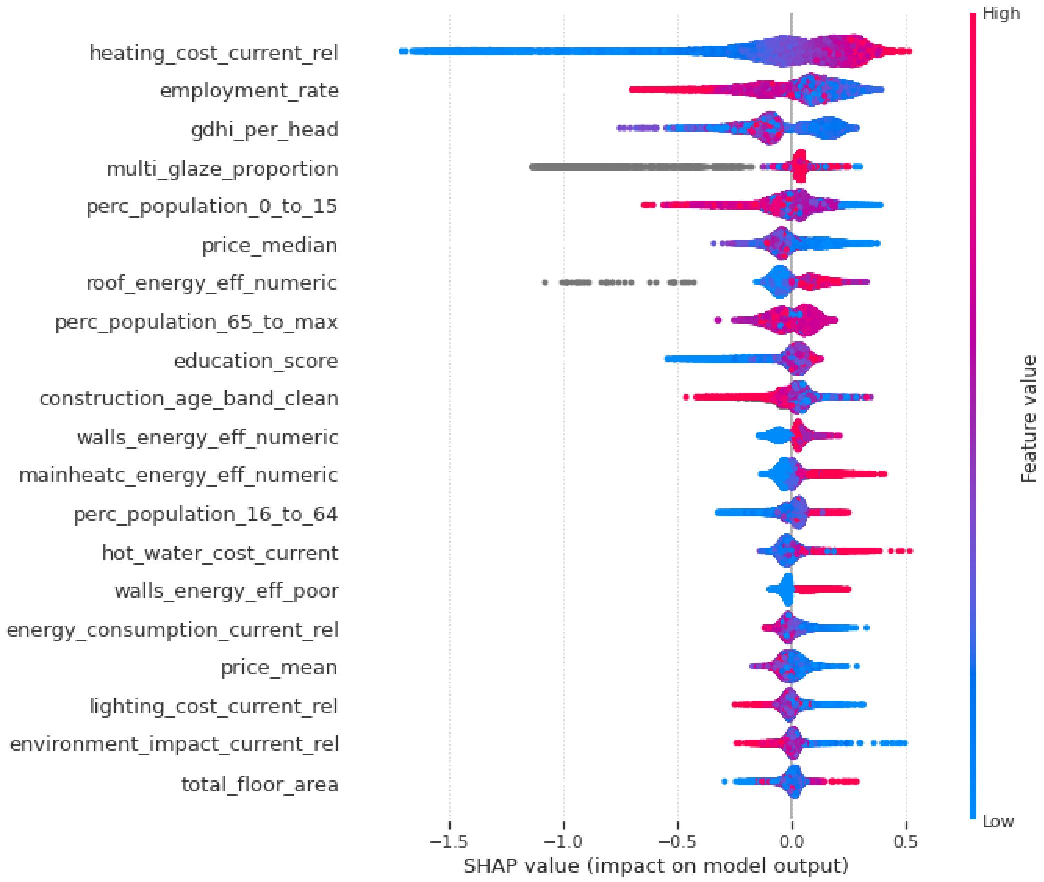

Figure 3. SHAP values for top influencing factors for and against retrofitting

The analysis succeeds in demonstrating very clearly which factors influence the implementation of retrofits and how suitable policy implications can be derived. Contributions and identified policy implications are as follows. First, combining supervised ML with approaches of XAI allows to corroborate findings previously obtained in qualitative or small-scale studies with a quantitative study using real-world data and identify additional influencing factors. Second, a method for extracting building retrofits from the UK EPC data that can be reproducibly applied in further studies is developed. In addition, the method can be used to extract and analyze changes in buildings over time from EPCs. Third, existing studies on the influence of house prices on retrofit behaviors can be confirmed. Since higher house prices lead to a lower likelihood of retrofits, making at least some comparatively low-cost retrofit measures mandatory for new rentals and sales in local authorities with high average house prices (e.g., London) seems appropriate. Further, green mortgages offering the customer beneficial mortgaging conditions might improve retrofit rates in high-price areas. Fourth, since families with children aged 15 or younger are less likely to carry out retrofits, special programs for families with children might be helpful considering their specific needs. These programs should be characterized by financial support and provide transparent information and quick, straightforward help in implementing retrofits minimizing burdens on families. Local authorities where the " Better Homes for Yorkshire" initiative was effective with corresponding characteristics showed a high number of retrofits, so the initiative might be replicated by other regions. Fifth, since low energy efficiency of walls and roofs is an important criterion for energy efficiency and has a positive impact on retrofits, incentivizing retrofits for buildings with EPCs, that exhibit poor levels of energy efficiency in walls and roofs might be suitable. Moreover, the abundance of problems related to the wall and roof efficiency evaluation process must be considered, which may require the introduction of higher quality standards in the preparation of EPCs. Sixth, with fuel poverty being a widespread phenomenon in England and Wales, retrofit-related carbon taxes are sensible. For higher-income households with a high energy consumption raising retrofitting-related CO_2 taxes would be an incentive to retrofit. No taxes could be levied on low-income households, and a cumulative subsidy could be granted depending on the heating costs for each year. This approach could be implemented through Her Majesty Revenue & Customs (UK Government department, responsible for collecting taxes) without much additional effort, as it already collects income taxes and is already aware of each household's income. Thus, an energy bill is the only additional document needed to calculate an additional CO_2 tax or retrofit grant. Summarizing, the findings show that existing studies can be confirmed with the help of data-driven approaches and that policy measures already found in individual cases should be rolled out broadly in the UK to increase retrofits in the domestic sector to achieve climate goals.

III. Risk and Inaccurate Building Energy Performance Predictions as Barriers for Retrofitting

III.1. Understanding the Risk Perception of Energy Efficiency Investments: Investment Perspective vs. Energy Bill Perspective

Achtnicht and Madlener (2014) attribute the failure to meet climate goals and low retrofit rates, i.e., the failure of current policy instruments, to a lack of understanding of individual investment decisions. Research Article #3, therefore, aims to contribute to a better understanding of investment decision-making in the field of energy efficiency. Energy efficiency investments are defined as investments resulting in reduced energy demand (Häckel, Pfosser and Tränkler, 2017; Ahlrichs et al., 2020). Thus, upfront investments are followed by (uncertain) cash flows, i.e., a reduced energy bill. Research Article #3 divides existing literature on investment decision-making behavior considering risk connected to energy efficiency in two streams and ends up in either one of two contrary conclusions. One stream of literature sees energy efficiency investments as projects with upfront investment and uncertain cash flows resulting from increased energy efficiency (Häckel, Pfosser and Tränkler, 2017). Here, literature defines cash flows as the resulting energy bill savings and argues that the uncertainty of these future cash flows is a central barrier to investment that prevents decision-makers from carrying out economically and ecologically beneficial energy efficiency measures due to their risk-aversion (Hirst and Brown, 1990; Mills, 2003; Farsi, 2010). These studies model energy efficiency measures as investments associated with financial risk of future cash flows. As future energy prices, among other sources of risk, are uncertain, investment in energy efficiency typically leads to volatile energy bill savings. To avoid this perceived risk, decision-makers invest less in energy efficiency. Research Article #3 summarizes this stream of literature under the *investment perspective.* The second stream of literature models energy efficiency measures as a mitigation of the uncertainty of future cash flows – future energy bill cost streams. Thompson (1997) was among the first to point out that energy efficiency is not a risky investment to invest in or not, but rather that a decision-maker faces the choice between two uncertain future cost streams. As Naumoff and Shipley (2007) illustrate, energy efficiency leads to a future cost stream with less uncertainty due to reduced energy price exposure and helps to reduce overall risk. This stream of literature represents the *energy bill perspective*. The differences between both perspectives in future cash flows, energy bill costs for the energy bill perspective and energy bill savings for the investment perspective, are illustrated in Figure 4. Simply, assuming a linear relation between the invested amount and energy saved, larger investments are followed by larger energy bill savings but also higher absolute volatility. Thus, the rationale in the investment perspective is that if I want to minimize risk, I minimize investment. Since larger investments simultaneously reduce the volatility of the remaining energy bill costs, the rationale in the energy bill perspective is to maximize the investments to minimize risk.

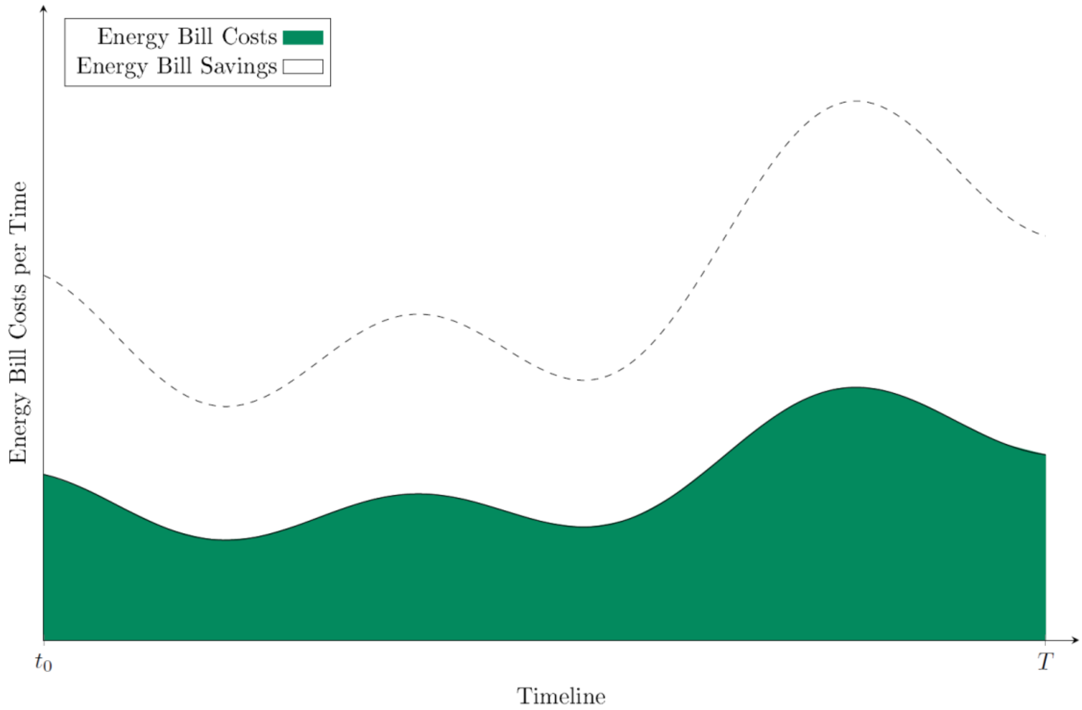

Figure 4. The different perspectives on risk: investment perspective (white area) vs. energy bill perspective (green area). Grey-dashed line for energy bill costs without and green line for energy bill costs with energy efficiency investment.

The two perspectives might give the impression that there exist two different types of risk connected to energy efficiency. However, as the sources of risk, e.g., uncertain energy prices, stay the same independent of the perspective, the two perspectives are not different types of objective risk but different perceptions of risk. The phenomenon of different perceptions of risk was, among others, analyzed by Slovic and Weber (2002). They pointed out that decision-makers use different models and assumptions to evaluate risk, leading to different perceptions of risk and behavior. Research Article #3 concludes that the two different streams in literature describe two different perceptions of risk, i.e., two different types of decision-makers, applying different models and assumptions impacting the effectiveness of policy instruments. To address the lack of understanding of investment decision-making for energy efficiency investments (Achtnicht and Madlener, 2014), Research Article #3 additionally illustrates with the help of Expected Utility Theory (EUT) (Bernoulli, 1954) the differences between both perspectives and their combination using a simple and understandable mathematical model with a Constant Absolute Risk Aversion utility function. Since categorizing decision-makers in either one of the two perspectives might not be sufficient, decision-makers accounting for both perspectives are analyzed. Consequently, the theoretical insights are validated with a Monte Carlo Simulation to predict the distribution of energy bill costs and savings after energetic retrofitting of a commercial building based on averaged data of German commercial buildings. Commercial buildings represent a suitable validation object, since decision-makers in a professional context tend to act more rationally than private decision-makers, and commercial buildings are the second largest energy consumer, accounting for 34% of the German building sector (Deutsche Energie-Agentur GmbH, 2021).

The theoretical and empirical analyses show how differently the two perspectives influence the decision-making for energy efficiency investments. Within the energy bill perspective, decision-makers invest much more in energy efficiency due to the mitigating effect on their perceived risk. Thereby, their expected utility grows with an increased investment amount. Contrarily, evaluating energy efficiency from an investment perspective results in a significantly lower optimal investment amount. A decision-maker integrating both perspectives in her/his decision has an optimal investment amount between the optima of the two stand-alone perspectives.

The research article's findings allow deriving two main implications for energy policy. First, the theoretical construct of the investment and energy bill perspective, at least in the context of rational decision-making, opens possibilities towards more sustainable investment behavior by promoting the energy bill perspective and convincing decision-makers that energy efficiency reduces the variance of their future energy bill. Naturally, this hypothesis that the energy bill perspective promotes investment requires real-world validation. Nevertheless, the potential for the theoretical considerations to enrich future information campaigns on energy efficiency by promoting the energy bill perspective and drawing attention to the risk mitigation potential of energy efficiency seems viable. Current subsidy programs and information campaigns (e.g., KfW (2021)) could elaborate on risk mitigation potential to set further effective incentives for sustainable investments. Second, the research article extends the current literature on influences of risk perception on energy efficiency investment decisions. The knowledge that decision-makers evaluate energy efficiency from different perspectives is important to evaluate, develop, and implement effective policy instruments. For instance, the effectiveness of traditional instruments like carbon taxes or subsidies depends on the risk perception of the decision-maker. Both instruments are designed to increase the expected financial return of energy efficiency investment. Nevertheless, decision-makers within the investment perspective demand an increased expected return of energy efficiency measures and decreased financial risk, resulting in potentially lower instrument effectiveness for these types of decision-makers. Above these implications for energy policy, the research's findings explain contradictions in existing literature. Potentially, differing results, which sparked discussions, align with either one of the two perspectives. Thus, important insights into decision-making for energy efficiency investments are added.

III.2. Risk Mitigating Effects of Political Instruments on Building Energy Retrofits

While Research Article #3 builds a solid basis for understanding the influence of risk on decision-making in energy efficiency investments, Research Article #4 investigates the risk-mitigating effect of different policy instruments on building energy retrofits. Therefore, a Risk-Integrated Thermal Energy Hub (RITEH) is developed utilizing the work by Fabrizio et al. (2010) and Mills et al. (2006) to address extrinsic and intrinsic factors driving risk (Wilde, 2014). The RITEH allows demonstrating how individuals evaluate thermal building retrofits based on financial risk and return. Given two retrofit options with the same expected financial return, rational decision makers will prefer the one with the lower financial risk. The RITEH is fitted with real-world data from 342 German one and two-family houses and calculates the mean and variance of the Net Present Value (NPV) of thermal building retrofits. Financial risk and return are evaluated within a two-dimensional mean-variance portrayal simultaneously. With this portrayal, estimating Pareto efficient thermal building retrofits and modeling the investment decision-making of rational acting individuals is possible. In a case study on an exemplary German two-story single-family house using the RITEH, retrofits with relatively high CO_2-equivalent Emission Savings (CES) are found to have higher financial risk and lower financial return for the homeowner what is in line with other studies (cf. Mills, 2003; Häckel et al., 2017). Consequently, political interventions are necessary to change this circumstance.

Additionally, the effect of *Pigouvian emission taxes* as a general regulatory instrument, *indirect subsidies* on investment costs, and *energy efficiency insurances* as technology-specific financial instruments on the attractiveness of environmentally friendly thermal building retrofits for investors are analyzed. Above that, comparative costs after implementing a specific instrument for either the policymaker (subsidy, insurance) or the homeowner (tax) are extracted. Findings illustrate that subsidies solely increased the financial return of a thermal building retrofit. Therefore, subsidies can save up to an additional 50% of CO_2 emissions. These findings support the presumption of Achtnicht and Madlener (2014) that subsidies, notwithstanding efficiency problems, can help promote investments in energy efficiency for the building sector. Additionally, it is demonstrated how energy efficiency insurance increases financial return and mitigates risk. By implementing insurance, policymakers would assume part of the risk inherent to thermal building retrofit investment. Therefore, energy efficiency insurance can influence the incentive of retrofitting efficiency and decrease emissions up to additional 35% for the example house analyzed. The results for energy efficiency insurance matches the results of Mills (2003) and Töppel and Tränkler (2019). They both found that energy efficiency insurances can positively affect investment decisions in energy efficiency by mitigating financial risk. Comparing subsidies and insurances leads to the conclusion that insurance is overall more efficient, compared to environmental impact and costs, but subsidies can be scaled up easily. Also, the article shows how an instrument without direct costs for the government, such as emission taxes, can help increase the allure of environmentally friendly retrofits. Nevertheless, CO_2 emission taxes must be sufficiently high to significantly change the decision-making regarding thermal building retrofits, which leads to higher costs for the homeowner. These findings are in line with the research team of Aasness et al. (1996) and Thonipara et al. (2019) who both found that a high emission tax causes “markedly different reductions in energy consumption” compared to lower taxes (Thonipara et al., 2019, p. 1166).

The research article’s results lead to multiple suggestions for policymakers. First, the results show an opposite pattern of environmental and financial benefits of energy efficiency investments. Policymakers must address this trade-off. Second, without any political intervention, private households cannot achieve current environmental policy targets. This is because of the high financial risk of thermal building retrofits combined with the loss aversion of investors. Therefore, it is not enough to consider only the estimated financial return of an energy efficiency investment for the design of political instruments. Risk must also be considered. Consequently, policymakers should consider supporting the development of innovative instruments like the proposed energy efficiency insurance that simultaneously reduce risk and increase return. Thus, resulting in higher investments in retrofits. Third, the case study shows how expensive it would be for policymakers to achieve a goal such as the German government's 2010 goal of reducing GHG emissions by 80% below 1990 levels by 2050 using only the instruments discussed[2]. Policymakers could consider the support of research for new technologies that are environmentally friendly and profitable for the homeowner concurrently. Fourth, the article shows how emission taxes that have an appreciable impact on environmental investments would burden private homeowners. In this case study, a CO_2 tax that leads to expected CES of 50% would result in additional costs for the homeowner at 1,000€ per year. Therefore, policymakers should reconsider how they could exonerate the population after implementing high CO_2 taxes. Promising ideas on how to do this were discussed by Diekmann (2019).

Based on the recent efforts in environmental policy, the German government announced a new climate protection program (Klimaschutzprogramm 2030) in October 2019 (Federal Government Germany, 2019). This package's two key points are especially interesting to Research Article #4. First, the German government announced that they plan to implement a CO_2 emission tax of 25€ per CO_2 ton by 2021 and increase the tax to a maximum of 60€ in the following years. The results of this and previous works (cf. Thonipara et al., 2019) emphasize that this emission tax is far too low to significantly impact investment decisions for private households since emission taxes would need to exceed 140€ per CO_2 ton. Second, Germany wants to implement subsidies for new heating systems at 40%.[3] The study results show that this could be a helpful instrument to promote environmental investment in thermal building retrofits. Nevertheless, energy efficiency insurance would have a more cost-effective impact.

[2] Note that the goal of reducing GHG emissions in Germany by 80% below 1990 levels by 2050 has now been tightened in the Climate Protection Act (Klimaschutzgesetz).

[3] For the sake of completeness, it should be mentioned that the regulations adopted in October 2019 have been tightened during the course of writing this doctoral thesis. Regarding the CO2 emission tax, the tax is to rise steadily until 2025 and a price corridor of at least 55 and at most 65 euros is planned from 2026 (Federal Government Germany, 2021). For the replacement of oil heating systems that use only renewable energies, the current subsidy rate is 45% and for oil heating systems that use both renewable energies and natural gas, the subsidy rate is 40% (Federal Office for Economic Affairs and Export Control, 2020).

III.3. The Potential of Data-Driven Approaches for Accurate Building Energy Performance Predictions

BEP prediction, especially its accuracy, plays a central role in retrofit decisions. EPCs, issued by qualified auditors, are intended to increase the retrofit rate by providing general information about buildings, their current BEP and BEP after possible retrofit measures (Arcipowska et al., 2014a). To achieve its full effect, accurate prediction of the BEP is important to decide on purposeful retrofit measures, as uncertainty and incomplete information are substantial investment barriers (Amecke, 2012). However, today's most frequently used and by law prescribed EQMs are strongly discussed in the research community, as they exhibit low prediction accuracy (Hardy and Glew, 2019). The prescribed engineering EQM is based on physical laws to calculate thermal dynamics and energy behavior (Zhao and Magoulès, 2012), requiring detailed information on building components gathered by auditors during on-site inspections (Arcipowska et al., 2014a). If the input data quality is low, e.g., because the insulation materials are unknown and cannot be determined with reasonable effort, the result will also be erroneous.

Data-driven EQMs were introduced in research to enhance the prediction accuracy and obtained promising results in preliminary studies (Sutherland, 2020). They learn underlying dependency structures from available data without relying on expert knowledge of building physics or precise information on building components (Amasyali and El-Gohary, 2018). This allows data-driven EQMs to potentially overcome the shortcomings of engineering EQMs. However, there is a lack of studies on data-driven EQMs in residential buildings considering heating energy focusing on long-term (annual) energy prediction, as required for EPCs (Amasyali and El-Gohary, 2018). Furthermore, most studies are based on simulated building and energy data, limiting their practical applicability and the validity of the findings (Wei et al., 2018). Therefore, it is unclear whether data-driven methods can outperform the engineering EQM concerning the annual BEP prediction of residential buildings necessary for EPCs. Moreover, if so, it is unclear which data-driven EQMs are particularly suited. Thus, for full comparability and transparency of the algorithms' performance in practice, Research Article #4 investigates which EQM yields the highest accuracy for predicting the BEP of real-world residential single- and two-family buildings in Germany.

Therefore, several ML algorithms – Artificial Neural Network (ANN), D-vine copula quantile regression, Extreme Gradient Boosting (XGB), Random Forest (RF), and Support Vector Regression (SVR) – are implemented and tuned on an extensive first dataset containing 25,000 real-world single and two-family buildings in Germany (see Figure 5). The output accuracy (predictive power) is then calculated by predicting the BEP of 345 additional buildings from a second dataset and comparing the prediction with the actual metered energy consumption. This second dataset was gathered by qualified energy auditors and also encompasses the BEP stated in the EPCs based on the prescribed engineering

EQM, which allows comparing the data-driven EQMs to the engineering EQM. To ensure robust results and comply with state-of-the-art ML practices, benchmarking the ML algorithms against each other in-depth is based on nested cross-validation on both building datasets. By stratifying the Performance Evaluation Measures (PEM) based on a third dataset containing information on the German building stock, representativeness is ensured.

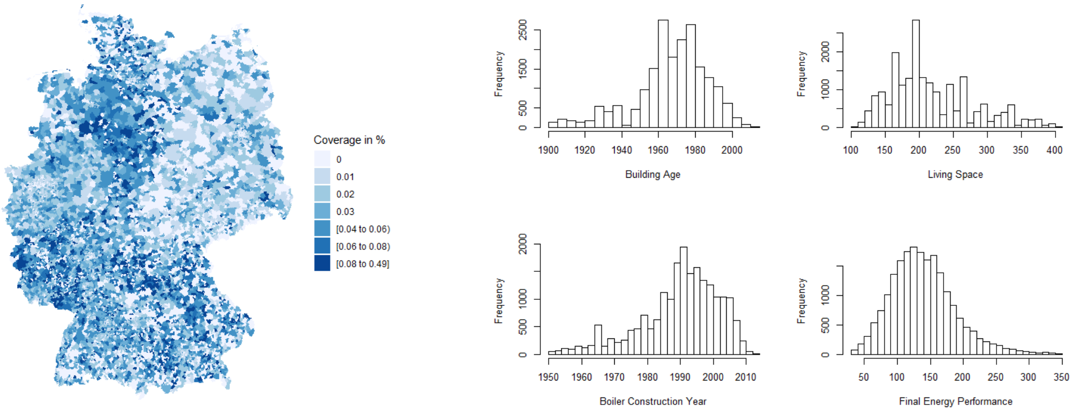

Figure 5. Descriptive statistics for the preprocessed dataset containing 25,000 real-world single- and two-family buildings in Germany

The results provide strong evidence that the data-driven EQMs outperform the engineering EQM by a large margin, reducing the prediction error by almost 50% (see Figure 6). Further, the results show that the energy performance gap generally holds for single- and two-family buildings in Germany with approximately the expected values for the energy performance gap based on literature. However, the analyses do not confirm previous findings on data-driven EQMs in literature that ANN and SVR have generally better prediction accuracy for BEP than less complex ML algorithms like RF (Amasyali and El-Gohary, 2018).

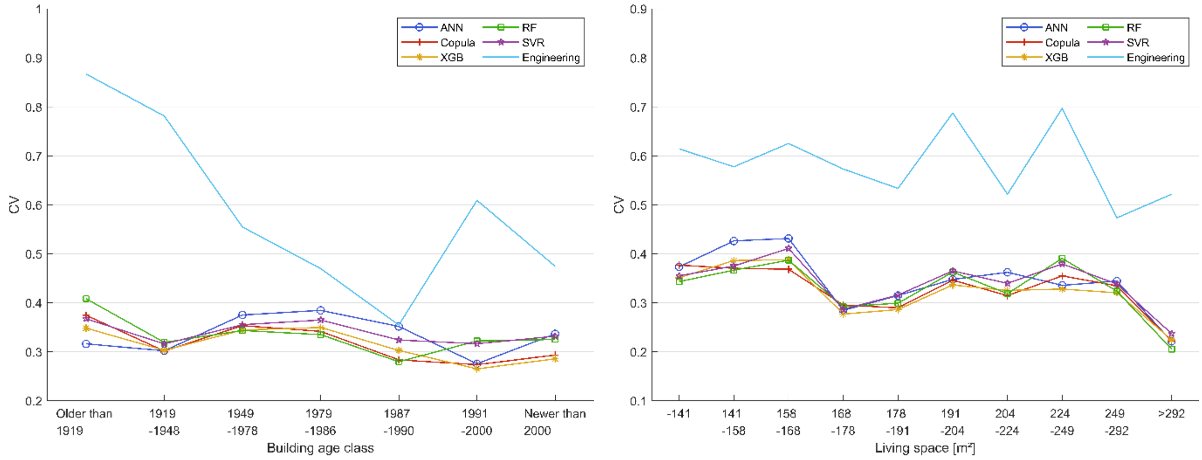

Figure 6. Coefficient of Variation as a performance measure for the different Energy Quantification Methods for instantiations of the variables building age on the left-hand side, aggregated into building age classes, and living space on the right-hand side, aggregated into living space bins

Instead, XGB exhibits the highest prediction accuracy for most analyses conducted, closely followed by SVR and RF. On the other hand, ANN performs worst to second-worst among the tested data-driven EQMs. However, the differences in prediction accuracy are slight, and the standard deviations indicate that these results should be treated with caution. Consequently, it cannot be argued that one specific data-driven EQM dominates all others in general for this task. Nonetheless, this supports that each application requires a specifically designed EQM to reach the highest accuracy and that there is no strictly dominant EQM (Kaymakci et al., 2021; Mosavi et al., 2019).

The article's findings lead to several managerial and policy implications. First, they provide clear guidelines for policymakers. The current low-carbon transition paths still require higher retrofit rates for residential buildings to reach the climate goals. Therefore, revising the current legislation to allow data-driven EQMs instead of the prescribed engineering EQM with significantly worse prediction accuracy seems appropriate. This potentially levers the residential building retrofit rate by decreasing the uncertainty of energy efficiency measures, thereby removing investment barriers and contributing to achieving the climate goals as identified in Research Articles #3 and #4. Two different applications are conceivable at present, either the direct replacement of the engineering EQM or the complementary application used for transitional quality assurance of the engineering EQM to check for outliers or incorrect data. The verification could be automated and thus be realized cost-efficiently and without human involvement. The quality assurance can be rolled out nationwide, increasing confidence in the EPC, thus offering a more reliable foundation for decision-making. Potential challenges are the acceptance and ensured quality of the underlying models. Homeowners may perceive unfair treatment if EPCs depicting low energy efficiency are issued based on calculation methods that are not or hardly comprehensible such as black-box approaches, as this reduces the resale value of the houses (see also Section III.4). When putting data-driven EQMs into a use case perspective, a distinction must be made between EPCs for existing and new buildings. Data-driven EQMs learn from available data, limiting their suitability for creating EPCs for new buildings. Since the construction rate in Germany is comparatively low and the energy-saving potentials in existing buildings are much more remarkable, as well as the determination of consumption is more costly and error-prone, the focus should be placed on this use case (Deutsche Energie-Agentur GmbH, 2016). Second, it is suggested to use data-driven EQMs for other applications, such as asset management, city planning or insurance, to enhance their business models with more economic decision-making, minimization of risk, and higher profits. The energy efficiency evaluation of buildings is a central element in many areas and can be decisive for the economic success of companies (Bozorgi, 2015). Cost-efficient information gathering is particularly relevant for the initial energy evaluation of real estate if EPCs are not yet at hand, as energy-efficient buildings yield higher returns and higher rents than energy-inefficient buildings (Cajias and Piazolo, 2013). Insurance companies could enhance claim prediction models, or asset management companies could optimize their portfolios with data-driven investment strategies. However, both should be extremely careful in the implementation since miscalculations in investment portfolios are comparatively worse than miscalculations in EPCs.

III.4. Unblackboxing Data-Driven Approaches for Building Energy Performance Predictions Using Explainable Artificial Intelligence

Even though, as analyzed in Research Article #5, data-driven EQMs exhibit considerable gains in prediction accuracy compared to engineering EQMs, they possess one drawback. Data-driven EQMs, also referred to as black-box models, suffer from the drawback that the mechanisms behind the predictions that are important for increasing trust and accountability are (often) not clear (Mohseni et al., 2018). So far, most studies focused on established ML algorithms, e.g., ANN, SVR, Multiple Linear Regression (MLR), or XGB, concentrating on prediction performance and computational efficacy without considering XAI (Amasyali and El-Gohary, 2018; Arjunan et al., 2020; Wei et al., 2018). XAI refers to methods and techniques to generate more explainable models that human users can understand, appropriately trust, and derive implications from while maintaining a high level of prediction performance (Barredo Arrieta et al., 2020). Therefore, XAI holds significant potential for predicting BEP, enabling occupants to follow and understand the EQMs applied. For experts such as energy consultants, the importance and influence of several building characteristics on the BEP can be demonstrated in a comprehensible way. In addition, findings from XAI can enhance engineering EQMs by delivering insights from real-world data. To analyze these promised benefits, Research Article #6 discovers the potential of the novel algorithm named QLattice to achieving the same BEP prediction performance compared to established data-driven EQMs while simultaneously increasing explainability. The QLattice, inspired by Richard Feynman’s path integrals, provides simple mathematical equations to solve classification and regression tasks (Broløs et al., 2021; Wilstup and Cave, 2021).

To this end, building on Research Article #5, the established ML algorithms ANN, SVR, XGB, and MLR are compared with the QLattice regarding prediction performance, computational times, and explainability in a case study. The results show that the QLattice achieves good prediction performance, albeit being slightly less accurate than the established black-box models, and performs best in prediction time, although exhibiting relatively long training times. In terms of explainability, the results obtained by applying post-hoc techniques to the established ML algorithms to determine variable importance are mostly consistent with the QLattice. Additionally, due to the QLattice’s transparent model structure and simplicity by design, the interaction of several variables can be derived without additional analysis allowing to derive further insights. This concludes that the QLattice is suitable for predicting the final energy performance of residential buildings and proves to be a viable option by combining ease of use, high prediction performance, and explainability by design.

In addition, several implications for research and practice regarding the QLattice's prediction performance and explainability can be derived. First, the QLattice may serve to improve existing white-box and grey-box models, thereby linking the knowledge domains of engineers and data scientists. Especially for grey-box models, the need for interdisciplinary knowledge about both white-box and black-box models is considered a challenge (Wei et al., 2018). The QLattice could be used to bridge this gap by allowing comprehensible insights obtained with the QLattice about important variables and their complex interactions to be interpreted by engineers and used to improve white-box models. Second, the QLattice's relative ease of use makes it suitable for newcomers to research on data-driven EQMs. In contrast to established algorithms, less effort must be put into data preprocessing, which means that initial results can be achieved more quickly and are less error-prone. This can effectively reduce entry barriers and enable the application of data-driven EQMs to a broader target audience. Third, the transparent structure of the QLattice increases trust and understanding of data-driven EQMs, reducing uncertainty. Consequently, more energetic retrofits with higher energy savings and emission reductions might be achieved. Fourth, the formula derived from the QLattice model enables a simple implementation and calculation of the BEP, which can be understood even by non-experts. This could serve as an online service that allows owners or tenants to initially assess their energy consumption and compare their building with others. Fifth, the results imply that more focus should be placed on the application of various XAI techniques in ML algorithms, as the sole focus on prediction performance neglects potentials of data-based knowledge gain.

IV. Conclusion

IV.1. Summary

The building sector offers great potential to achieve the climate goals and face human-induced climate change. Since the current building stock also will account for the largest share of energy consumption of buildings in the future due to low new construction rates, a successful heat transition and extensive retrofitting are crucial (Fylan et al., 2016; Stanica et al., 2021). Although researchers are intensively investigating various aspects of retrofitting and the heat transition to design efficient policy instruments, nations struggle to meet climate goals by increasing retrofit rates. Addressing calls and research gaps in literature, this doctoral thesis focusses on two aspects of barriers against retrofitting and energy efficiency, allowing to derive managerial and policy implications. First, the analysis of general factors influencing retrofitting practices at the regional level. Second, the investigation of risk in general and inaccurate predictions of BEP in particular as barriers to individual retrofit decisions.

On the first aspect, Section II offers insights into factors influencing energy efficiency and retrofitting practices on a regional level in the residential building stock using the example of UK data, for evaluating data-driven approaches of unsupervised and supervised ML. Applying unsupervised ML methods on publicly available EPC data, additional house price data, and sociodemographic data, Research Article #1 finds strong evidence for regional differences in building energy efficiency and discovers that factors associated to employment mainly affect buildings with lower energy efficiency whereas the impact on more efficient buildings is limited. In addition, initiatives such as "Energiesprong", which use prefabricated building facades, roof elements, and home automation modules, could help shorten construction time for retrofits in areas where many people work from home and find life disruption a barrier to retrofitting. Upon this, combining supervised ML and XAI Research Article #2 identifies factors influencing retrofitting practices. Current heating costs, the regional employment rate, the mean regional gross disposable household income, and the share of people younger than 15 years in a region are among the top influencing factors. The results confirm the findings of previous qualitative or small-scale studies and lead to the conclusion that at least some comparatively low-cost retrofit measures should be mandatory for new rentals and sales in communities with high average house prices, since higher house prices reduce the likelihood of retrofits. Further, retrofitting-related CO_2 taxes might be reasonable and easy to implement. While higher-income households with high energy consumption would be incentivized to retrofit by charging retrofit-related CO_2 taxes, lower-income households could be exempt from taxes and receive a cumulative subsidy based on heating costs for each year. Findings from both research articles show the potential of data-driven approaches for targeted policy implications on the regional level to increase residential building stock energy efficiency.

On the second aspect, Section III provides insights on risk in general and inaccurate predictions of BEP in particular as barriers to individual retrofit decisions. Shifting the focus from regional factors previously examined to individual retrofit decisions enables further insights. Research Article #3 lays the theoretical foundation for the influence of risk perception on individual retrofit decisions. Based on a theoretical model and a case study, the results show that risk-averse decision-makers invest more in energy efficiency when evaluating from the energy bill perspective instead of the investment perspective. Thus, promoting the energy bill perspective and convincing decision-makers that energy efficiency reduces the variance of their future energy bill opens possibilities towards more sustainable investment behavior. Building on this, Research Article #4 examines the impact of policy instruments of risk and return on investment for retrofit measures. The findings reveal the effectiveness of energy efficiency insurances in mitigating risk by promoting environmentally friendlier investments relatively cost-efficient compared to subsidies. Further, findings indicate that current emission taxes are far too low and need to exceed 140€ per CO_2 ton to significantly influence investment decisions. Research Article #5 analyzes the potential of data-driven approaches for BEP predictions to reduce uncertainty in retrofit decisions. The results, tested for robustness and systematic bias, show that data-driven approaches exceed the currently by law prescribed engineering method (in Germany) by almost 50% in prediction accuracy. Given this, revising the current legislation seems appropriate. Also, asset managers and insurance companies could benefit from data-driven EQMs to reduce financial risk and cut expenses. Regarding the disadvantage often associated with data-driven EQMs of being black-box approaches and thus untrustworthy, Research Article #6 shows that there are data-driven EQMs that are both explainable and accurate. The novel QLattice algorithm achieves good prediction performance, albeit somewhat less accurate than established black-box models, and that its transparent model structure and simple design allow further insights into the interaction and influence of multiple variables to be derived without additional analysis. Thus, data-driven EQMs can provide deeper insights into factors influencing BEP in addition to high prediction accuracy.

Summarizing, this doctoral thesis emphasizes the potential of data-driven approaches in research on aspects for a successful heating transition in the building sector. Data-driven approaches are suitable for conceptual and analytical tasks, as Section II demonstrated, and for operational tasks such as BEP prediction for EPCs. By combining data-driven approaches with risk modeling, further potential can be leveraged. This and the multiple analyses in this doctoral thesis also indicate that the heat transition might not be solved with a single policy instrument or solution but rather with a broad mix of instruments to provide holistic incentives to achieve climate goals.

IV.2. Limitations and Future Research

Naturally, as any research endeavor, the results of this doctoral thesis have some limitations but likewise give rise to new research potentials. Rather than discussing the limitations and prospects for further research of each research article, the following section presents overarching limitations and prospects for further research of this doctoral thesis. Further details on the research articles' individual limitations can be found in the supplementary material.

The first and central limiting factor is the quality and availability of the underlying data. All research articles are based on data to a certain extent, and Research Articles #3 and #4 considered data for the case studies conducted. More precisely, regarding data quality, a significant number of research papers have revealed quality problems concerning EPCs because, especially for older buildings, not all building characteristics have been recorded. Thus, EPCs are, to a certain degree, subjective since they rely on the conscientiousness of the energy advisor (Hardy and Glew, 2019). The same holds for the datasets used in Research Articles #5 and #6 since several important building characteristics were missing in the dataset, e.g., upper floor insulation and basement insulation. Thus, some assumptions were made to specify several variables and building characteristics following current norms. Moreover, for the rectification of weather effects, the mean of the climate factor for each weather station over the period the datasets were gathered was used because the datasets did not contain the exact year of data collection but a span of seven years. These assumptions and simplifications could lead to minor deviations in the articles' results. More importantly, no information on socio-economic factors (for Research Articles #5 and #6) or occupant behavior was available, which leaves a large margin of variance in the data unexplained. In terms of data availability, this doctoral thesis is limited to the analyzed geographical areas and focuses on residential buildings. Future research may relax this focus, incorporating other geographical areas with different characteristics of buildings, climate conditions, and other normative frameworks for EPC calculation to assess whether the findings are generalizable for these areas and circumstances. Summarizing data limitations, further research is necessary, as current research is scarce. This most likely is due to scarce publicly available and processable data as highlighted in literature (Carpino et al., 2019). Since there are mostly state-regulated institutions with the necessary database, it is evident that policymakers enter into cooperation with scientific institutions. A sufficiently large and high-quality database is essential to obtain reliable and more generally valid results from which to derive meaningful long-term political incentive mechanisms to curb climate change. In the same course of the structured recording of large quantities of quality-assured data, data on occupant behavior should be recorded. This enables analyzing the causes of the significant differences between measured and calculated EPCs and between the different EQMs. More precise statements can be made about energy consumption and savings after potential retrofit measures based on the obtained knowledge. This, in turn enables investment decisions to be made on a sound basis while at the same time reducing barriers to energy efficiency investments by minimizing the investment risk. Going hand in hand with the availability of data, Research Articles #1 and #2 are limited by using aggregated information of local authorities for the socio-economic factors since granular data with information about residents is not available. Even if these sensible data might harm privacy concerns, future research might use socio-economic data at a more granular level, preferably at the household level, to obtain a deeper understanding of socio-economic drivers and barriers to energy efficiency. This allows identifying the influence of socio-economic factors on individual behavior and decision-making for or against retrofitting. In addition, the factors investigated in research articles #1, #2, #5, and #6 that influence energy efficiency or BEP prediction do not allow for a statement about causality. Therefore, the results should be interpreted with caution, as correlation does not imply causality. Future studies might apply first ML approaches to discover aspects of causality to derive and design even more targeted policy implications. Approaches such as the counterfactuals proposed by Pearl et al. (2019), which build on retrospective reasoning, may prove helpful.

Second, as the field of ML is growing rapidly, the articles' findings are only valid at present and may have to be examined again in the future. Thus, in future research, further algorithms, different hyperparameter tuning techniques as evolutionary optimization instead of Bayesian optimization (Hutter et al., 2019), or other model-agnostic approaches to post-hoc explainability, such as SHAP or Local Interpretable Model-Agnostic Explanations (LIME), to explain data-driven EQMs that are not transparent by design can be investigated (Barredo Arrieta et al., 2020). With the help of such investigations, further insights can be obtained, and optimization potentials can be raised to enhance BEP predictions. In addition, with the increasing availability of data across the globe, federated learning might be a suitable approach to take advantage of decentralized datasets for large-scale ML.

Third, to date, research has remarkably only examined whether and to what extent data-driven methods perform better than engineering-based methods in terms of BEP predictive accuracy (Tsanas and Xifara, 2012; Wenninger and Wiethe, 2021). However, the reasons and cause-effect relationships leading to the frequently observed and reported better prediction accuracy of data-driven methods are less clear. To identify further potential improvements for both, it is essential to capture the mechanisms behind both methods embedded in the real-world process of issuing EPCs outside the laboratory. Therefore, developing and discussing a grounded and testable theory to identify reasons and causes why data-driven methods yield better prediction performance might be subject to future studies.

Fourth, Research Article #5 focused on comparing and enhancing the BEP prediction accuracy of various EQMs. Although there is plenty of literature on the BEP prediction performance of different EQMs, the resulting impact of the prediction performance gain, i.e., the relationship to the retrofit rate and the CO_2 emission reduction potential, has not yet been determined. Therefore, the question arises to what extent BEP prediction performance affects the retrofit rate and the CO_2 emissions released in the residential building sector. Against the backdrop of limited (financial) resources, this question is important, especially on a national or even international level, so that the appropriate course can be set for the further development of EQMs and EPCs in particular. Future research may analyze this relationship within empirical or simulative studies. This allows determining the CO_2-emission reduction potential of changing regulatory frameworks and altering the legally prescribed EQMs.

Fifth, in Research Article #3, it was shown with the help of a mathematical model that the perspective under which risk is considered in energy efficiency investments has a decisive influence. Since the article focuses on describing the decision-making process and does not advise how an optimal evaluation method could be based on the two perspectives, these descriptive analyses can be a good foundation for further normative studies. E.g., surveys could be used to empirically validate the theoretical findings and investigate how energy efficiency decision-making can be influenced from the outside or how a new evaluation method can be found.

Sixth, Research Articles # 5 and #6 investigated data-driven EQMs from a prediction performance perspective. Thereby, aspects such as the often error-prone step of data collection done today by qualified auditors within on-site inspections and the general design of a data-driven EQM involving its entire process were neglected. Thus, there exceeds a gap between the theoretical findings and practical implementation. Future studies might address this research vacuum and analyze how to analyze systematically selected building variables that qualified auditors, or even occupants can reliably collect and that have high predictive power for more accurate BEP predictions. Here, findings from Research Articles #5 and #6 on variable importance may serve as a good starting point to identify variables and building parameters with high predictive power.

Seventh, this doctoral thesis focused on the application of ML approaches for energy efficiency aspects. However, on the way to achieving the climate goals, the necessary expansion of renewable energies for power generation must also be considered, which poses major challenges for power grids due to the volatile power supply (Halbrügge et al., 2021; Lindner et al., 2022). Demand side management offers a potential solution to these challenges by increasing energy flexibility on the demand side, such as in buildings. Future research might apply data-driven methods also for the analysis of demand side management, i.e., to identify flexibility potential in buildings, or the prediction of future energy consumption to optimize the use of energy storages.

In sum, there are various levers to address the necessary needs for a successful heat transition in the building sector. As a result, research, practice, and policymakers will face interdisciplinary questions towards meeting climate goals.

IV.3. Acknowledgement of Previous and Related Work

In all research projects, I worked closely with colleagues from the Project Group Business & Information Systems Engineering of the Fraunhofer Institute for Applied Information Technology (FIT), the Research Center Finance & Information Management (FIM) in Augsburg and Bayreuth, the Fraunhofer Institute for Manufacturing Engineering and Automation IPA, the Institute for Energy Efficiency in Production (EEP) of the University of Stuttgart, and the Institute of Production Management, Technology and Machine Tools (PTW) of the Technical University of Darmstadt. Therefore, I present how my work builds on previous and related work at the various institutes and beyond in the following paragraphs.

Previous work of Baltuttis et al. (2019), Töppel and Tränkler (2019), and Häckel et al. (2017) formed a viable basis for Research Articles #3 and #4 discussing various aspects of risk on retrofit decision-making. For Research Article #5, the work of Kratsch et al. (2021), Kaymakci et al. (2021), and Niemierko et al. (2019), who address related topics on data-driven prediction and AI systems, were appropriate sources in terms of methodologically sound approaches and technical details on ML. Moreover, Arjunan et al. (2020) and Miller (2019) motivated Research Article #6 by concluding that more research is necessary to release the full potential of data-driven models in the building energy sector. Finally, Research Articles #1 and #2 were motivated twofold. From a methodological perspective, Athey (2017) encouraged the use of AI beyond plain predictions to derive data-driven policy implications. The thematic motivation that drives Research Articles #1 and #2 comes from the work of Tziogas et al. (2021), Magnani et al. (2020), and Gómez-Navarro et al. (2021) in the Energy Policy Journal, which indicates a trend toward data-driven research to analyze circumstances and barriers to implementing energetic retrofits. This doctoral thesis contributes to this trend and extends the work of Pasichnyi et al. (2019), who proposed to use EPC databases for data-driven urban energy policy instruments.

With this thesis, I hope to encourage researchers, practitioners, and policymakers to use the potential of data-driven methods for effective and efficient policymaking to progress towards climate goals set.

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VI. Appendix

VI.1. Research Articles Relevant to this Doctoral Thesis

Research Article #1: Impact of Socio-Economic Factors on Local Energetic Retrofitting Needs - A Data Analytics Approach

Ahlrichs, J.; Wenninger, S.; Wiethe, C.; Häckel, B. (2022). „Impact of Socio-Economic Factors on Local Energetic Retrofitting Needs - A Data Analytics Approach". In: *Energy Policy*. DOI: 10.1016/j.enpol.2021.112646.

(VHB-JQ3 Category: B)

Research Article #2: Data-Driven Policy Implications - Evidence for Residential Building Retrofitting Practices Using Explainable AI

Wenninger, S.; Karnebogen, P.; Lehmann, S.; Menzinger, T.; Reckstadt, M. (2021). „Data-Driven Policy Implications - Evidence for Residential Building Retrofitting Practices Using Explainable AI". Submitted.

Research Article #3: Understanding the Risk Perception of Energy Efficiency Investments: Investment Perspective vs. Energy Bill Perspective

Rockstuhl, S.; Wenninger, S.; Wiethe, C.; Häckel, B. (2021). „Understanding the Risk Perception of Energy Efficiency Investments: Investment Perspective vs. Energy Bill Perspective". In: *Energy Policy*. DOI: 10.1016/j.enpol.2021.112616

(VHB-JQ3 Category: B)

Research Article #4: The Impact of Political Instruments on Building Energy Retrofits: A Risk-Integrated Thermal Energy Hub Approach

Ahlrichs, J.; Rockstuhl, S.; Tränkler, T.; Wenninger, S. (2020). „The Impact of Political Instruments on Building Energy Retrofits: A Risk-Integrated Thermal Energy Hub Approach". In: *Energy Policy*. DOI: 10.1016/j.enpol.2020.111851

(VHB-JQ3 Category: B)

Research Article #5: Benchmarking Energy Quantification Methods to Predict Heating Energy Performance of Residential Buildings in Germany

Wenninger, S.; Wiethe, C. (2021). "Benchmarking Energy Quantification Methods to Predict Heating Energy Performance of Residential Buildings in Germany". In: *Business & Information Systems Engineering*. DOI: 10.1007/s12599-021-00691-2

(VHB-JQ3 Category: B)

Research Article #6: Explainable Long-Term Building Energy Consumption Prediction Using QLattice

Wenninger, S.; Kaymakci, C.; Wiethe, C. (2022). „Explainable Long-Term Building Energy Consumption Prediction Using QLattice”. In: *Applied Energy*. DOI: 10.1016/j.apenergy.2021.118300

(VHB-JQ3 Category: -; Impact Factor: 9.746; 5-Year Impact Factor: 9.953)

I also co-authored the further book chapters, white papers, and research papers throughout the dissertation, which are not part of this doctoral thesis. Articles published up to the submission of the doctoral thesis can be found below:

– Wederhake, L.; Wenninger, S.; Wiethe, C.; Fridgen, G. (2022). “On the surplus accuracy of data-driven energy quantification methods in the residential sector”. In: *Energy Informatics*. DOI: https://doi.org/10.1186/s42162-022-00194-8.
– Rockstuhl, S.; Wenninger, S.; Wiethe, C.; Ahlrichs, J. (2022). „The influence of risk perception on energy efficiency investments: Evidence from a German survey”. In: *Energy Policy*. DOI: https://doi.org/10.1016/j.enpol.2022.113033.
– Konhäuser, K.; Wenninger, S.; Werner, T.; Wiethe, C. (2022). „Leveraging advanced ensemble models to increase building energy performance prediction accuracy in the residential building sector“. In: *Energy and Buildings*. DOI: https://doi.org/10.1016/j.enbuild.2022.112242.
– Kreuzer, T.; Lanzl, J.; Römmelt, J.; Schoch, M.; Wenninger, S. (2022). „Ein integriertes Konzept für nachhaltige hybride Arbeit – Erkenntnisse und Handlungsempfehlungen aus einem Transformationsprojekt“. In: *HMD Praxis der Wirtschaftsinformatik*. DOI: https://doi.org/10.1365/s40702-022-00882-9.
– Wenninger, S.; Wiethe, C. (2022). „The Human’s Comfort Mystery—Supporting Energy Transition with Light-Color Dimmable Room Lighting”. In: *sustainability*. DOI: https://doi.org/10.3390/su14042311.
– Duda, S.; Kaymakci, C.; Köberlein, J.; Wenninger, S.; Haubner, T.; Sauer, A.; Schilp, J. (2022). „Structuring the Digital Energy Platform Jungle: Development of a Multi-Layer Taxonomy and Implications for Practice”. In: *Proceedings of the 3rd Conference on Production Systems and Logistics (CPSL)*.
– Kaymakci, C.; Wenninger, S.; Pelger, P.; Sauer, A. (2022). “ A Systematic Selection Process of Machine Learning Cloud Services for Manufacturing SMEs“. In: *Computers*. DOI: 10.3390/computers11010014.
– Lindner, M.; Wenninger, S.; Fridgen, G.; Weigold, M. (2022). „Aggregating Energy Flexibility for Demand-Side Management in Manufacturing Companies – A Two-Step Method”. In: Behrens BA., Brosius A., Drossel W. G., Hintze W., Ihlenfeldt S., Nyhuis P. (eds) *Production at the Leading Edge*

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- Donnelly, J.; John, A.; Mirlach, J.; Osberghaus, K.; Rother, S.; Schmidt, C.; Voucko-Glockner; H.; Wenninger, S. (2021). „Enabling The Smart Factory – A Digital Platform Concept For Standardized Data Integration”. In: Herberger, D.; Hübner, M. (Eds.): *Proceedings of the 2nd Conference on Production Systems and Logistics (CPSL 2021)*. DOI: 10.15488/11275.
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VI.2. Individual Contribution to the Research Articles

This doctoral thesis is cumulative and consists of six research articles that comprise the main body of work. All articles were developed in teams with multiple co-authors. This section provides details on the respective research settings and highlights my contributions to each article.

Research Article #1, titled "Impact of Socio-Economic Factors on Local Energetic Retrofitting Needs - A Data Analytics Approach" (cf. Subsection VI.3), was written by a team of four. Three authors, including myself, were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. As a team, we agreed that two co-authors and I should assume the roles of lead authors of the research article. The other co-author contributed as a subordinate author, mainly in the form of feedback during the submission and review process and in his role as a scientific supervisor and mentor. All lead authors jointly elaborated on the methodological approach to combine and analyze the different data sources so that the impact of socio-economic factors on local energetic retrofitting needs could be identified. Further, all lead authors contributed equally to evaluating and analyzing the results and the derivation of locally tailored policy measures considering retrofitting needs and socio-economic factors. Regarding the necessary intensive data preparation, I was particularly responsible for extracting and identifying variables from the engineering disciplines and their application.

Research Article #2, titled "Data-Driven Policy Implications - Evidence for Residential Building Retrofitting Practices Using Explainable AI", was co-authored by a team of five. All authors, including myself, were jointly responsible for writing the text of the originally submitted version of the article. As a team, we agreed that I should assume the role of the sole lead author of the research article. The other co-authors contributed as subordinate authors, mainly in the form of the implementation of the XGBoost and SHAP approaches and the graphical visualizations and literature work. Further, I was particularly responsible for supervision and management of the research project, for stimulating the idea of the work, the conception, and development of the methodological approach, the evaluation and interpretation of the results, and the revision of the article.

Research Article #3, titled "Understanding the Risk Perception of Energy Efficiency Investments: Investment Perspective vs. Energy Bill Perspective", was co-authored by a team of four. Three authors, including myself, were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. As a team, we agreed that two of the co-authors and I should assume the roles of lead authors of the research article. The other co-author contributed as a subordinate author, mainly in the form of feedback during the submission and review process and in his role as a scientific supervisor and mentor. All lead authors jointly elaborated on the methodological approach to analyze how the investment and energy perspective influence decision-making with a theoretical model and a case study based on real-world data of the German retrofitting market. Further, all lead authors contributed equally to the evaluation and analysis of the results and the derivation of policy measures promoting the energy bill perspective for higher investments in energetic retrofitting. In the case study conducted, I was particularly responsible for the correct settings of the underlying model to calculate accurate energy savings and to represent the building type used properly.

Research Article #4, titled “The Impact of Political Instruments on Building Energy Retrofits: A Risk-Integrated Thermal Energy Hub Approach”, was co-authored by a team of four. All co-authors were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. All co-authors worked jointly on the analysis and interpretation of the case study results conducted. In addition, all co-authors contributed equally to the evaluation and analysis of the results and to the derivation of policies for risk-mitigating energy efficiency insurance, which is relatively inexpensive compared to subsidies. In the research project, I was particularly responsible for ensuring the high quality of submitted and revised article versions and contributing experience and feedback.

Research Article #5, titled “Benchmarking Energy Quantification Methods to Predict Heating Energy Performance of Residential Buildings in Germany”, was co-authored by a team of two. Both co-authors were jointly responsible for writing the text of the originally submitted version and the revised versions of the article. All co-authors collaborated to develop a methodological approach for benchmarking different methods for quantifying the energy performance of buildings, which allows for comparing the predictive performance of approaches from engineering and data science. Further, all co-authors contributed equally to the evaluation and analysis of the results and the derivation of managerial and policy implications to enhance the prediction performance for BEP (e.g., in EPCs). In the research project, I was specifically responsible for literature review, extracting weather effects in the data used, and considering changing norms and standards that were in effect during the data collection period.

Research Article #6, titled “Explainable Long-Term Building Energy Consumption Prediction Using QLattice”, was co-authored by a team of three. As the leading author of this article, I developed the basic idea and created its content to a large extent. Specifically, I determined the research methodology, analyzed and structured literature, graphically visualized the results, and was responsible for considering current norms and standards for comparing buildings at sites with different weather conditions. I was also largely responsible for evaluating and discussing the results and deriving implications for practice and research and communicating and managing with staff from "Abzu", who provided the algorithm "QLattice". Although I am the leading author of this project, the co-authors were involved in analyzing the results, implementation, and discussions throughout the project.

VI.3. Research Article #1: Impact of Socio-Economic Factors on Local Energetic Retrofitting Needs - A Data Analytics Approach

Authors:	Jakob Ahlrichs; Simon Wenninger; Christian Wiethe, Björn Häckel
Published in:	Energy Policy (2022)
Abstract:	Despite great efforts to increase energetic retrofitting rates in the residential building stock, greenhouse gas emissions are still too high to counteract climate change. One barrier is that policy measures are mostly national and do not address local differences. Even though there is plenty of research on instruments to overcome general barriers of energetic retrofitting, literature does not consider differences in local peculiarities. Thus, this paper aims to provide guidance for policy-makers by deriving evidence from over 19 million Energy Performance Certificates and socio-economic data from England, Scotland, and Wales. We find that building archetypes with their respective energetic retrofitting needs differ locally and that socio-economic factors show a strong correlation to the buildings' energy efficiency, with the correlation varying depending on different degrees of this condition. For example, factors associated to employment mainly affect buildings with lower energy efficiency whereas the impact on more efficient buildings is limited. The findings of this paper allow for tailoring local policy instruments to fit the local peculiarities. We obtain a list of the most important socio-economic factors influencing the regional energy efficiency. Further, for two exemplary factors, we illustrate how local policy instruments should consider local retrofitting needs and socio-economic factors.
Keywords:	Energy Efficiency; Local Environmental Policy; Residential Building Stock; Socio-Economic Effects; Data Mining; Environment; England; Scotland; Wales; Energy Performance Certificates; Socio-Economic

VI.4. Research Article #2: Data-Driven Policy Implications - Evidence for Residential Building Retrofitting Practices Using Explainable AI

Authors:	Simon Wenninger, Philip Karnebogen, Sven Lehmann, Tristan Menzinger, Michelle Reckstadt
Extended Abstract[4]:	Rising international interest in climate change and the ambitious climate goals defined under the Paris Climate Agreement require policy decisions and actions to limit the recent shift towards increased investments in fossil fuel-based infrastructure. The global buildings sector is responsible for nearly 38% of global greenhouse gas emissions and 39% of global energy consumption and thus holds great potential to progress towards climate goals (Somu et al., 2020). Therefore, extensive retrofitting of energy-inefficient buildings is necessary to achieve the climate goals (Fylan et al., 2016). Policymakers need to increase the effectiveness and attractiveness of support measures and programs, e.g., subsidies to maximize greenhouse gas savings per monetary value invested against the backdrop of limited financial resources to promote and incentivize retrofitting (Csutora and Zsóka, 2011). Thus, the circumstances of and existing barriers against retrofitting must be meticulously analyzed to design effective support measures for retrofits (Fylan et al., 2016). Research on these circumstances and barriers to implementing energetic retrofits is diverse (Ahlrichs et al., 2022; Ben and Steemers, 2018; Bertoldi and Mosconi, 2020; Gómez-Navarro et al., 2021; Tziogas et al., 2021). Most of this research can be summarized under the term energy efficiency gap, which discusses reasons against the implementation of retrofit investments with seemingly clear economic and environmental benefits (Ahlrichs et al., 2020). However, research to date is often limited to qualitative studies or only investigates influencing factors on energy efficiency (Ahlrichs et al., 2022) instead of factors influencing retrofitting. Thus, research does not fully exploit the opportunities created by advancing digitization and data availability. In recently published papers, two different needs for future research in the field of building energy consumption using data-driven

[4] At the time of writing, this research article is submitted for publication in a scientific journal. Therefore, an extended abstract is provided here.

	methods were highlighted. On the one hand, Pasichnyi et al. (2019) proposed using the (openly accessible) databases of building Energy Performance Certificates (EPC) for data-enabled urban energy policy instruments. They conclude that EPC data might have a broader spectrum of applications than initially intended and is suitable to design policy instruments for energy efficiency. On the other hand, literature suggests using explainable artificial intelligence (XAI) in the building sector to derive insights about the relations of different parameters and variables (Golizadeh Akhlaghi et al., 2021). In this context, prior research such as (Athey, 2017) also encouraged using artificial intelligence (AI) beyond plain predictions to derive data-driven policy implications. With our study, we addressed this research gap with a case study of the UK's residential building stock, which represents the oldest building stock in western Europe and accounts for more than a quarter of the UK's total energy consumption (Dowson et al., 2012; Filippini et al., 2014; Fylan et al., 2016; Piddington et al., 2020). With more than 82% of buildings constructed before 1991, the building stock is characterized by loose building regulations and poor insulation, reflected in high energy consumption and greenhouse gas emissions (Dowson et al., 2012). Thereby, we used multiple data sources of EPC data from England and Wales, additional house price data and socio-demographic data, and the application of AI and XAI techniques. This involved extracting from the EPC data whether a building had been retrofitted and what measures had been implemented, using a self-developed method. We then applied machine learning to the datasets using an eXtreme Gradient Boosting (XGBoost) model to predict whether a building has been retrofitted or not before we used SHapley Additive exPlanations values (SHAP) as an XAI technique to identify the key factors and relationships that influence the implementation of retrofits. We finally derived policy implications for the effective design of support instruments and programs for retrofits based on the insights of building characteristics, house prices, and sociodemographic data. We succeeded in showing very clearly which factors have an influence on the implementation of retrofits and how suitable policy implications can be derived. Current heating costs, the regional employment rate, the mean regional gross disposable household income, and the share of people younger than 15 years in a region are among the top factors. Our contribution

	to the theoretical body of knowledge, as well as identified policy implications, can be divided into several points. First, to the best of our knowledge, we are the first to introduce and use the combination of supervised machine learning to classify building retrofits and XAI techniques to derive important insights and correlations on retrofitting circumstances. Our approach allows us to corroborate findings previously obtained in qualitative or small-scale studies with a quantitative study using real-world data and additionally to identify additional influencing factors. Second, we present a method for extracting building retrofits from the UK EPC data that can be reproducibly applied in further studies. In addition, the method can be used to extract and analyze changes in buildings over time from EPCs referenced to a single point in time. Third, we confirm existing studies on the influence of house prices on retrofit behaviors. Since higher house prices lead to a lower likelihood of retrofits, we propose to make at least some comparatively low-cost retrofit measures mandatory for new rentals and sales in local authorities with high average house prices, such as London. Further, green mortgages offering the customer beneficial mortgaging conditions might improve retrofitting rates in high-price areas. Fourth, since families with children aged 15 or younger are less likely to carry out retrofits, special programs for families with children might be helpful considering their specific needs. These programs should be characterized by financial support and provide transparent information and quick, straightforward help in implementing retrofits minimizing burdens from families. Local authorities where the " Better Homes for Yorkshire" initiative was effective with corresponding characteristics showed a high number of retrofits, so the initiative might be replicated by other regions. Fifth, since low energy efficiency of walls and roofs is an important criterion for energy efficiency and has a positive impact on retrofits, we propose to emphasize the need for appropriate retrofits in EPCs that exhibit poor levels of energy efficiency in walls and roofs. Moreover, the abundance of problems related to the wall and roof efficiency evaluation process must be considered, which may require the introduction of higher quality standards in the preparation of EPCs. Sixth, with fuel poverty being a common phenomenon in England and Wales we consider retrofitting-related CO_2 taxes as reasonable. For higher-income households with a high energy consumption raising retrofitting-related CO_2 taxes would be an incentive to

	retrofit. No taxes could be levied on low-income households, and a cumulative subsidy could be granted depending on the heating costs for each year. This approach could be implemented through Her Majesty Revenue & Customs without much additional effort, as it already collects income taxes and is already aware of each household's income. Thus, an energy bill is the only additional document needed to calculate an additional CO_2 tax or retrofit grant. In summary, our results demonstrate the great potential of data-driven policymaking by confirming and extending existing studies and conclude that policies already available in individual cases should be rolled out broadly. Despite some limitations, this study provides important insights to better understand retrofitting practices and thus assists policymakers in the UK to develop more effective measures to increase retrofits in the domestic sector to achieve climate goals.
Keywords:	Energy Performance Certificates; Retrofitting; Energy Efficiency Policy; Explainable AI; Data Analytics; Policy Implications
References:	Ahlrichs, J., Rockstuhl, S., Tränkler, T., Wenninger, S., 2020. The impact of political instruments on building energy retrofits: A risk-integrated thermal Energy Hub approach. Energy Policy 147, 111851. https://doi.org/10.1016/j.enpol.2020.111851. Ahlrichs, J., Wenninger, S., Wiethe, C., Häckel, B., 2022. Impact of socio-economic factors on local energetic retrofitting needs - A data analytics approach. Energy Policy 160, 112646. https://doi.org/10.1016/j.enpol.2021.112646. Athey, S., 2017. Beyond prediction: Using big data for policy problems. Science (New York, N.Y.) 355, 483–485. https://doi.org/10.1126/science.aal4321. Ben, H., Steemers, K., 2018. Household archetypes and behavioural patterns in UK domestic energy use. Energy Efficiency 11, 761–771. https://doi.org/10.1007/s12053-017-9609-1. Bertoldi, P., Mosconi, R., 2020. Do energy efficiency policies save energy? A new approach based on energy policy indicators (in the EU Member States). Energy Policy 139, 111320. https://doi.org/10.1016/j.enpol.2020.111320.

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VI.5. Research Article #3: Understanding the Risk Perception of Energy Efficiency Investments: Investment Perspective vs. Energy Bill Perspective

Authors:	Sebastian Rockstuhl; Simon Wenninger; Christian Wiethe, Björn Häckel
Published in:	Energy Policy (2021)
Abstract:	Promoting energy efficiency is an important element of environmentally friendly energy policy and necessary to avert climate change. In this context, understanding the investment decision-making of individuals is important to develop and implement effective policy instruments. Literature analyzing decision-making of energy efficiency investments and especially the influence of connected risk finishes with two different conclusions, i.e., analyzes risk from two different perspectives. First, studies within the investment perspective describe investment risk, caused by volatile future energy bill savings, as a key barrier for energy efficiency investments. Second, studies within the energy bill perspective argue that energy efficiency is reducing energy price exposure and the resulting decrease of overall risk is described as investment promoting. This dichotomy in risk perception is the focus of our study. With the help of a theoretical model as well as a case study based on real-world data of the German retrofitting market, we analyze how the contrary perspectives influence expected utility, i.e., decision-making. Thereby, we find that decision-makers invest more in energy efficiency when evaluating from the energy bill perspective and derive important implications for environmentally friendly energy policymaking.
Keywords:	Energy Efficiency; Risk Evaluation; Expected Utility Theory; Case Study

VI.6. Research Article #4: The Impact of Political Instruments on Building Energy Retrofits: A Risk-Integrated Thermal Energy Hub Approach

Authors:	Jakob Ahlrichs, Sebastian Rockstuhl, Timm Tränkler, Simon Wenninger
Published in:	Energy Policy (2020)
Abstract:	Thermal building retrofits are one of the key approaches to mitigate greenhouse gas emissions. Nevertheless, the current rate of retrofits in Germany is around 1%, and the building sector lags behind environmental goals of saving damaging emissions. A potential reason inhibiting investments is the financial risk connected to thermal building retrofits. While recent research focuses on various political instruments to promote environmental investments, their influence on the financial risk of energy efficiency investments has scarcely been considered. In this study, a method to include risk in the financial evaluation of thermal building retrofits is developed. With this method, named as the Risk-Integrated Thermal Energy Hub, the impact of various political instruments such as emission taxes, subsidies, and energy efficiency insurances on investment decisions of homeowners is analyzed. Based on real-world data of 342 one and two-family houses in Germany, this study illustrates how political instruments influence the financial risk and return of example building retrofits. The findings reveal the effectiveness of energy efficiency insurances in mitigating risk, by promoting environmentally friendlier investments relatively cost-efficient compared to subsidies. Further, this case study indicates that emission taxes need to exceed 140€ per CO_2 ton to significantly impact investment decisions.
Keywords:	Thermal Building Retrofit; Energy Efficiency Investment; Greenhouse Gas Emissions; Environmental Policy; Pareto Analysis; German Energy Transition

VI.7. Research Article #5: Benchmarking Energy Quantification Methods to Predict Heating Energy Performance of Residential Buildings in Germany

Authors:	Simon Wenninger, Christian Wiethe
Published in:	Business & Information Systems Engineering (2021)
Abstract:	To achieve ambitious climate goals, it is necessary to increase the rate of purposeful retrofit measures in the building sector. As a result, Energy Performance Certificates have been designed as important evaluation and rating criteria to increase the retrofit rate in the EU and Germany. Yet, today's most frequently used and legally required methods to quantify building energy performance show low prediction accuracy, as recent research reveals. To enhance prediction accuracy, the research community introduced data-driven methods which obtained promising results. However, there are no insights in how far Energy Quantification Methods are particularly suited for energy performance prediction. In this research article the data-driven methods Artificial Neural Network, D-vine copula quantile regression, Extreme Gradient Boosting, Random Forest, and Support Vector Regression are compared with and validated by real-world Energy Performance Certificates of German residential buildings issued by qualified auditors using the engineering method required by law. The results, tested for robustness and systematic bias, show that all data-driven methods exceed the engineering method by almost 50% in terms of prediction accuracy. In contrast to existing literature favoring Artificial Neural Networks and Support Vector Regression, all tested methods show similar prediction accuracy with marginal advantages for Extreme Gradient Boosting and Support Vector Regression in terms of prediction accuracy. Given the higher prediction accuracy of data-driven methods, it seems appropriate to revise the current legislation prescribing engineering methods. In addition, data-driven methods could support different organizations, e.g., asset management, in decision-making in order to reduce financial risk and to cut expenses.
Keywords:	Energy Informatics; Energy Quantification Methods; Energy Performance Certificate; Benchmarking; Data-Driven Methods; Machine Learning Algorithms; Building Energy; Data Analytics

VI.8. Research Article #6: Explainable Long-Term Building Energy Consumption Prediction Using QLattice

Authors:	Simon Wenninger, Can Kaymakci, Christian Wiethe
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Abstract:	The global building sector is responsible for nearly 40% of total carbon emissions, offering great potential to move closer to set climate goals. Energy performance certificates designed to increase the energy efficiency of buildings require accurate predictions of building energy performance. With significant advances in information and communication technology, data-driven methods have been introduced into building energy performance research demonstrating high computational efficiency and prediction performance. However, most studies focus on prediction performance without considering the potential of explainable artificial intelligence. To bridge this gap, the novel QLattice algorithm, designed to satisfy both aspects, is applied to a dataset of over 25,000 German residential buildings for predicting annual building energy performance. The prediction performance, computation time, and explainability of the QLattice is compared to the established machine learning algorithms artificial neural network, support vector regression, extreme gradient boosting, and multiple-linear regression in a case study, variable importance analyzed, and appropriate applications proposed. The results show quite strongly that the QLattice should be further considered in the research of energy performance certificates and may be a potential alternative to established machine learning algorithms for other prediction tasks in energy research.
Keywords:	Building Energy Performance; Energy Quantification Methods; Energy Performance Certificates; Explainable AI; Machine Learning Algorithms; QLattice