

**AI-DRIVEN ANALYSIS OF USER BEHAVIOR FOR
ENERGY PERFORMANCE ASSESSMENT IN
RESIDENTIAL BUILDINGS IN KSA**

BY

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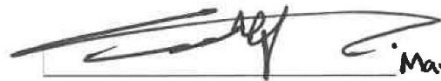
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*Dedicated to those who stood beside me with quiet strength and unwavering belief—
whose presence, though often unspoken, became the foundation of this journey*

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LIST OF ABBREVIATIONS

AC:	Air Conditioning
AI:	Artificial Intelligence
ANN :	Artificial Neural Networks
AUC:	Area Under Curve
BIPV:	Building-Integrated Photovoltaic
EC:	Energy Conservation
EE:	Energy Efficiency
EIA:	Energy Information Administration
EUB :	Energy Use Behaviour
EUI :	Energy Use Intensity
GBM:	Gradient Boosting Machine
GHGs:	Greenhouse Gases
IEA:	International Energy Agency
IoT:	Internet Of Things
KSA:	Kingdom Of Saudi Arabia
ML:	Machine Learning
RS:	Recommendation Systems
SEMS:	Smart Energy Management Systems

|

ABSTRACT

Full Name : [Bushra Jan]

Thesis Title : [AI-Driven Analysis Of User Behavior For Energy Performance Assessment In Residential Buildings In KSA]

Major Field : [Architectural engineering]

Date of Degree : [May 2025]

[This study explores how user behavior influences energy consumption in residential buildings in Saudi Arabia (KSA) and investigates the application of artificial intelligence (AI) and machine learning (ML) techniques to predict and optimize these behaviors. By integrating statistical analysis, machine learning models, and qualitative insights, the research provides a comprehensive understanding of the factors that shape energy consumption patterns in KSA's residential sector.

The study considered a wide range of factors, including sociodemographic characteristics, building features, and behavioral aspects. The first objective of the study was to identify and analyze critical user behaviors affecting energy consumption. Through a combination of bibliometric and systematic literature reviews, a survey, statistical analysis, and machine learning models, key behaviors such as thermostat settings, air conditioning (AC) usage, and lighting habits were identified as relatively influential. Among these, AC usage and thermostat settings emerged as the most influential predictors within the behavioral category. However, building characteristics, particularly the floor area feature, were found to be the strongest overall predictor of energy consumption, emphasizing the importance of structural factors in energy management.

The second objective focused on developing an AI-driven predictive model for energy consumption. Models including Ridge, Lasso, Random Forest, and Gradient Boosting achieved modest predictive power, with $R^2 \sim 0.27$ for regression and AUC ~ 0.73 for classification. While these performance metrics may appear modest, they are not unexpected given the nature of behavioral data, where human actions are shaped by complex, often unobserved contextual factors. Additionally, the reliance on self-reported survey responses introduces a degree of noise that can affect model precision. Despite these limitations, the models were designed to emphasize interpretability and generalizability over purely optimizing predictive accuracy. Feature importance analysis and behavioral segmentation using K-Means clustering highlighted key factors driving energy use patterns and revealed distinct household archetypes that can guide targeted interventions.

The third objective aimed to craft actionable strategies for optimizing user behavior. The study recommends focusing on optimizing cooling systems, promoting energy-efficient appliances, and encouraging behaviors such as improved thermostat management and reduced AC usage. Additionally, addressing economic constraints, cultural attitudes, and institutional barriers is essential for promoting sustainable energy behaviors.

Overall, this research contributes to the understanding of user behavior in residential energy consumption and highlights the role of both behavioral and building characteristics in shaping energy use. The study offers valuable insights for policymakers and energy management professionals in Saudi Arabia and similar regions, providing a data-driven framework for more targeted and effective energy conservation strategies. |

ملخص الرسالة

الاسم الكامل: بشري جان

عنوان الرسالة: التحليل المعتمد على الذكاء الاصطناعي لسلوك المستخدم لتقييم كفاءة الطاقة في المباني السكنية في المملكة العربية السعودية

التخصص: الهندسة المعمارية

تاريخ الدرجة العلمية: مايو 2025

تستكشف هذه الدراسة كيف يؤثر سلوك المستخدم على استهلاك الطاقة في المباني السكنية في المملكة العربية السعودية، وتبحث في تطبيق تقنيات الذكاء الاصطناعي وتعلم الآلة للتنبؤ بهذه السلوكيات وتحسينها. ومن خلال دمج التحليل الإحصائي، ونماذج تعلم الآلة، والرؤى النوعية، تقدم الدراسة فهماً شاملاً للعوامل التي تشكل أنماط استهلاك الطاقة في القطاع السكني في المملكة.

وقد أخذت الدراسة في الاعتبار مجموعة واسعة من العوامل، بما في ذلك الخصائص الاجتماعية والديموغرافية، وسمات المبنى، والجوانب السلوكية. وكان الهدف الأول من الدراسة هو تحديد وتحليل السلوكيات الحاسمة للمستخدمين التي تؤثر على استهلاك الطاقة. ومن خلال مراجعة بيبيوميترية ومنهجية للأدبيات، واستطلاع للرأي، وتحليل إحصائي، ونماذج تعلم آلي، تم تحديد سلوكيات رئيسية مثل إعدادات منظم الحرارة، واستخدام أجهزة التكييف، وعادات الإضاءة كسلوكيات ذات تأثير نسبي. ومن بين هذه السلوكيات، برز استخدام التكييف وإعدادات منظم الحرارة كأكثر المتنبئات تأثيراً في الفئة السلوكية. ومع ذلك، وُجد أن خصائص المبنى، وخاصة مساحة الأرضية، هي أقوى مؤشر عام لاستهلاك الطاقة، مما يبرز أهمية العوامل الهيكلية في إدارة الطاقة.

وتركز الهدف الثاني على تطوير نموذج تنبؤي لاستهلاك الطاقة قائم على الذكاء الاصطناعي. وقد حققت النماذج، بما في ذلك Ridge و Lasso و Random Forest و Gradient Boosting، قدرة تنبؤية متوسطة، حيث بلغ معامل التحديد R^2 حوالي 0.27 في نماذج الانحدار، ومجال تحت المنحنى AUC حوالي 0.73 في التصنيف. وعلى الرغم من أن هذه المؤشرات قد تبدو متواضعة، فإنها غير مفاجئة بالنظر إلى طبيعة البيانات السلوكية، حيث تتأثر أفعال البشر

بـعـوـامـل سـيـاقـيـة مـعـقـدة و غـالـباً غـيـر مـرـصـودـة. كـمـا أـن الـاعـتـمـاد عـلـى إـجـابـات الـاسـتـبـانـات الـذاتـيـة يُدخـل درجـة مـن الـضـوـاء قـد تـؤثـر عـلـى دقـة النـمـاـذـج. و عـلـى الرـغـم مـن هـذـه القـيـود، قـد تم تصـمـيم النـمـاـذـج لثـركـز عـلـى قابـليـة التـفـسيـر والتـعـمـيم أكـثـر مـن مـجـرد تحسـين الدقـة التـنبـؤيـة. و قـد أظـهـرت تحـلـيـلات أهـمـيـة السـمـات وتقسـيم السلوكيات بـاسـتـخـدام خـوارزمية-K Means العـوـامـل الرئـيسـيـة الـتي تـؤثـر عـلـى أنـمـاط اسـتـخـدام الطاقـة، وكشفت عـن نـمـاـذـج أسـريـة مـمـيزـة يـمـكـن أن تـوجـه التـدخـلات المـسـتـهـدفـة.

أما الهدف الثالث فقد سعى إلى صياغة استراتيجيات قابلة للتنفيذ لتحسين سلوك المستخدمين. وتوصي الدراسة بالتركيز على تحسين نظم التبريد، وتشجيع استخدام الأجهزة الموفرة للطاقة، وتعزيز سلوكيات مثل الإدارة المحسنة لمنظم الحرارة وتقليل استخدام التكييف. بالإضافة إلى ذلك، فإن معالجة القيود الاقتصادية، والمواقف الثقافية، والحواجز المؤسسية يعد أمراً ضرورياً لتعزيز السلوكيات المستدامة في استخدام الطاقة.

بشكل عام، تسهم هذه الدراسة في فهم سلوك المستخدم في استهلاك الطاقة السكني، وتبرز دور كل من العوامل السلوكية والهيكلية في تشكيل استخدام الطاقة. وتقدم الدراسة رؤى قيمة لصناع السياسات والمتخصصين في إدارة الطاقة في المملكة العربية السعودية والمناطق المشابهة، من خلال توفير إطار قائم على البيانات لاستراتيجيات أكثر استهدافاً وفعالية في الحفاظ على الطاقة.

CHAPTER 1

INTRODUCTION

1.1 Background

The International Energy Agency identifies buildings as significant contributors to the dramatic rise in energy usage, with 55% and 30% of worldwide electricity generation and of total final energy use to this sector, respectively . U.S. Energy Information Administration (EIA) forecasts the energy demand in both residential and commercial structures to surge by 65% from 26,669 TWh in 2018 to 40,737 TWh by 2050. This increase is driven by factors such as rising incomes, urbanization, and expanded access to electricity [1]. Additionally, the environmental impacts go side by side to the economic costs associated with this growing energy with greenhouse gas emissions and global warming being some of the major impacts. Indeed, buildings account for about 40% of total global carbon emission[2]. The EIA has noted that between 1990 and 2018, energy-related CO₂ emissions grew at an average annual rate of 1.8%, and between 2018 to 2050, the projections indicate a 50% rise in global energy consumption [3]. In 2021, global energy-related CO₂ emissions reached an unprecedented high, increasing by 6% from the previous year [4]. As a result, enhancing building performance, particularly in terms of energy efficiency, has become a focal point of research initiatives aiming for sustainable building practices, given the sector's major consumption of produced energy. The use of energy by buildings constitutes a significant portion of total energy production in regions

with extreme climates like the KSA. For example, the residential sector alone accounts for 50% of the energy demand in Saudi Arabia[2]. The estimates put forward by Saudi Energy Efficiency Center show that over half of the country's electricity supply is consumed by this sector [5]. In 2017 alone, Saudi Arabia's residential sector utilized approximately 143,000 GWh of electricity, with air conditioning accounting for 70% of this consumption [6]. A considerable amount of energy is expended on maintaining the balanced indoor temperatures and maintain comfortable conditions through proper heating during winters and cooling during summers [7].

Despite significant technological advancements, there is a well-documented disparity between predicted and actual energy usage in buildings, commonly referred to as the "energy performance gap". Energy performance gap has been frequently observed in a variety of buildings, including residential [8], office [9], commercial [10], industrial [11], and educational buildings [12].

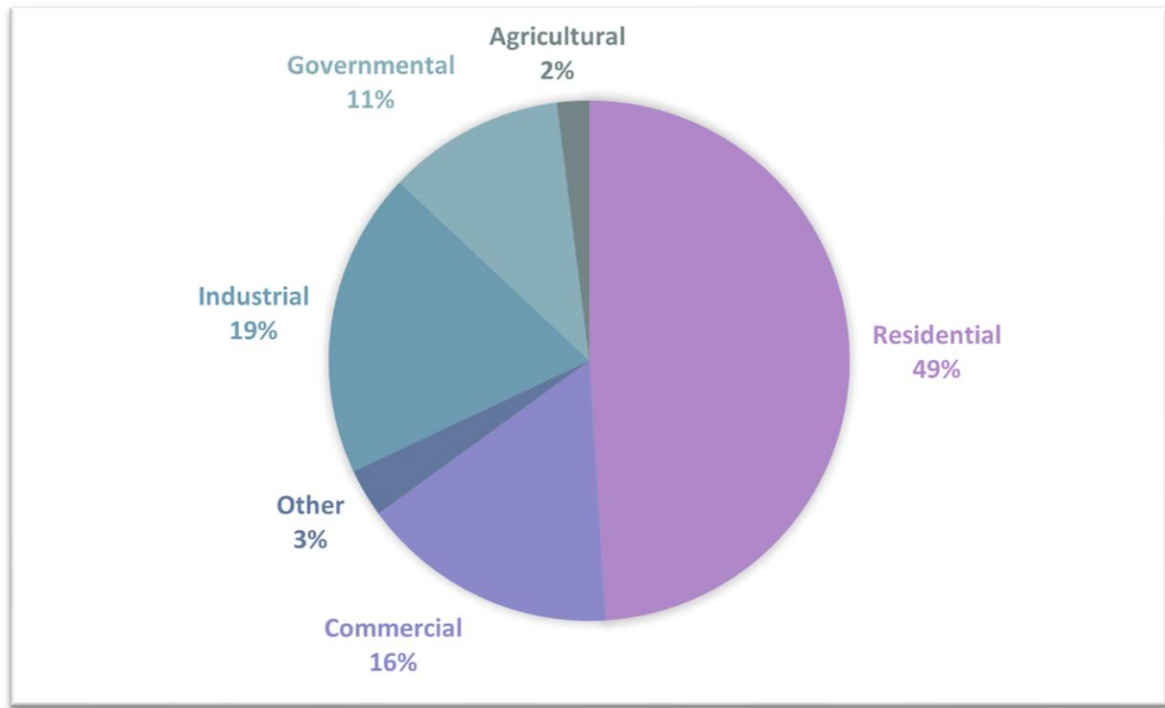
This gap arises from various factors throughout the lifecycle of a building. During the design stage, common issues stem from inadequate or overly optimistic energy modeling and simulation, which fail to accurately predict real-world performance [13]. In the construction stage, poor workmanship, the use of substandard materials or equipment, and deviations from specified designs can further widen this gap. In the operations stage, inefficient building management systems and practices can exacerbate energy wastage [14]. Additionally, user behavior is a critical yet often underexplored factor [15]. Although potential significant energy savings could be realized through behavior modification, the impact of user behavior on energy consumption has been frequently overlooked [16].

The integration of user behavior into energy performance models represents a promising yet largely untapped opportunity to narrow this performance gap. Traditional approaches have prioritized technological enhancements for energy efficiency but have not adequately addressed the complex interplay of human factors that influence energy use. By leveraging advanced AI techniques to better understand and predict user behavior, there is significant potential to enhance the accuracy of energy consumption forecasts and implement more effective energy conservation strategies. This research aims to bridge the gap in existing methodologies by developing an AI-driven predictive model that incorporates a nuanced understanding of user behavior alongside traditional energy consumption metrics. Such an approach is crucial for crafting more personalized and effective energy-saving strategies and aligning with Saudi Arabia's ambitious sustainability goals under Vision 2030 and the 2060 neutrality target.

1.2 Problem Statement

In KSA, the focus has predominantly been on leveraging technological advancements to improve energy efficiency in buildings [17], [18]. However, there is a notable scarcity of studies examining the influence of user behavior on energy conservation. The International Energy Agency highlights that buildings are responsible for 55% of global electricity consumption and 30% of total final energy use, emphasizing the critical role that residential and commercial structures play in the global energy landscape[19], [20]. Moreover, buildings contribute approximately 40% to global carbon emissions, with energy-related CO₂ emissions having increased by an average of 1.8% annually from 1990 to 2018, and an anticipated 50% rise in global energy consumption expected by 2050 [21]. In Saudi

Arabia, where extreme climatic conditions predominate, the residential sector is particularly energy-intensive, accounting for 50% of the nation's energy demand[22] as shown in the Figure 1 Over half of the country's electricity supply is consumed by residential buildings, with air conditioning alone representing 70% of this usage in 2017, totaling approximately 143,000 GWh [2], [6], [23] . Recognizing that energy consumption patterns are not solely determined by technological efficiencies but are deeply influenced by human behaviors, this research aims to construct a more holistic understanding of energy dynamics in residential settings. This oversight is significant as the region advances towards its ambitious environmental targets outlined in Vision 2030 and the 2060 neutrality goal. The lack of attention to user behavior analysis in energy studies limits the effectiveness of strategies intended to reduce overall energy consumption in residential sectors.



[Figure 1: Sector Wise Energy Consumption in Saudi Arabia.]

1.3 Aim

To identify user behavior trends and practices in the residential sector of KSA and utilize AI-based models to forecast residential energy consumption by integrating user behavior analytics.

1.4 Objectives

The research question guiding this thesis is “In what ways does user behavior impact energy consumption in KSA’s residential buildings, and how can AI and machine learning techniques be employed to predict this impact?”

- Identify and analyze critical aspects of user behavior that significantly impact energy consumption.
- Develop an AI-driven predictive model to forecast energy consumption based on analyzed behaviors.
- Craft actionable strategies and recommendations to improve user behavior towards optimizing energy consumption.

1.5 Scope and Limitations

1.5.1 Scope of Study

This study aims to improve energy efficiency in residential buildings throughout Saudi Arabia by examining user behavior and creating a predictive model using machine learning techniques as shown in Figure 2.

Geographic Scope: The study targets the residential sector across various provinces in Saudi Arabia, considering different climatic conditions and architectural styles that significantly impact energy consumption.

Behavioral Scope: The research will examine a wide range of user behaviors related to energy usage, including daily usage patterns, preferences for heating and cooling, and responsiveness to energy conservation measures.

Technological Scope: The study will deploy machine learning algorithms to assess behavior and energy usage data, aiming to predict and optimize energy consumption more accurately than current models.

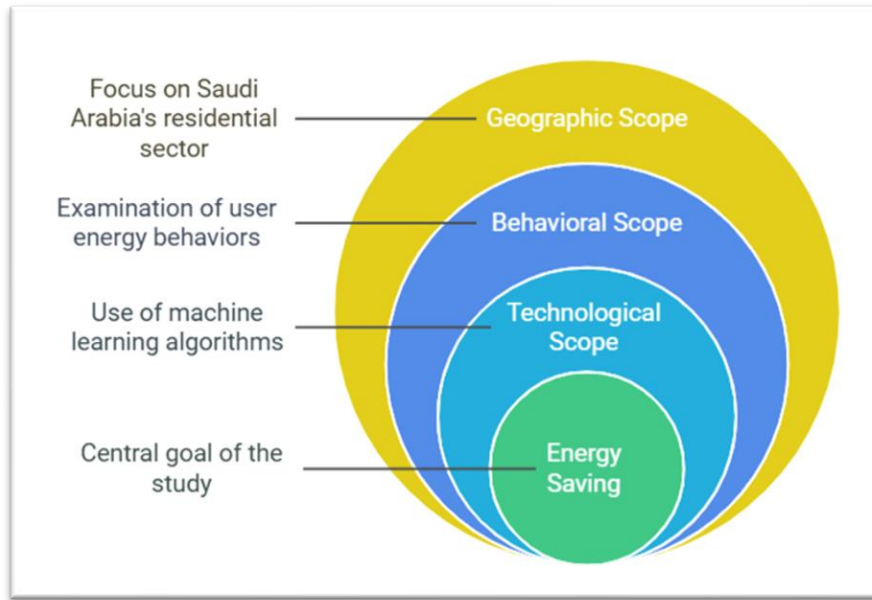


Figure 2: Scope of Thesis.

1.5.2 Limitations of the Study

While the study aims to provide comprehensive insights into energy consumption behaviors and predictive modeling, several limitations are anticipated:

- **Data Availability and Quality:** The quality of data collected through surveys and interviews may vary.
- **The number of responses** could affect the comprehensiveness and reliability of the dataset.
- **Generalizability of the Models:** The AI models developed may primarily be applicable to Saudi Arabian residential settings and might not directly apply to other countries or regions without modifications due to different cultural behaviors, building standards, and climatic conditions.

- Scope of AI Techniques: The study will focus on specific AI techniques that are deemed most appropriate based on preliminary literature review and data characteristics.

1.6 Significance Of Study

Understanding user behavior in energy consumption is crucial for implementing effective energy-saving strategies. This research addresses the gap in understanding how user behavior impacts energy consumption in residential settings within Saudi Arabia. In Saudi Arabia, where extreme climatic conditions predominate, the residential sector is particularly energy-intensive, accounting for 50% of the nation's energy demand with the increasing demand for energy and the urgent need for sustainability, understanding and predicting energy usage including user behavior using AI is pivotal. This study offers potential to significantly enhance energy efficiency strategies and policies, directly contributing to Saudi Arabia's Vision 2030 and the 2060 carbon neutrality goal.

1.7 Structure of Thesis

The structure of this thesis as shown in Figure 3 is designed to methodically address the investigation into how various factors influence energy consumption in residential buildings across Saudi Arabia. It begins with an introductory chapter that sets the stage by outlining the background, problem statement, research objectives, and significance of the study. The second chapter reviews existing literature, both qualitative and quantitatively, focusing on energy efficiency and conservation with special attention to user behavior and building characteristics. The methodology used in the study is detailed in the third chapter,

explaining the data collection and analysis procedures, including the implementation of machine learning techniques. The fourth chapter presents the data analysis and results, illustrating the patterns identified and their implications. The fifth chapter discusses these findings in relation to the existing literature and their impact on energy policy and building management practices in Saudi Arabia. The thesis concludes with the sixth chapter, summarizing the research and offering recommendations for future work and policy implementations, supplemented by appendices and references that provide detailed supporting materials and documentation of the research process.

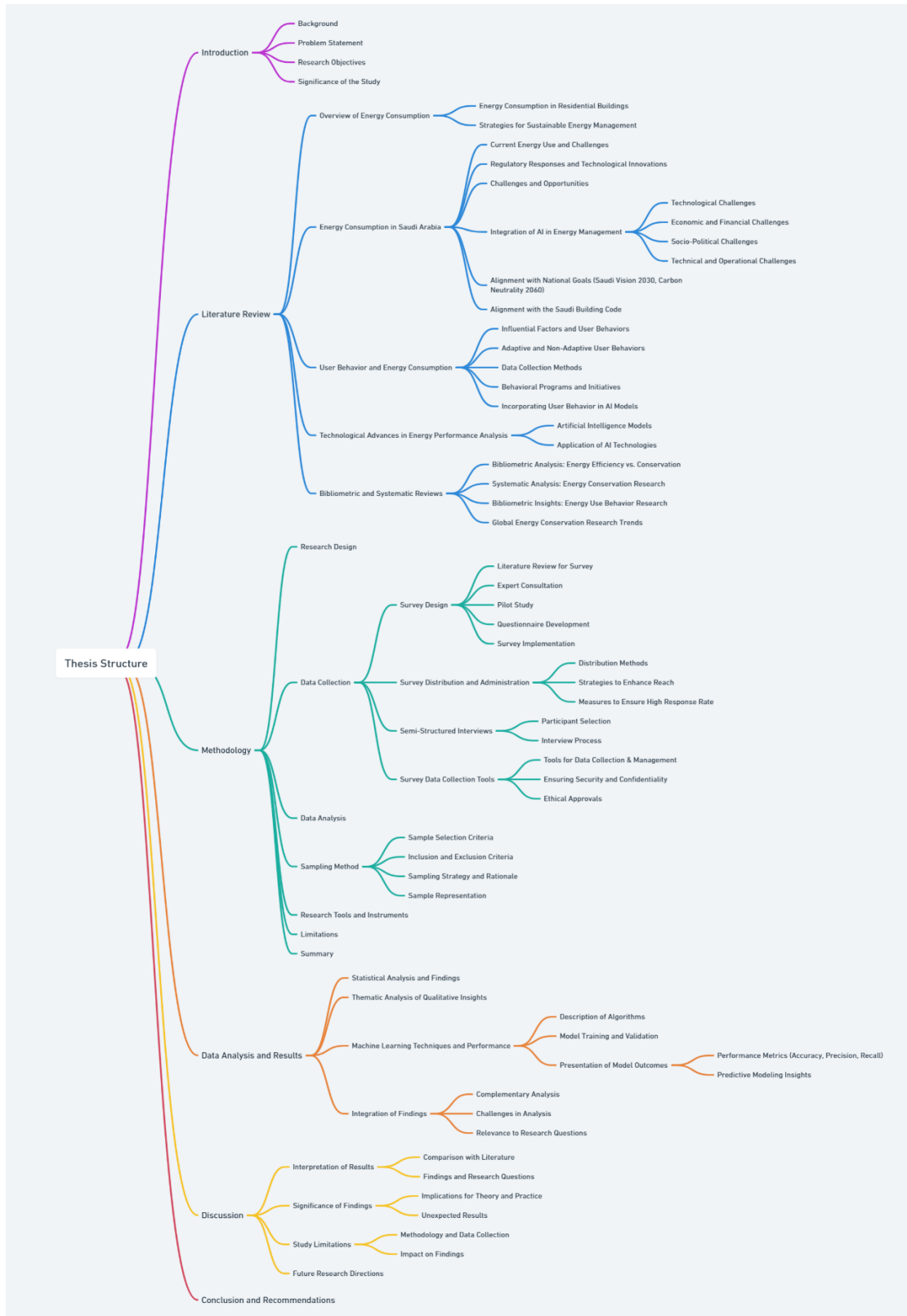


Figure 3: Thesis Structure

CHAPTER 2

LITERATURE REVIEW

This chapter systematically explores the extensive landscape of energy consumption, with a focused review on the evolving dynamics in energy use, particularly within the context of Saudi Arabia as shown in Figure 4 . It begins with a broad overview of global energy consumption trends and the strategic imperatives for sustainable energy management, emphasizing the critical role of energy efficiency and conservation. The discussion then narrows down to the specific energy consumption patterns, regulatory challenges, and technological advancements in Saudi Arabia, aligning with national strategic goals like Saudi Vision 2030 and Carbon Neutrality 2060, and compliance with the Saudi Building Code. Subsequently, the review delves into user behavior and its profound impact on residential energy consumption, exploring both adaptive and non-adaptive behaviors, and discussing methodologies for data collection and behavioral influence. The role of advanced technologies, particularly artificial intelligence, in enhancing energy performance analysis is thoroughly examined, showcasing AI's transformative potential in predictive analytics and energy management. In synthesizing the insights from bibliometric and systematic reviews, the chapter identifies global research trends and highlights significant gaps that this thesis aims to address. By articulating these gaps, the justification for this study is clearly established, setting the stage for the subsequent chapters which detail the methodology employed to explore these identified areas further, aiming to contribute valuable insights to the field of energy conservation.

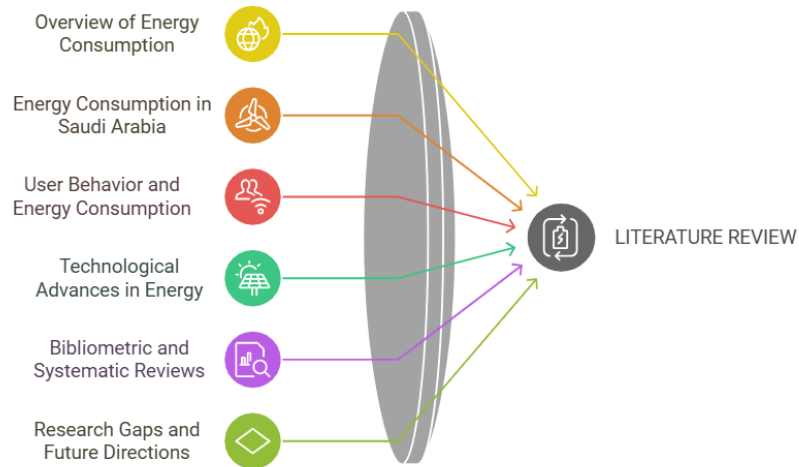


Figure 4: Literature Review Overview.

2.1 Overview of Energy Consumption

Energy consumption is a fundamental driver of economic and social progress, but its environmental and economic implications are significant [24]. With increasing global demand for energy, the strain on natural resources and the environment has become more evident, particularly in sectors like residential buildings [25]. This section provides a broad overview of global energy consumption trends, with a focus on the role of residential buildings in contributing to energy use.

2.1.1 Energy Consumption in Residential Buildings

Energy consumption, especially from fossil fuels, has a significant environmental impact, largely due to the emission of substantial quantities of greenhouse gases (GHGs) such as CO₂, NO_x, and CFCs into the atmosphere. Notably, buildings are responsible for approximately 40% of the world's annual energy consumption, with the majority used for lighting, heating, cooling, and air conditioning systems, highlighting the significant impact

of energy use on environmental degradation. [26]. The extraction and processing of fossil fuels, along with the waste they generate, pose risks to human health, exert economic pressures, and inflict environmental damage[27]. The consequences of global warming, fueled by GHG emissions, include severe weather events, disruptions to food supplies, health problems, and scarcity of water resources[28]. Addressing these challenges requires a shift towards renewable energy sources and improving energy efficiency and conservation measures. Renewable sources like biofuels from microorganisms, and solar, wind, hydropower, and geothermal energy present viable alternatives that diminish GHG emissions and help mitigate the effects of global warming[29].

2.1.2 Strategies for Sustainable Energy Management

Energy efficiency (EE) and energy conservation (EC) are two crucial but distinct strategies in sustainable management and utilization of energy. Energy efficiency involves the use of advanced technology to achieve the same functions while consuming less energy, ensuring service quality remains unaffected. This strategy is supported by technological innovations and improvements that increase the capacity to do more with less energy, such as the deployment of energy-efficient appliances and the enhancement of industrial processes. Conversely[30], energy conservation focuses on changing behaviors and habits to reduce energy usage, including actions like turning off lights when they are not needed or optimizing production processes to decrease energy consumption[31]. Both approaches are essential in tackling the global challenges associated with increasing energy demand, climate change, and sustainability goals. Specifically, energy conservation effectively

reduces overall energy demand, thereby lessening dependence on fossil fuels and alleviating their environmental impacts[32].

While this global perspective underscores the urgent need for energy-efficient solutions, the subsequent section will delve into the unique challenges and opportunities presented by Saudi Arabia, illustrating the country's specific context and its strategies toward energy sustainability.

2.2Energy Consumption in Saudi Arabia

Saudi Arabia, as one of the leading energy consumers globally, faces distinct challenges in managing its energy consumption, particularly in the residential sector. With energy use among the highest per capita in the world, residential buildings in the Kingdom account for nearly half of the total electricity demand, largely driven by factors such as air conditioning needs, rapid urbanization, and cultural preferences [33]. This section explores the current state of energy consumption in Saudi Arabia, highlighting the challenges that arise from these consumption patterns. It also examines the regulatory and technological efforts underway to address these challenges and the potential for future improvements, setting the stage for a discussion on the integration of AI technologies to optimize energy use and align with the Kingdom's sustainability goals.

2.2.1 Current Energy Use and Challenges

KSA faces considerable challenges in managing its residential energy consumption, which is among the highest per capita in the world. Residential buildings alone account for almost half of the total electricity usage in the country's building sector, with air conditioning

systems consuming about half of this electricity for residential purposes [7]. This elevated demand is propelled by rapid urbanization, inefficient energy usage, and insufficient enforcement of energy conservation measures

A specific study in the Qassim region disclosed that average monthly and annual energy consumption per household varies from 30,832 to 36,166 kWh and 1,500 to 4,500 kWh, respectively, with air conditioning, water heating, lighting, and other domestic appliances being the primary consumers of energy. Furthermore, another study indicated that residential energy consumption patterns are substantially affected by occupant behavior, weather conditions, and the technical state of building envelopes and air conditioning systems [6]. In response to these challenges, Saudi Arabia has implemented several regulatory measures to curb excessive energy consumption.

2.2.2 Regulatory Responses and Technological Innovations

In response to these issues, Saudi Arabia has implemented measures such as the Saudi energy conservation code (SBC602), which promotes reduced energy consumption through the application of thermal insulation in residential structures across various climate zones[34]. Energy retrofitting actions, including upgrading windows, walls, and roof insulation, as well as replacing air conditioning units, have shown potential energy savings ranging from 25% to 66%[35]. Additionally, building-integrated photovoltaic (BIPV) technology offers a viable option for producing sustainable energy in residential buildings, with research showing significant potential for energy production and CO₂ emissions reduction by using rooftop areas for photovoltaic systems[36]. Despite these

advancements, the path to achieving lower energy consumption is fraught with cultural and technological challenges.

2.2.3 Challenges and Opportunities

Despite these technological and regulatory advancements, further efforts are needed to enhance awareness and adoption of energy efficiency measures among residents. Cultural preferences for cooler indoor temperatures continue to drive high energy demand[37]. Overall energy and exergy efficiencies in the residential sector also show opportunities for substantial improvement, with findings suggesting that significant energy savings could be realized through combined technological, regulatory, and behavioral modifications[38].

The significance of energy use behavior in residential settings in the Kingdom of Saudi Arabia (KSA) is crucial, given that residential buildings account for nearly half of the country's total electricity consumption from the building stock [6]. This substantial energy use is compounded by KSA's heavy reliance on fossil fuels, with forecasts suggesting that oil production and consumption may converge by 2035, underscoring an urgent need for enhanced energy efficiency in homes(Advances in Building Energy Research). Various factors influence residential energy use in KSA, including inadequate thermal properties of buildings, cultural practices such as hospitality and family dynamics, and a preference for cooler indoor temperatures, all contributing to higher energy consumption, particularly for cooling[39].

Although updated energy codes for new buildings have been implemented, existing buildings still exhibit high energy consumption levels, pointing to an opportunity for reducing energy use through behavioral adjustments and energy retrofitting[40]. The

integration of modern technologies such as Artificial Intelligence (AI) presents new challenges but also opens up substantial opportunities for energy management.

2.2.4 Integration of AI in Energy Management

Building Information Modeling (BIM), integrated with Machine Learning (ML) algorithms, is pivotal in optimizing energy performance in Saudi Arabia. These technologies enable the simulation of various building features to predict Energy Use Intensity (EUI) effectively. Specifically, in Riyadh, ML models such as the Gradient Boosting Machine (GBM) have demonstrated high accuracy in predicting EUI. Critical factors influencing energy consumption include roofs, external walls, and windows, which can be optimized for enhanced energy efficiency. Additionally, the implementation of green building envelopes, like cavity green walls and green roofs, significantly boosts energy efficiency in residential settings[41]. Smart Energy Management Systems (SEMS) that utilize IoT and Artificial Neural Networks (ANN) optimize energy consumption by leveraging data from various sensors to predict future energy demands. This predictive capability facilitates significant cost savings and reduces environmental impacts by dynamically adjusting energy usage based on real-time data. Furthermore, IoT devices such as motion and temperature sensors enrich SEMS with valuable data, enabling dynamic energy management and enhancing the efficiency of residential buildings [42]. The integration of AI and IoT technologies transforms energy efficiency in residential buildings through recommendation systems (RS) that offer energy-saving advice based on user habits. This personalized advice promotes sustainable energy practices by reinforcing energy-efficient routines [43]. Additionally, real-time data collection from IoT sensors

allows AI algorithms to fine-tune electricity usage trends, automatically adjusting building functions like lighting and HVAC systems to optimize energy use without compromising comfort [44]. AI-driven algorithms such as EnerGAIN employ techniques like Bayesian Optimization and Random Forests to refine energy consumption patterns and reduce carbon emissions in residential communities. This sophisticated approach has proven successful in fostering sustainable energy practices and achieving significant energy efficiency improvements [45]. Retrofitting existing housing stocks with energy efficiency measures, such as enhanced insulation and smart thermostats, can significantly lower electrical peak demand and annual energy consumption, providing a cost-effective alternative to more extensive infrastructural changes like deploying rooftop PV systems [46]. At the core of integrating AI into Saudi Arabia's energy management strategies is the recognition of unique regional challenges that influence energy consumption. The extreme temperatures prevalent in most parts of the Kingdom necessitate robust air conditioning systems, which are major energy consumers. AI-driven systems can dynamically adjust cooling based on real-time temperature data, reducing energy wastage while maintaining comfort levels [47]. Moreover, cultural practices such as extended family gatherings and the prevalent use of large residential spaces further increase energy demands [48]. Here, AI technologies like smart energy management systems (SEMS) and IoT can play a critical role by optimizing energy usage across larger areas and during peak times. Additionally, as Saudi Arabia continues to expand its urban infrastructure, AI can assist in designing energy-efficient buildings from the outset [49], integrating green technologies that align with both the Saudi Vision 2030 and the ambitious goals of Carbon Neutrality by 2060. While the deployment of AI and IoT technologies offers transformative potential for Saudi

Arabia's energy sector, the adoption and implementation of these technologies are not without significant challenges. The following section examines these challenges, providing insights into the complexities of integrating advanced AI solutions within existing energy infrastructures. The integration of Artificial Intelligence (AI) into energy performance systems introduces a series of technological, economic, and socio-political challenges. Addressing these challenges is pivotal to maximize the efficacy of AI in enhancing energy efficiency and management. This section of the literature review will delineate the primary challenges based on insights drawn from recent research.

2.2.4.1 Technological Challenges

The integration of sophisticated AI technologies in energy systems introduces several technological challenges that are critical to address for successful deployment.

- **Complexity and Scalability:** The complexity of AI algorithms and the vast amount of data they require pose significant scalability issues. Chander & Gopalakrishnan [50] and Komala et al.[51] discuss how these systems must manage data from disparate sources, including smart grids and renewable energy systems, which demand extensive computational resources and sophisticated data processing capabilities.
- **Data Management and Privacy:** Effective AI integration requires robust data management strategies to address the sheer volume of data generated. Olatunde et al. [52] highlight the importance of maintaining data privacy and security, considering the sensitive nature of the data involved in energy systems.
- **Interoperability and System Integration:** Integrating AI with existing, often outdated, energy infrastructures presents significant challenges. Mseer & Ahmed [53] noted the

need for substantial system upgrades and enhanced interoperability to accommodate new AI technologies without disrupting legacy systems.

2.2.4.2 Economic and Financial Challenges

- **Cost of Implementation:** The initial costs associated with deploying AI technologies in energy systems can be prohibitive. Alkhhayat et al. [54] emphasize the financial burden of acquiring the necessary hardware, software, and skilled personnel.
- **Return on Investment (ROI):** The uncertainty surrounding the ROI from AI technologies can deter investment. Kaur et al. [55] argue that while AI can potentially reduce operational costs and optimize energy usage, the significant upfront investment and the time required to realize these benefits pose considerable challenges.

2.2.4.3 Socio-Political Challenges

- **Regulatory and Policy Barriers:** Danish [56] points out that existing regulations may not be well-suited to the unique demands of AI technologies, requiring a reevaluation of policy frameworks to better support AI integration in energy systems.
- **Public Perception and Acceptance:** The implementation of AI in energy systems may encounter public resistance due to fears of job displacement and ethical concerns regarding AI decision-making. Kaur et al. [55] stress the importance of building public trust and ensuring transparency to facilitate the acceptance and successful integration of AI technologies.

2.2.4.4 Technical and Operational Challenges

- **Algorithmic Efficiency and Robustness:** AI algorithms need to be both efficient and robust to effectively manage the dynamic and complex nature of energy systems. Dong & Wang [57] and Sruthi et al. [58] discuss the necessity for AI models to maintain stability and reliability, especially in critical real-time applications like grid management and energy trading.
- **Skill and Expertise Gap:** The shortage of skilled professionals capable of developing and managing sophisticated AI systems in the energy sector is a significant hurdle. Olatunde et al. [52] call for increased investments in training and education programs to cultivate the necessary expertise.

2.2.5 Alignment with National Goals (Saudi Vision 2030 and Carbon Neutrality 2060)

KSA stands as a major force in the Middle East due to its large population, robust economy, and extensive geographic influence. Its vast reserves of oil and gas, among the world's largest, along with significantly subsidized energy costs, have led to a highly energy-intensive Saudi society. Since the 1950s, Saudi Arabia has experienced a significant transformation from a Bedouin lifestyle to a modern one, primarily fueled by substantial economic growth and infrastructure development, particularly evident in the rapid expansion of the building sector. [25], [59]. This sector alone consumes approximately 80% of the country's total electricity, with residential buildings using nearly 51% of national electricity. Reports indicate that the electricity demand in the residential sector is

expected to double by 2025 compared to levels in 2009 [25], [60] [61]. Currently, Saudi Arabia is one of the leading nations globally in per capita energy use and CO₂ emissions. Under a business-as-usual scenario, the continued rapid development of the building sector will significantly heighten the energy and environmental challenges the country faces [62]. This underscores the urgent need for a fundamental change in energy consumption practices and trends within the building sector.

Saudi Arabia's strategic Vision 2030 and its commitment to achieving carbon neutrality by 2060 set forth a comprehensive agenda for reducing dependence on oil, diversifying the economy, and drastically cutting greenhouse gas emissions. These goals align with global movements toward sustainability and highlight the urgency for innovative solutions to combat climate change.

This thesis on AI-driven predictive modeling of user behavior for energy performance in residential buildings actively supports these national initiatives. By enhancing energy efficiency through detailed user behavior analysis, the research tackles a significant area for reducing carbon emissions. Employing advanced AI and machine learning techniques, the study predicts and optimizes energy consumption patterns, thereby minimizing unnecessary energy use and its associated carbon emissions.

The practical implications of this research are significant. It provides detailed insights that support the development of targeted energy conservation strategies, which can inform policy decisions. This could lead to changes in building codes, heightened energy standards, and the promotion of energy-efficient practices among residents. Additionally, the predictive models developed in this study could facilitate the integration of renewable

energy sources in residential buildings by optimizing energy demand profiles to better match renewable energy supply, enhancing overall energy sustainability.

The findings and methodologies of this thesis are invaluable resources for policymakers, urban planners, and energy providers, aiding them in making informed decisions that align with the carbon neutrality objectives. The research approach exemplifies how technological innovations can underpin and accelerate national sustainability efforts. Furthermore, by disseminating its findings through academic and industry channels, this research contributes to educational and public awareness, emphasizing the crucial role of individual and collective behavior changes in achieving broader environmental goals. This fosters a culture of sustainability that is vital for the long-term environmental and economic health of the nation.

In summary, this thesis not only aligns with but actively supports the advancement of Saudi Arabia's strategic goals under its Vision 2030 and the 2060 carbon neutrality initiative. By leveraging cutting-edge technology to address key challenges in energy management and efficiency, this research supports the Kingdom's transition towards a sustainable and environmentally responsible future [63]. This alignment with national priorities underscores the relevance and potential impact of the thesis, marking it as a pivotal contribution to the country's environmental and sustainability objectives.

2.2.6 Alignment with the Saudi Building Code

The Saudi Building Code (SBC) sets forth a comprehensive framework designed to ensure buildings are constructed and maintained according to standards that promote safety, efficiency, and environmental sustainability. As Saudi Arabia intensifies its focus on

reducing energy consumption within its built environment, the SBC plays an important role in guiding the design and operation of residential buildings towards greater energy efficiency and sustainability.

This thesis on AI-driven predictive modeling of user behavior for energy performance assessment in residential buildings directly supports the objectives of the SBC. By integrating advanced machine learning techniques to analyze how user behavior impacts energy consumption, this research provides critical insights that can enhance compliance with the SBC's energy efficiency mandates. The predictive models developed through this thesis will help to bridge the gap between theoretical energy savings and actual energy usage, thereby supporting the SBC's goal to foster more sustainable building practices.

Key contributions of this thesis to the SBC objectives include:

- **Enhanced Model Accuracy:** By incorporating user behavior into energy consumption models, the thesis enhances the accuracy of predictions used in building design and energy assessments, aligning with the SBC's requirements for precision in energy management systems.
- **Informed Regulatory Updates:** The findings from this research could inform updates to the SBC, particularly in areas concerning energy efficiency and user interaction with building systems. This could lead to more dynamic regulations that adapt to changing technology and usage patterns.
- **Decision-Making Support:** The empirical data and insights provided by the thesis will aid policymakers and building professionals in making informed decisions about building design, operation, and maintenance, ensuring that buildings are not

only compliant with current codes but are also optimized for future energy challenges.

- **Sustainability and Environmental Protection:** By demonstrating the significant impact of user behavior on energy efficiency, the research supports the SBC's broader objectives of environmental protection and sustainability. It highlights the critical role of behavioral factors in achieving the energy efficiency targets set forth in the code.
- **Promotion of Best Practices:** The thesis serves as a resource for promoting best practices in building management and operations, encouraging the adoption of smart technologies that can dynamically respond to user behavior and environmental conditions.

In conclusion, this thesis significantly enhances the application and effectiveness of the Saudi Building Code by providing a deeper understanding of user behavior's role in energy consumption. This alignment not only underscores the relevance of the research within the national context but also contributes to Saudi Arabia's ongoing efforts to promote sustainability in its urban development, as outlined in Saudi Vision 2030 and the 2060 carbon neutrality goal. The integration of behavioral insights into building energy models represents a forward-thinking approach to addressing the challenges of energy efficiency and sustainability in residential construction. [64]

2.3 User Behavior and Energy Consumption

In the quest for energy saving, understanding and influencing user behavior is as crucial as technological advancements. This section delves into the multifaceted aspects of user

behavior in residential energy consumption, exploring the myriad factors that shape energy usage patterns, from individual actions to broader socio-economic influences. It also examines the effectiveness of various data collection methods and behavioral programs aimed at promoting energy-efficient practices. By integrating insights from behavioral science with technological solutions, we can better address the challenges and opportunities in optimizing residential energy efficiency.

2.3.1 Influential Factors and User Behaviors in Residential Energy

Consumption

Residential energy consumption is shaped by various factors including climate, building characteristics, occupant demographics, and behavior. Climate and housing size notably impact space heating and cooling needs [65]. Electricity consumption is heavily influenced by the number of air conditioners per household and per capita disposable income, while urbanization and population growth have a lesser effect [66]. In cold and arid regions, energy consumption is significantly affected by the heat transfer coefficients of roofs, walls, and windows, along with building orientation and ventilation rates[67]. Household composition, such as the number of family members and their age groups, plays a critical role in energy usage for cooling, domestic hot water, and appliances [68]. Demographic factors like household size, median age, and occupancy rates are also important, with geographical location further affecting consumption patterns [69]. Technological factors, including the efficiency of air conditioning systems and internal loads like lighting and equipment power, are crucial in determining total energy use [70]. Additionally, socio-economic status, family size, and house size influence energy consumption behaviors[71].

In multifamily housing, the building's condition, technological solutions, and occupant behavior are key determinants, with occupant behavior alone accounting for up to 80% of the variation in energy use[72].

While these factors set the stage for energy use patterns, it is the behaviors—both adaptive and non-adaptive—that directly influence energy efficiency outcomes.

2.3.2 Adaptive and Non-Adaptive User Behaviors in Energy Consumption

Energy user behavior can be generally divided into adaptive and non-adaptive actions, each having unique characteristics and effects on energy consumption and efficiency. Adaptive actions involve users actively modifying their behavior or environment to optimize energy use, such as adjusting thermostats, turning off lights, or enhancing insulation to improve comfort and reduce energy usage[73], [74]. These behaviors are often influenced by individual preferences, socioeconomic factors, and awareness of the benefits of energy conservation[75]. Conversely, non-adaptive actions are marked by habitual, often unconscious behaviors that do not actively seek to optimize energy use, such as leaving lights on unnecessarily [76]. These behaviors can be deeply ingrained and difficult to change without targeted interventions. Research has demonstrated that promoting pro-environmental behavior (PEB) through education and awareness can significantly affect energy consumption patterns, particularly in residential sectors[77]. Advanced analytical methods, such as unsupervised learning and clustering, can enhance our understanding of user behavior in complex power grid environments, facilitating better resource coordination and optimization [78]. Overall, integrating adaptive actions into energy policies and interventions, while addressing the habitual nature of non-adaptive actions, is

essential for achieving sustainable energy consumption and reducing CO₂ emissions[79], [80].

Recognizing the distinctions between adaptive and non-adaptive behaviors allows for targeted energy-saving strategies. To effectively analyze these behaviors, robust data collection methods are employed, each offering unique insights into the nuances of energy use.

2.3.3 Data Collection Methods in Energy Use Behavior Studies

To understand energy use behavior, various methods and criteria for data collection are employed, each with unique strengths and challenges. Traditional methods include the use of smart meters and surveys. Smart meters provide reliable, granular data on energy consumption but lack semantic information about the specific use, such as which appliances are in operation [81]. Surveys, while rich in semantic detail, are labor-intensive and may suffer from biases[82]. Social media data has emerged as an alternative, offering semantically rich and publicly available information, though it is noisy and requires sophisticated data processing techniques to extract relevant insights[83].

Additionally, systems that analyze energy usage behavior through micro-moments—short-timed, energy-based events—are being developed to capture detailed end-user behavior [84].

Data collection methods must consider the specific needs of the study, such as the type of data required (e.g., frequency, timestamp, power usage) and the context (e.g., household, building) [85]. Clustering and classification techniques are used to predict occupant

behavior and identify patterns in energy use, achieving high accuracy in some cases [86]. Furthermore, qualitative-quantitative research methods, including online surveys, help identify energy-wasteful behaviors and their underlying reasons, such as indifference or habit [87]. Incorporating psychological, cultural, and sociodemographic factors as explanatory variables, without resorting to circular reasoning, strengthens the robustness of the data collected. [88]. To thoroughly understand energy use behavior through surveys, several criteria must be included. First, socio-demographic variables such as skills, family size, knowledge, age, income, occupation, and ownership status (owner/tenant) are crucial to capture the diverse backgrounds of respondents [89]. Furthermore, evaluating factors like motivation to conserve energy, attitudes towards energy efficiency, comfort perception, perceived behavior effectiveness, and social norms is essential for understanding the psychological and social influences on energy use. [90].

Behavioral variables like set temperatures, global temperature management, occupation patterns, and ventilation habits are vital for capturing actual energy-related actions[91], [92]. Including questions on the use of domestic appliances and the presence of smart technologies, such as smart meters, can provide insights into the impact of technological interventions on energy consumption [93]. It is also important to consider the influence of norms and attitudes towards environmental issues, as these can significantly affect energy-related decisions [94].

Surveys should explore the effectiveness of policy interventions and the role of government in fostering sustainable behavior, as well as the barriers to changing energy behaviors, such as financial costs and social values [95]. Armed with detailed behavioral data, energy conservation programs can be tailored to address specific behaviors and barriers. The

following subsection examines various initiatives that leverage these insights to foster more sustainable energy practices.

2.3.4 Behavioral Programs and Initiatives

Studies have demonstrated that modifications in energy-related behaviors can significantly decrease energy consumption in residential settings[96]. For example, optimizing the use of windows and curtains has proven effective in lowering cooling loads and overall power use, thus illustrating how energy-efficient behaviors can work in tandem with technological advancements to enhance building energy performance.

Additionally, behavioral programs that offer feedback, education, and incentives have shown some success in reducing energy use, generally by less than 5%[97]. The integration of behavioral science into energy efficiency initiatives, such as in the Community Energy Services program, has improved the effectiveness of these programs by combining behavior change strategies with direct installations and extensive retrofits [84].

This comprehensive approach, which addresses both the structural attributes of buildings and promotes specific energy usage behaviors, emphasizes the importance of holistic strategies that incorporate both technological and behavioral interventions to boost residential energy efficiency.

2.3.5 Incorporating User Behavior in AI Models

AI models leverage machine learning and deep learning to recognize patterns in energy consumption influenced by user behavior. This capability is crucial for accurate energy

demand forecasting and optimizing energy use [98]. AI-driven systems in smart buildings are designed to adapt to user behavior dynamically. By managing HVAC systems and lighting based on occupancy patterns, these systems ensure energy is utilized efficiently without sacrificing comfort [99]. Ensemble methods such as Random Forest and Gradient Boosting improve the accuracy of energy demand forecasts by considering diverse user behaviors and environmental factors, thus enhancing the predictive performance[100].

The interplay between user behavior and technological solutions is fundamental to advancing residential energy efficiency. The following discussion will explore how emerging technologies, particularly AI, are utilized to enhance energy management systems, demonstrating the practical applications of these findings.

2.4 Technological Advances in Energy Performance Analysis

In the contemporary landscape of energy management, Artificial Intelligence (AI) has emerged as a cornerstone technology, fundamentally transforming how energy consumption is analyzed, predicted, and optimized. AI's capability to model complex, nonlinear relationships within vast datasets makes it an invaluable tool in addressing the intricate challenges of energy systems. This section delves into the various AI technologies that have revolutionized energy performance analysis, offering insights into their applications, benefits, and the challenges they present.

2.4.1 Artificial Intelligence Models in Energy Performance Analysis

Artificial Intelligence (AI) models have become instrumental in enhancing energy performance analysis due to their ability to model complex, nonlinear relationships

inherent in energy systems. This section reviews the various AI techniques that have been employed to predict and optimize energy consumption and load profiles effectively.

- **Artificial Neural Networks (ANNs):** ANNs are prominent for their flexibility in handling complex and non-linear data structures, making them particularly useful in predicting energy consumption and load forecasting. Le et al [101] highlight the effectiveness of ANNs in detailed resource planning across various energy systems. Moreover, innovative variants like the Data Information integrated Neural Network (DINN) have enhanced predictive performance by integrating correlation information from datasets, thereby improving both the model's accuracy and interpretability.[102]
- **Ensemble Methods:** Recognized for their superior generalization capabilities, ensemble methods such as Random Forest and Gradient Boosting mitigate common issues like overfitting. These methods are invaluable in scenarios requiring high prediction accuracy and are particularly enhanced by feature engineering techniques to fine-tune forecast precision [100]
- **Support Vector Machines (SVM):** SVMs are favored for their robustness and ability to efficiently handle large datasets, outperforming other predictive models such as ARIMA and LSTM in terms of prediction accuracy, particularly in measuring RMSE values [103]
- **Hybrid Models:** Hybrid AI models integrate multiple computational techniques to capitalize on their individual strengths. For instance, ANFIS-GA (Genetic Algorithm) and ANFIS-PSO (Particle Swarm Optimization) models combine neuro-fuzzy systems with optimization algorithms. This integration not only enhances prediction accuracy but also facilitates significant input identification through sensitivity analysis, optimizing overall energy performance [104]

- **Explainable AI (XAI) :** The application of XAI within AI-based energy analytics has bridged the gap between advanced computational models and practical application by enhancing the interpretability of model outcomes. This is particularly valuable in benchmarking energy performance, where understanding the causal relationships between predictors and target variables is crucial [105]
- **Traditional Statistical and Regression Methods :** Despite the rise of advanced AI techniques, traditional methods such as ARIMA still play a crucial role in energy forecasting. These methods often serve as a baseline for comparison and are increasingly being integrated into hybrid models to refine accuracy and reliability in predictions [103]. Additionally, regression methods like SVMs and Random Forest continue to be pivotal due to their robust capability to model complex relationships within energy data [106]

2.4.2 Application of AI Technologies

- **Smart Grid Management and Optimization :** AI significantly enhances smart grid operations by providing sophisticated demand forecasting and load balancing, which ensure efficient energy distribution and minimize wastage. Manoharan et al. [107] and Al-Haddad et al. [108] demonstrate how Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), effectively manage time-series data from IoT devices to forecast energy consumption accurately. These AI-driven systems are pivotal in integrating renewable energy sources, optimizing usage, and significantly reducing carbon emissions.
- **Building Automation and Energy Efficiency :** In building automation, AI models optimize HVAC systems and other energy-intensive operations to reduce consumption

without compromising comfort. Goel [109] and Sarma et al.[110] highlight the application of ensemble models like Random Forest and Gradient Boosting, which provide detailed insights into baseline energy use and identify potential savings in real-time, greatly enhancing building energy efficiency.

- **Industrial Process Optimization :** AI's impact extends to industrial settings, where it optimizes energy usage by adjusting operations based on predictive models, thereby cutting costs and boosting efficiency. Goel [109] and Chander & Gopalakrishnan [50] discuss the integration of AI in Energy Management Systems (EMS) and Renewable Energy Systems (RES), which improves system design, control, and fault diagnosis, leading to more sustainable industrial operations.
- **Renewable Energy Integration :** AI is crucial in managing the variability of renewable energy sources such as wind and solar. Iriakuma et al. [111] and Le et al. [101] show how AI models predict renewable energy outputs, allowing for better grid integration and stability. These models also optimize power output from renewables, enhancing the efficiency and cost-effectiveness of these energy systems [50].
- **Predictive Analytics and Energy Forecasting:** Advanced predictive analytics using AI, particularly ANNs, are central to forecasting energy consumption with high accuracy. Le et al. [101] illustrate that AI models, including LSTM and STL, effectively capture seasonal and trend variations in energy data, enabling optimized energy management strategies in diverse settings, such as department stores [112].
- **Challenges and Future Directions:** Despite the advancements, AI in energy management faces challenges such as data integration, model robustness, and scalability. Addressing these issues requires innovative approaches and collaboration among various

stakeholders to fully leverage AI's potential in sustainable energy systems. Furthermore, regularizing AI models to prevent overfitting is critical for maintaining their reliability and effectiveness in practical applications [100], [107], [108], [109]. AI technologies represent a transformative force in energy performance analysis, providing powerful tools that help meet the growing demands for energy efficiency and sustainability. As AI continues to evolve, its integration into energy systems promises to yield significant advancements in managing and conserving energy resources. The continued innovation and adaptation of AI technologies will be crucial for achieving long-term sustainability goals in energy management.

2.5 Bibliometric and Systematic Reviews

The bibliometric and systematic reviews undertaken in this research serve as foundational elements to establish a comprehensive understanding of the field of energy conservation. These reviews are instrumental in delineating the current academic and practical landscape, offering a structured and empirical overview that supports the thematic exploration of global and regional research trends, disparities in focus areas, and methodological diversity. By employing scientometric tools and systematic methodologies, these reviews critically assess the volume, provenance, and orientation of the research conducted over several decades, thereby illuminating the evolution of the field and its alignment with global energy policies and practices.

The bibliometric and systematic reviews are designed to answer a series of pivotal research questions that guide the overall direction of the thesis. These include:

- What are the predominant trends in global research on energy conservation and energy use behaviour over the last four decades? This question seeks to identify temporal shifts and thematic evolutions within the field.
- How is research distributed geographically, and what disparities exist between contributions from developed and developing regions? This addresses the global spread of research efforts and highlights potential biases or concentrations in knowledge production.
- What methodological approaches dominate the field, and how have they evolved to address the complexities of energy conservation and efficiency research? This question examines the tools and frameworks used by researchers to investigate and interpret energy data, offering insights into the robustness and adaptability of research designs.

2.5.1 Global Trends in Energy Research

- **Bibliometric Analysis:** The bibliometric review on "Energy Efficiency Vs. Energy Conservation" reveals a significant imbalance, with a predominant focus on energy efficiency over conservation. This analysis, which spans articles from 1984 to 2024, highlights an urgent need to rebalance research towards energy conservation practices.
- **Systematic Analysis** Complementing the bibliometric findings, the systematic review on "Energy Conservation Research Trajectories" echoes similar disparities, underscoring insufficient focus on practical, field-validated energy conservation methods, particularly in developing regions.

2.5.1.1 Bibliometric Analysis: Energy Efficiency vs. Energy Conservation

The bibliometric analysis from "Energy Efficiency Vs. Energy Conservation: Analysis of Trends, Disparities, and Future Directions in Global Energy Research" examined articles from 1984 to 2024. It revealed a stark imbalance with 88.7% of the research focused on energy efficiency, compared to just 11.24% on energy conservation as shown in Figure 5. This disparity underscores a critical gap in research attention towards energy conservation measures, suggesting an urgent need for rebalancing towards sustainable practices. The key contributors to this research trend include the United States, the United Kingdom, and China, indicating a skewed geographic focus that necessitates a broader, global perspective as shown in the network Figure 6.

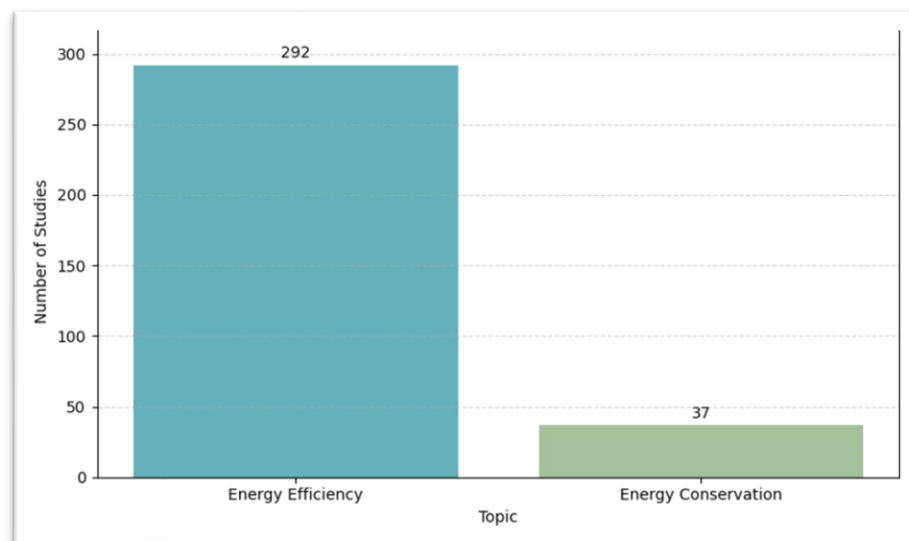


Figure 5: Comparison of research Volume between Energy Efficiency and Energy Conservation.

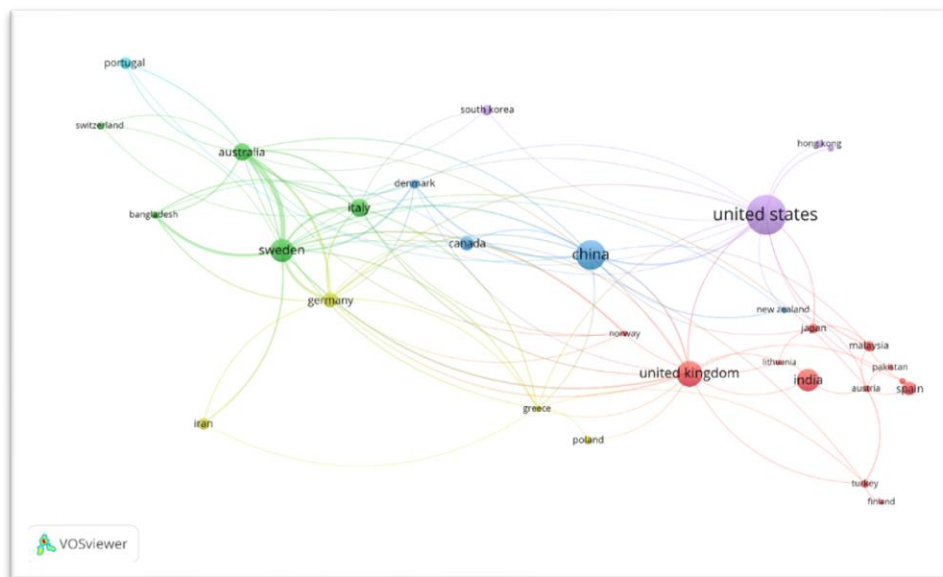


Figure 6: Key contributors to Energy Saving Research

2.5.1.2 Systematic Analysis: Energy Conservation Research Trajectories

Complementing the bibliometric findings, the systematic review titled "Energy Conservation Research Trajectories: A Systematic Analysis of Methods, Technologies, and Knowledge Gaps" highlights similar disparities, where studies on energy efficiency dominate the research landscape consistently as shown in Figure 7 . It points to an insufficient focus on field-validated energy conservation methods, especially in developing regions. This analysis emphasizes the lack of practical applications and the need for enhanced methodological approaches to support energy conservation initiatives in these underrepresented areas.

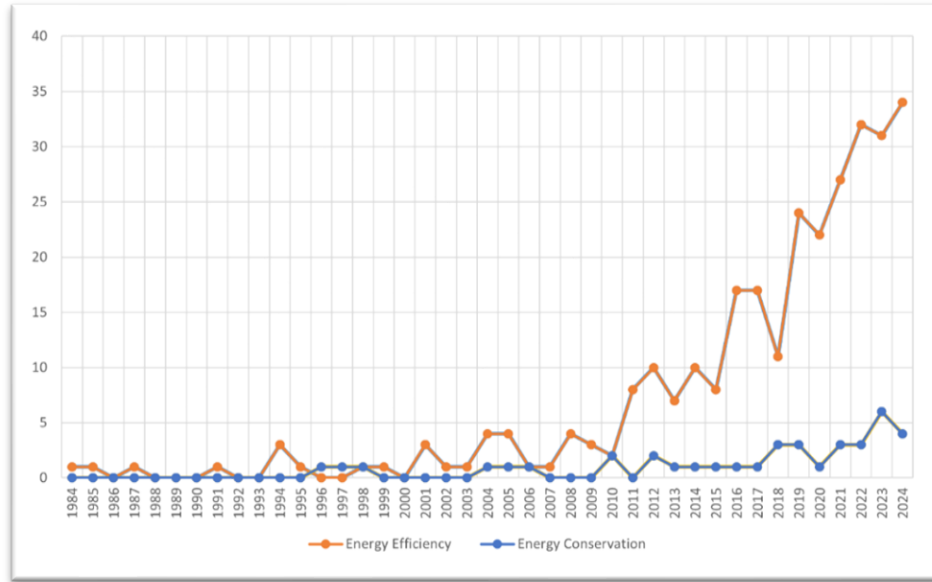


Figure 7: Annual Publication Trend Comparison between Energy Efficiency and Energy Conservation Research Domains.

These reviews critically inform the thesis by substantiating the need for a focused investigation into energy conservation strategies. They directly influence the research questions formulated to explore why energy conservation is less emphasized and how it can be better integrated into energy policies and practices. By adopting a similar multifaceted methodological approach as observed in the systematic review, this thesis aims to provide a holistic understanding of energy behaviors and conservation strategies, particularly in developing regions like Saudi Arabia.

The insights from these reviews not only guide the academic inquiry of this thesis but also have significant implications for future research agendas and policy formulations. By addressing the noted disparities, the research aims to foster a more balanced approach to energy studies, contributing to more comprehensive environmental sustainability efforts globally. The discussions and recommendations derived from these reviews will also

support the development of targeted interventions and policies to promote energy conservation across diverse geographical contexts.

2.5.1.2.1 Bibliometric Insights: Energy Use Behavior Research

The bibliometric review from "Energy Use Behavior Research: A Scientometric Evaluation and Critical Synthesis" delves into the evolution of research themes from 1981 to 2024. This analysis underscores a marked increase in publications since 2005, aligned with global shifts towards energy conservation and efficiency.

2.5.1.2.2 Keyword Analysis and Emerging Themes

Dominant Keywords like "Energy efficiency" and "occupant behavior" are the most prevalent, as shown in Figure 8 , highlighting the core focus on how individual behaviors impact energy usage. The frequent co-occurrence of these terms with "building performance" and "energy consumption" indicates a strong research emphasis on the interaction between user behaviors and technological solutions in buildings.

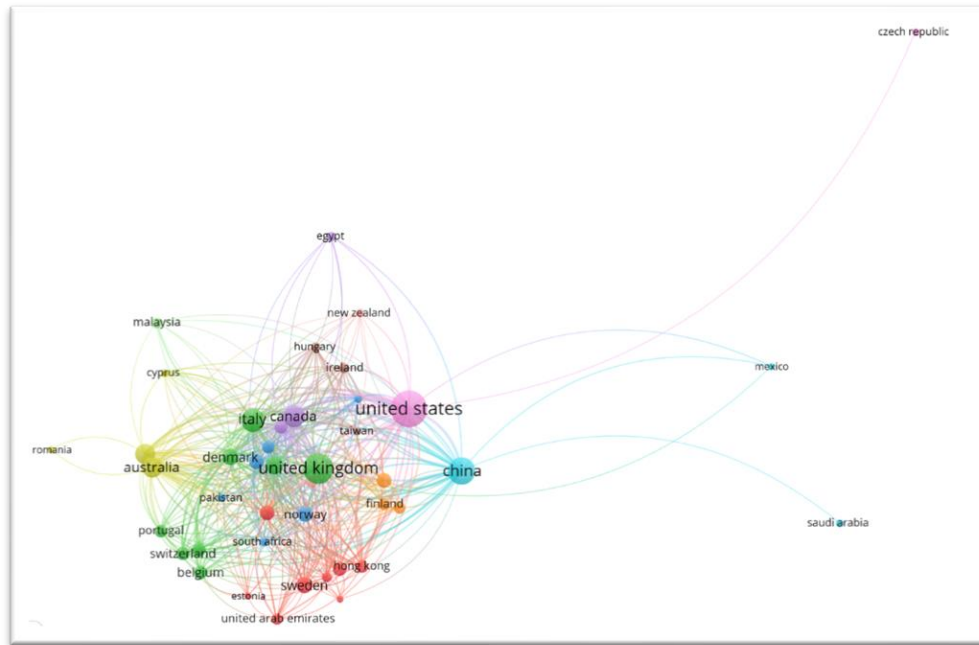


Figure 9: Countries Prominent in Energy Use Behaviour Research.

- Current Themes observed in energy Use Behavior Analysis are shown in Figure 11 from cluster analysis done on the network diagram shown in Figure 10 are:
 - Building Environment and Control Systems: Explores the influence of building design and integrated control systems on energy use, focusing on the interaction between building infrastructure and occupant behavior to optimize energy efficiency.
 - Socio-Demographic Influences: Examines how age, income, education, and cultural background impact energy consumption behaviors, essential for crafting targeted energy conservation programs.
 - Simulation and Performance Analysis: Utilizes simulation tools to predict and assess the impacts of energy-saving measures, aiding in the evaluation of new technologies and strategies.

- Policy, Sustainability, and Human Factors: Studies the role of policy frameworks and human factors in energy usage, integrating behavioral science insights to develop effective energy conservation measures.

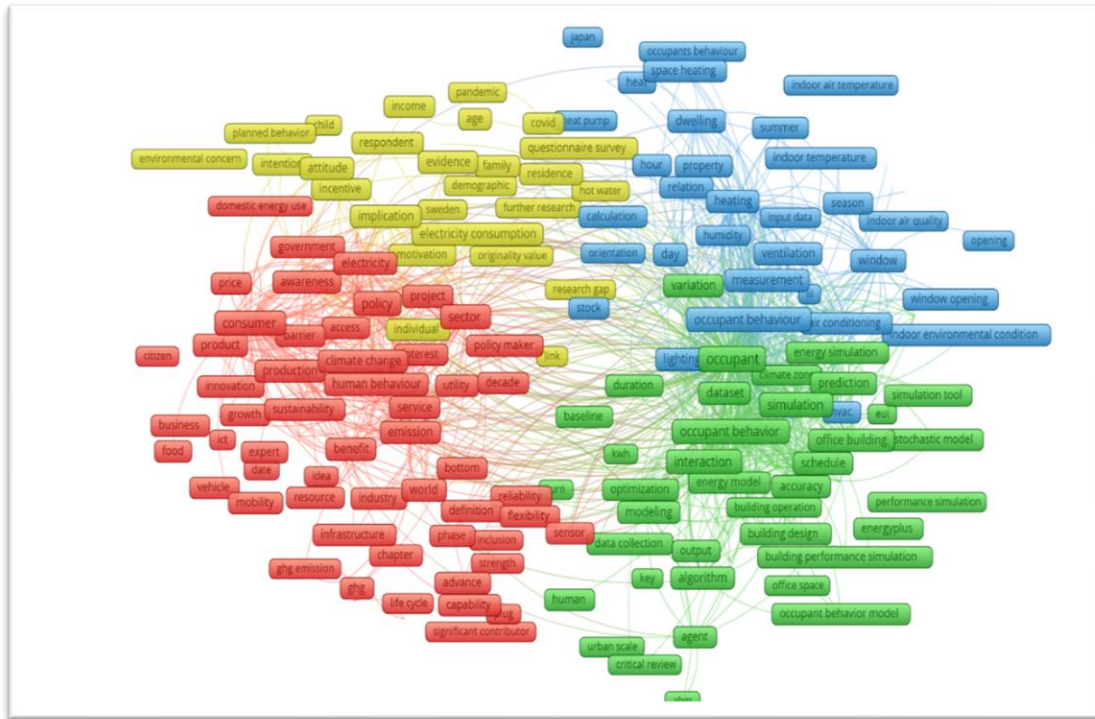


Figure 10: Clusters of Main Research Areas in Energy Use Behaviour Domain

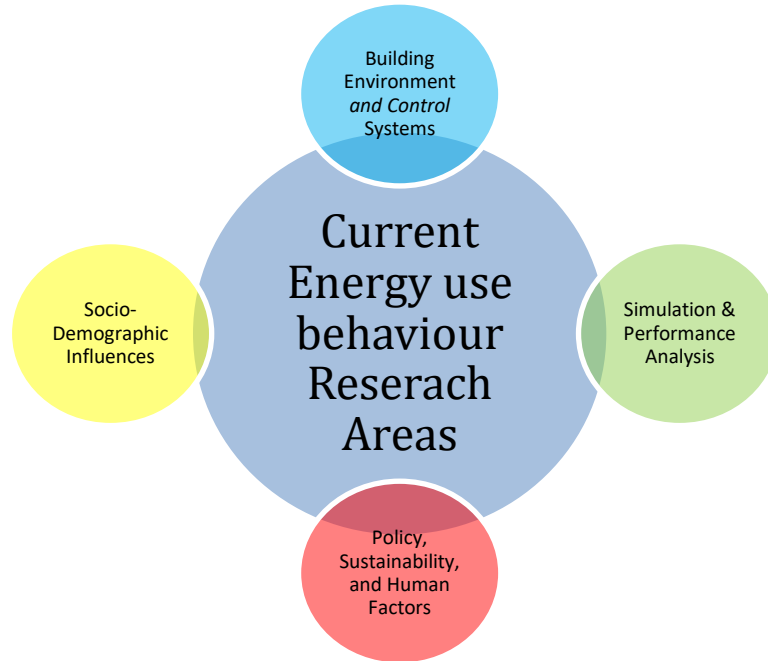


Figure 11: Current Energy Use Behaviour Research Areas.

2.5.1.3 Global Energy Conservation Research: A Systematic Analysis of Thematic Areas, Methodologies and Geographic Distribution

This review provides a critical overview of how behavioral interventions for energy conservation are being approached differently across developed and developing regions.

2.5.1.3.1 Annual Trend of Articles

- **Publication Trends:** Research in energy conservation has shown a fluctuating but overall increasing trend from 1982 to 2024, as shown in Figure 12, with notable peaks in publication activity post-2010.
- **Influence of Global Events:** Peaks in research correlate with significant global events such as the adoption of international policies like the Paris Agreement and advancements in renewable energy technologies.

- **Research Gaps Identified:** Despite advancements, gaps remain in integrating renewables into existing grids, behavioral strategies for energy saving, and the development of cost-effective energy storage solutions.
- **Future Research Directions:** There is a call for future research to both continue advancing technological innovations and address identified gaps to support more comprehensive energy conservation strategies.

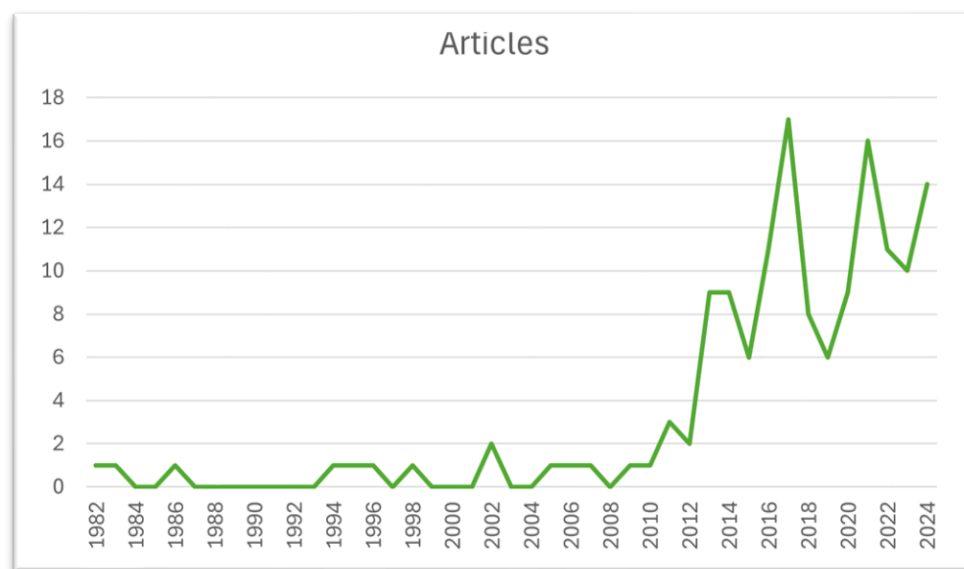


Figure 12: Annual Trend of Publications of Energy Conservation Studies

2.5.1.3.2 Countries' Scientific Production In Energy Conservation Research

Domain

- **Leading Contributors:** The United States, China, and the United Kingdom are the top contributors to energy conservation research, with significant volumes of published articles as shown in Figure 13 . Top 15 Countries among these

contributing to Energy Conservation Research are mentioned in Table 1: Top 15 Countries Contributing to Energy Conservation Research.

- **Geographical Disparities:** There is a notable geographical disparity in research output, with developed countries like Italy, Australia, and Germany also contributing actively.
- **Emerging Economies:** Countries with emerging economies, notably China and India, are increasingly engaging in energy conservation research, reflecting their rapid industrial growth and escalating energy demands.
- **Research Disparity:** While some nations are advanced in their research contributions, many others show minimal or no contributions, highlighting the uneven distribution of research activity.
- **Global Collaboration:** The data underscores the need for increased involvement from underrepresented nations and greater support for international collaborations to effectively address global energy sustainability challenges.

In this review, countries have been classified into 'developed' and 'developing' categories for the purposes of analysis. It is acknowledged that such classifications can oversimplify the complex economic landscapes of certain countries. Notably, China is often categorized as a transitional economy due to its rapid industrialization and unique economic characteristics [113]. However, for the purposes of this systematic review and to maintain consistency with the literature reviewed [114], [115], China has been included in the 'developing' category. This classification reflects its historical context and the comparative focus of many studies within the scope of this research. The criteria for classification have followed the guidelines provided in the report by the

United Nations, which employs various data sources and aggregation methods to analyse global economic trends, ensuring a well-founded basis for distinguishing between developed and developing countries [116].

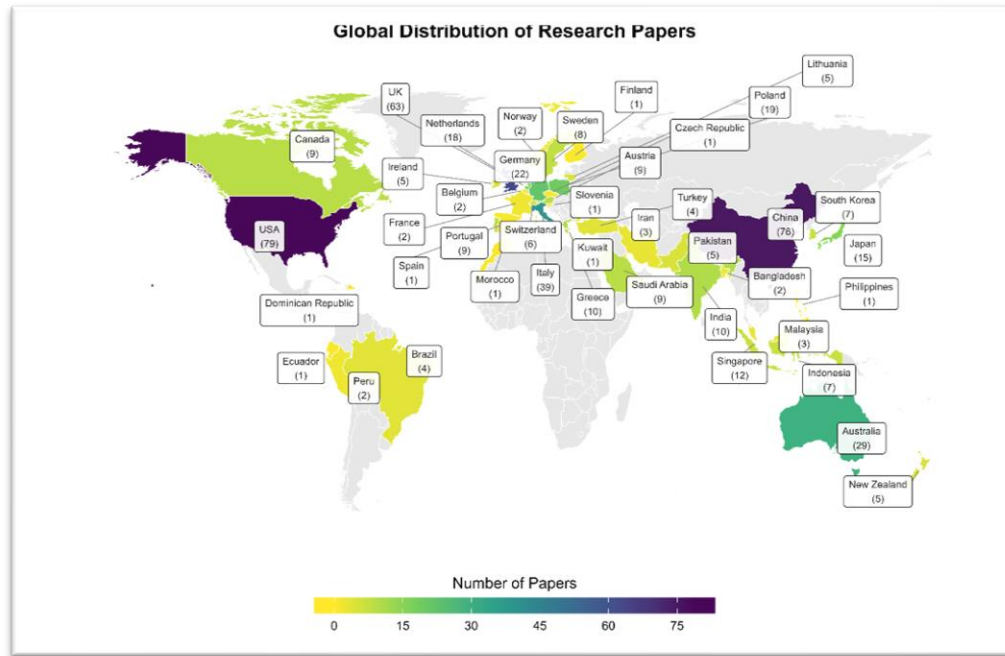


Figure 13: Countries Contributing to Energy Conservation Research

Table 1: Top 15 Countries Contributing to Energy Conservation Research.

Country	Frequency	Classification
USA	79	Developed
CHINA	76	Developing
UK	63	Developed
ITALY	39	Developed

AUSTRALIA	29	Developed
GERMANY	22	Developed
POLAND	19	Developed
NETHERLANDS	18	Developed
JAPAN	15	Developed
SINGAPORE	12	Developed
GREECE	10	Developed
INDIA	10	Developing
AUSTRIA	9	Developed
CANADA	9	Developed
PORTUGAL	9	Developed

2.5.1.3.3 Geographical Focus of Studies

The research is significantly concentrated in certain regions, with China, the USA, and the UK being the most studied countries. Table 2: Geographical Focus of Energy Conservation Studies. shows Geographical Focus of Energy Conservation Studies . This highlights their high level of engagement and established research agendas in energy conservation.

- **Distribution of Studies:** Among the 144 studies reviewed, as shown in Figure 14 and Figure 14: Geographical Focus of Energy Conservation Studies (Development Status -wise), most research (65.6%) targets developed countries, while 34.4% focuses on developing countries, and 13% adopt a global perspective. This indicates a predominant interest in developed regions which may be driven by advanced technological infrastructures and regulatory frameworks.
- **Focus on Developing Countries:** Developing regions like India and Brazil are also receiving significant attention, underscoring a growing recognition of the need for tailored energy conservation strategies that address specific developmental challenges. Figure 15 shows that among the top 15 geographically concentrated countries, only two countries i.e., China and India are developing countries.
- **Global and Cross-border Studies:** The studies with a global focus are crucial for exploring cross-border policies and international agreements, reflecting a broad, international approach to tackling energy conservation issues.
- **Implications for Future Research and Policy:** The geographical distribution of studies highlights the need for a more balanced research focus that includes more developing regions. Enhancing focus on these areas can significantly impact sustainable development and address global energy conservation challenges effectively.

Table 2: Geographical Focus of Energy Conservation Studies.

No.	Country	No. of Articles	Classification

1	China	20	Developing
2	USA	15	Developed
3	UK	11	Developed
4	Germany	4	Developed
5	Italy	4	Developed
6	Netherlands	4	Developed
7	Singapore	4	Developed
8	Sweden	4	Developed
9	Hong Kong	3	Developed
10	Japan	3	Developed
11	Poland	3	Developed
12	South Korea	3	Developed
13	India	2	Developing
14	Australia	2	Developed
15	Canada	2	Developed
16	Indonesia	2	Developing

17	Iran	2	Developing
18	Saudi Arabia	2	Developing
19	Malaysia	2	Developing
20	Pakistan	2	Developing
21	Switzerland	2	Developed
22	Turkey	2	Developing
23	Austria	1	Developed
24	Bangladesh	1	Developing
25	Brazil	1	Developing
26	Ecuador	1	Developing
27	Finland	1	Developed
28	Guinea	1	Developing
29	Ireland	1	Developed
30	Israel	1	Developed
31	Lithuania	1	Developed
32	New Zealand	1	Developed

33	Peru	1	Developing
34	Philippines	1	Developing
35	Portugal	1	Developed
36	Qatar	1	Developing
37	Saint Lucia	1	Developing
38	Mixed	31	-

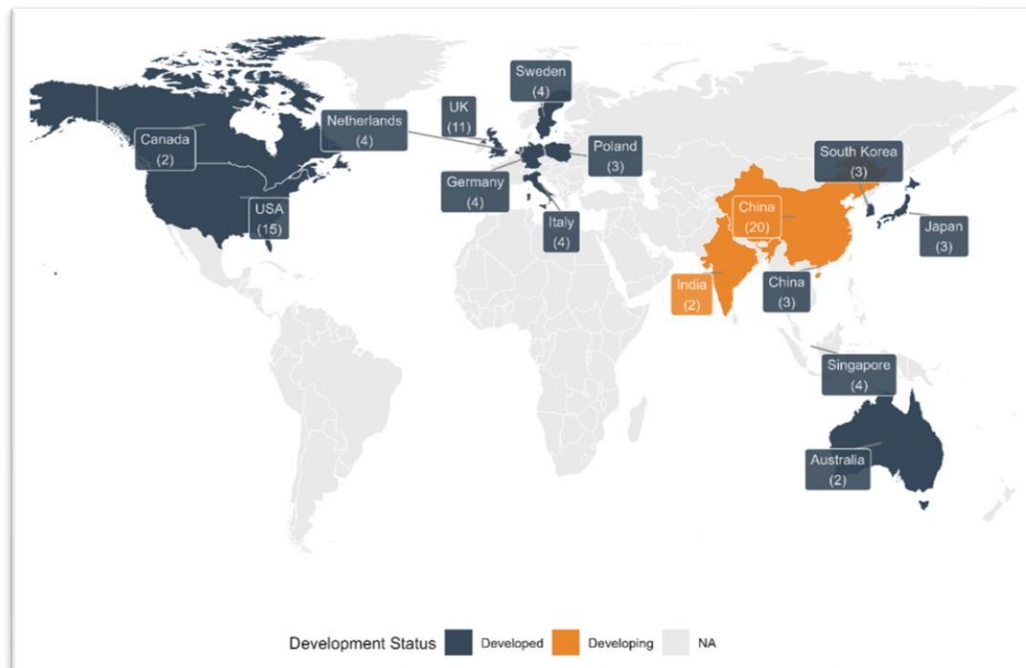


Figure 14: Geographical Focus of Energy Conservation Studies (Development Status -wise)

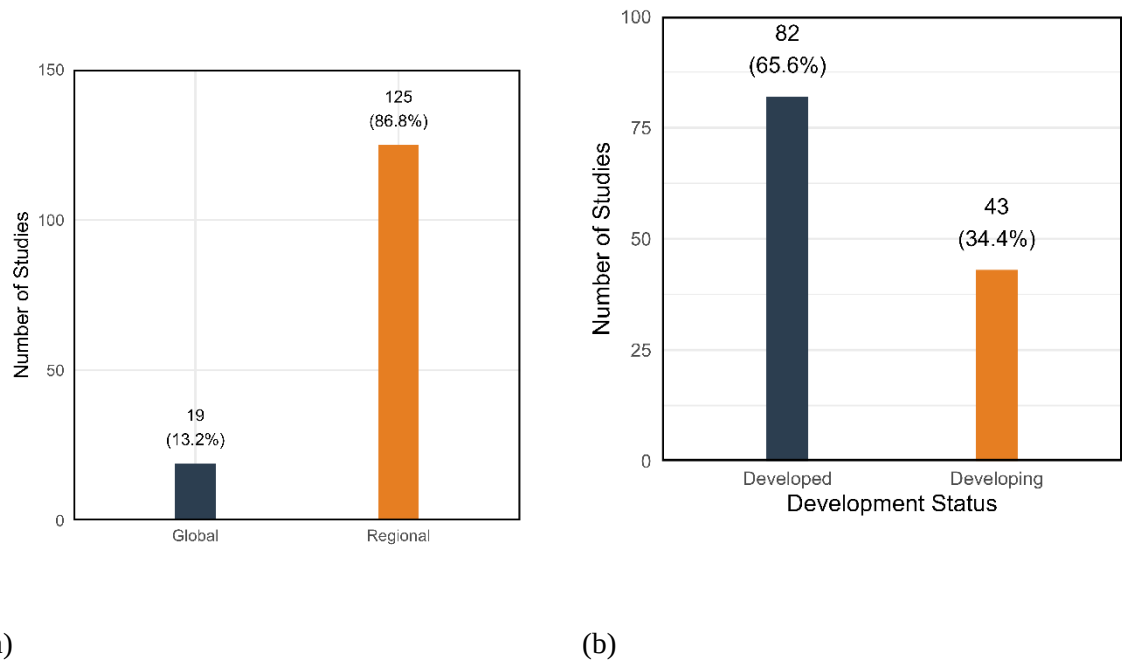


Figure 15: (a) Global v/s Regional Focus of Research . (b) Developed v/s Developing Country Focus of Research.

2.5.1.3.4 Comparative Trends in Energy Conservation Research Publications

- **Longitudinal Trends:** This analysis provides a deeper look into the evolution of research output over time, comparing developed and developing regions. Developed regions consistently exhibit higher publication rates, as shown in Figure 16, indicative of more established research infrastructures and greater resource allocation.
- **Annual Fluctuations:** Fluctuations in annual publication rates reflect global economic cycles, policy shifts, and key international environmental events. Peaks in publication volumes are often aligned with periods following major environmental protocols or significant investments in sustainable technologies, particularly in developed countries.

- **Recent Surges in Developing Regions:** Developing regions display a more recent increase in research publications, likely due to growing international support and local policy initiatives aimed at enhancing sustainability.
- **Cumulative Publication Trends:** The cumulative publications graph shown in Figure 16 highlights a steady increase in output from developed countries over the decades, while for developing countries, the growth becomes more noticeable starting in the early 2000s. This reflects an escalating commitment to energy conservation as these regions face more direct impacts of energy issues on their economic and social development.
- **Implications for Policy and Collaboration:** The comparative analysis underscores the need for enhanced collaborative efforts and knowledge exchange between developed and developing regions. Leveraging research advancements from developed areas could help accelerate sustainable practices in developing countries, highlighting the importance for policymakers to focus on investments in research and fostering international collaborations to tackle global energy challenges.

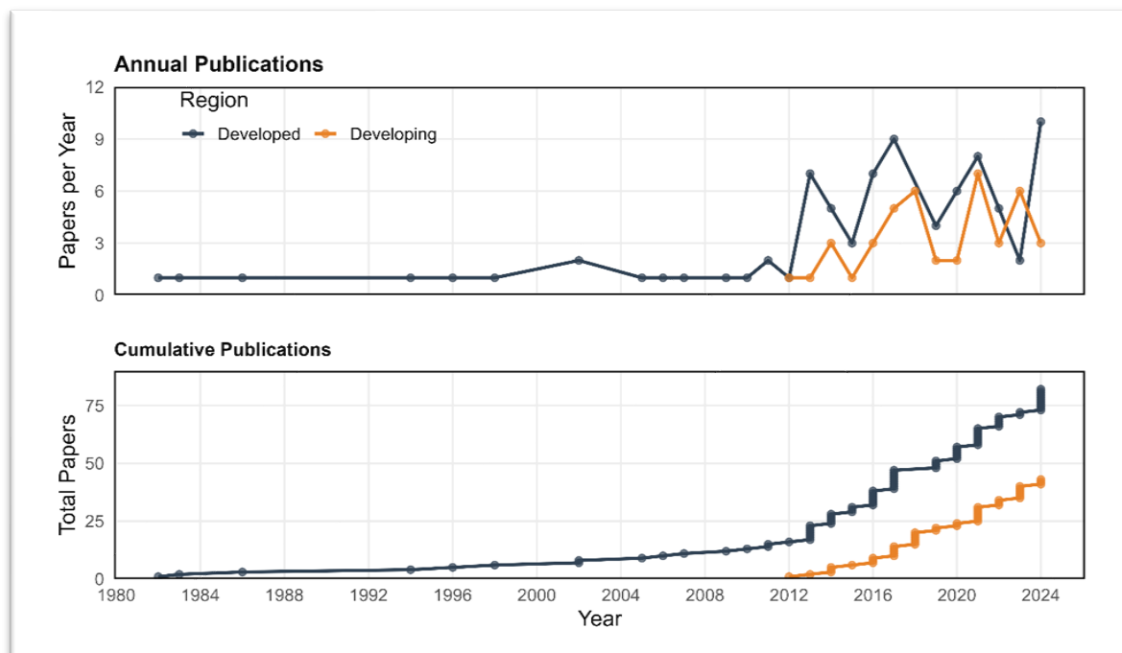


Figure 16: Comparative Trends in Energy Conservation Research Publications.

2.5.1.3.5 Methodological Approaches in Energy Conservation Research

The review categorizes the methodological approaches used in the 144 studies into quantitative, qualitative, and mixed methods, showing a clear preference across different regions that reflects their unique research needs and contexts. Figure 17 and Figure 18 in the report illustrate the breakdown of methodological approaches by region, providing a clear visual representation of the preferences and trends in research methodology within the field of energy conservation.

- **Predominant Methods in Developed Regions:** In developed regions, mixed methods are the most used approach (48.8%), followed by quantitative methods (39%). This preference likely reflects the complexity of energy conservation challenges, where

combining qualitative insights with quantitative data provides a more holistic understanding of the issues.

- **Methods in Developing Regions:** Developing regions show a similar inclination towards mixed methods (48.8%), but with a greater reliance on quantitative methods (46.5%) and less on qualitative approaches (4.7%). This trend suggests a focus on empirical data to inform practical applications and policy-making, reflecting the rapid changes and urgent needs in these areas.
- **Comparative Insights:** Both developed and developing regions recognize the value of mixed-methods studies, indicating a global trend towards integrating various types of data to tackle multifaceted energy conservation challenges effectively. Table 3 details the methodological approaches used in the studies analysed, highlighting the preferences for quantitative, qualitative, and mixed methods across developed, developing, and global studies

Table 3: Methodological Approaches Followed in the Studies.

	Quantitative	Qualitative	Mixed	Total	Quantitative (%)	Qualitative (%)	Mixed (%)
Developed	32	10	40	82	39	12.2	48.8
Developing	20	2	21	43	46.5	4.7	48.8

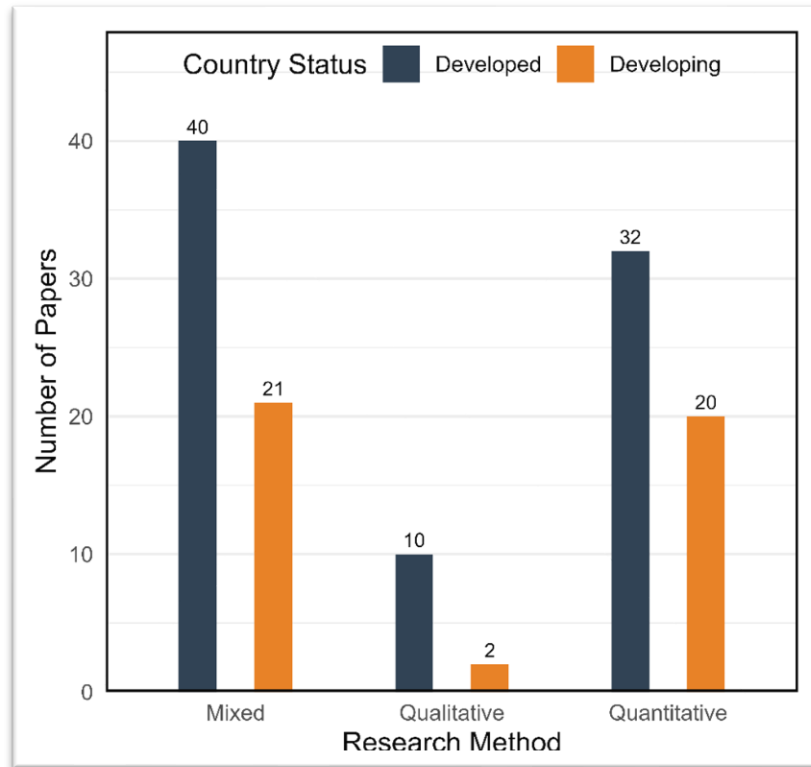


Figure 17: Breakdown of Methodological Approaches by Region.

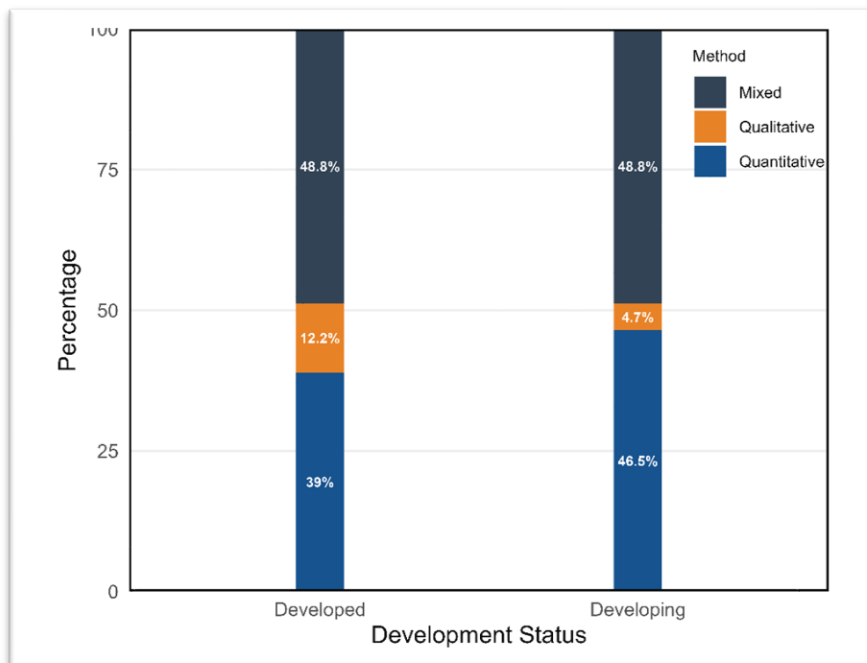


Figure 18: Percentage Breakdown of Methodological Approaches by Region

2.5.1.3.6 Analysis of Research Themes and Their Distribution in Energy

Conservation Research.

The research themes within energy conservation were systematically categorized into primary and second-order themes through a detailed analysis process as shown in Figure 19. This structured approach helped highlight major focus areas and methodological orientations across different geographic regions. The identified second-order themes are Behavioral Interventions (BI), Policy and Governance (P&G), Educational and Awareness Campaigns (E&AC), and Technological and Data-Driven Solutions (T&DS). Each theme represents a cluster of studies related to specific aspects of energy conservation. Table 4 presents the distribution of studies according to identified second order themes.

➤ **Distribution Across Regions:**

- **Developed Countries:** Show a significant focus on all four themes but particularly strong in Behavioral Interventions , Policy and Governance and Technological and Data Driven Solutions indicating a balanced approach that integrates policy, technology, and behavioral science to drive energy conservation.
- **Developing Countries:** Also emphasize all themes but with a notable focus on Behavioral Interventions and Policy and Governance. There is a greater emphasis on Educational and Awareness Campaigns compared to developed countries, reflecting a need to foster awareness and education to support energy conservation efforts.

➤ Comparative Focus:

- Studies in developed countries often incorporate advanced technological solutions and robust policy frameworks, reflecting their higher resource allocation and technological capacity.
- In contrast, developing countries focus more on direct community engagement and cost-effective educational and behavioral interventions, addressing unique local challenges and resource constraints.

➤ Interconnections and Implications:

- The research underscores the interconnected nature of behavioral, technological, educational, and policy dimensions within energy conservation.
- It highlights the need for integrated approaches that combine these dimensions to effectively address the complex challenges of energy conservation in different developmental contexts.

Figure 20 and Figure 21 visualizes these distributions, offering a clear comparison of how different regions prioritize various aspects of energy conservation.

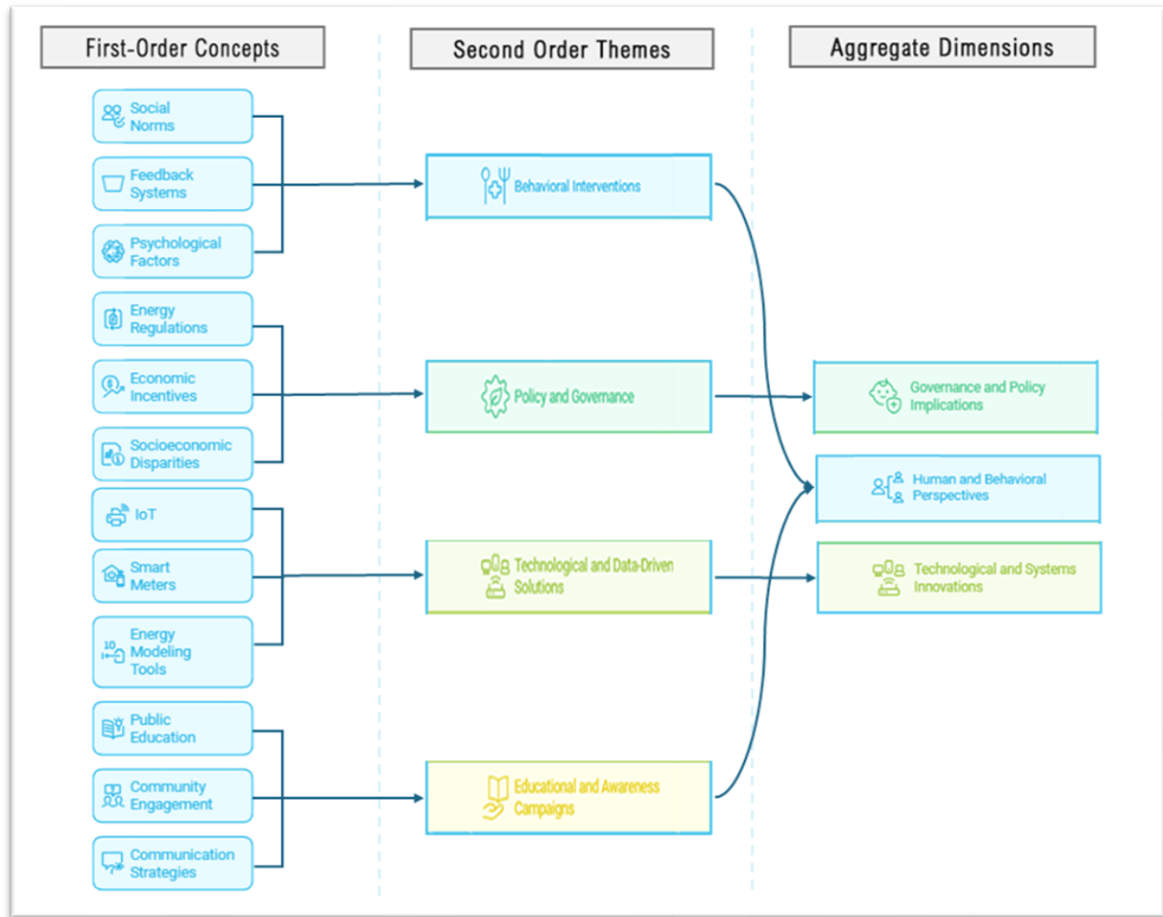


Figure 19: Research Themes in Energy Conservation Research

Table 4: Number of Studies Classified Under Each Second-Order Theme

Theme	Developed		Developing	
	No. of Studies	% of Studies	No. of Studies	% of Studies
Behavioral Interventions (BI)	30	36.6%	18	41.9%

Educational and Awareness Campaigns (E&AC)	11	13.4%	7	16.3%
Policy and Governance (P&G)	27	32.9%	15	34.9%
Technological and Data-Driven Solutions (T&DS)	14	17.1%	3	7.0%

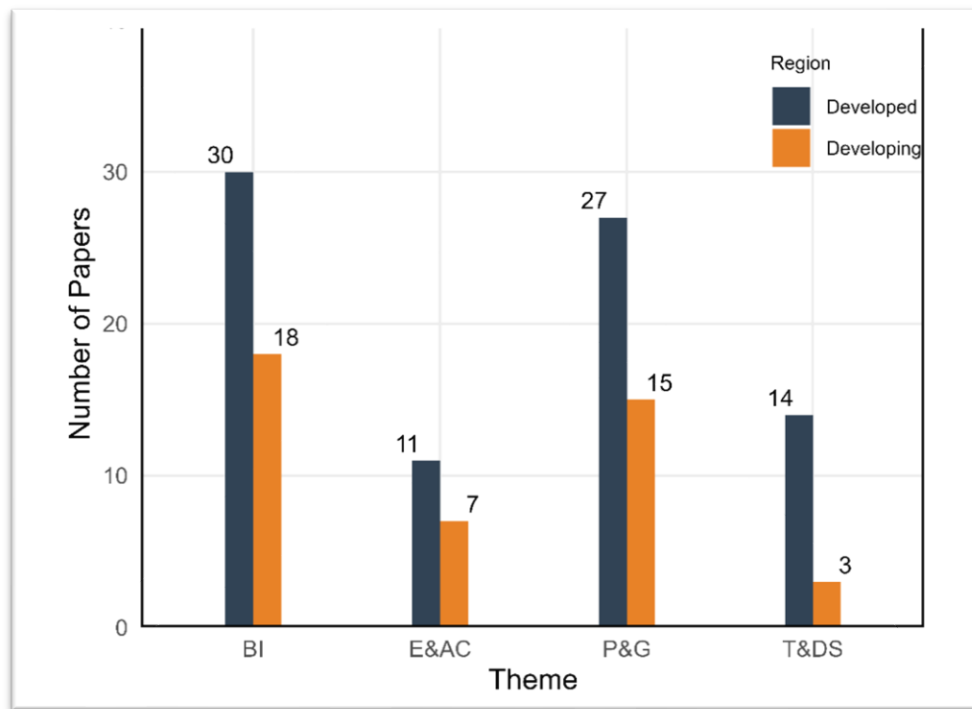


Figure 20: Distribution of Research Themes by Region

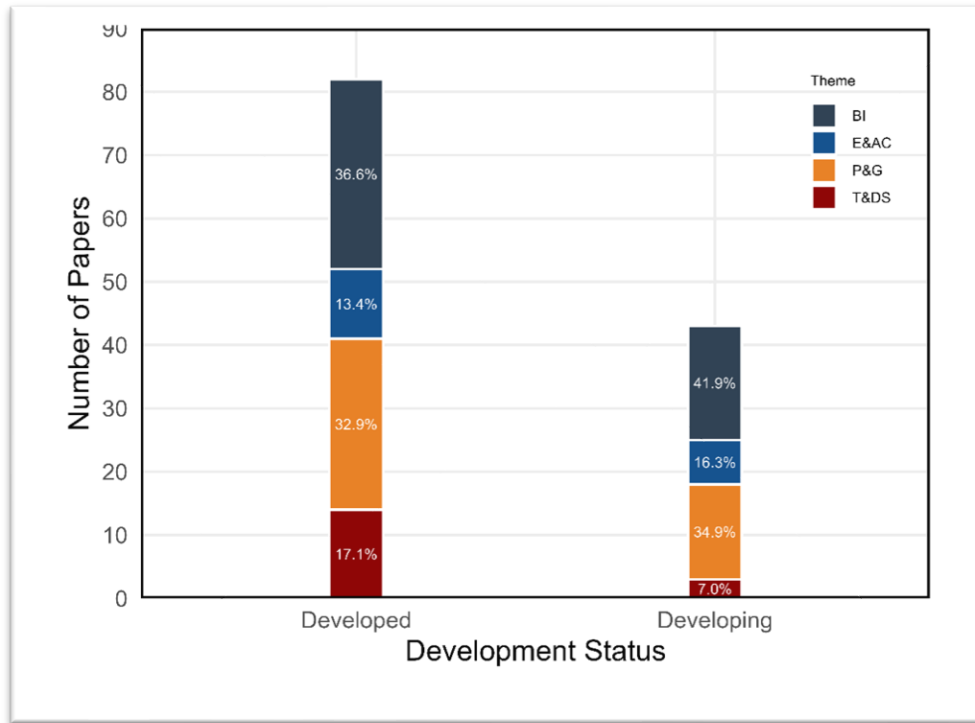


Figure 21: Percentage Contribution of Each Theme

The conclusion of the systematic review on global energy conservation emphasizes the critical role of energy conservation in achieving sustainable development, highlighting the significant disparities in focus and methodologies across different regions. Here's a succinct summary of the key takeaways:

1. **Geographical Focus:** A substantial portion of energy conservation research (87%) is region-specific, with a notable 65.6% concentrated in developed countries. This indicates a strong infrastructural and institutional backing in these regions for energy conservation initiatives.
2. **Methodological Preferences:** The studies predominantly utilize mixed methods, indicating a holistic approach to tackling the multifaceted challenges associated with energy conservation.

3. **Thematic Areas:** The review categorizes the research into four main themes: Behavioral Interventions, Educational and Awareness Campaigns, Policy and Governance, and Technological and Data-Driven Solutions. These categories reflect the diverse strategies employed by different regions, tailored to their unique needs.
4. **Disparities Between Regions:** There is a clear distinction between the strategies used in developed and developing countries. Developed regions tend to focus on technological and policy-driven approaches, leveraging their advanced infrastructures. Conversely, developing regions prioritize behavioral changes and education, adapting strategies to their socio-economic realities.
5. **Call for Global Collaboration:** The review advocates enhanced global collaboration and knowledge sharing to address the regional disparities in energy conservation research. This approach is vital for developing strategies that are culturally and economically appropriate across different global contexts.
6. **Alignment with SDGs:** The findings support the United Nations' Sustainable Development Goal 7 (SDG 7), aiming to ensure access to affordable, reliable, sustainable, and modern energy for all. The review stresses the importance of leveraging global strengths to improve energy conservation efforts universally.
7. **Future Directions:** The conclusion calls for focused research and policy actions to bridge the identified gaps, ensuring equitable resource distribution and fostering comprehensive sustainable energy solutions globally.

2.5.1.3.7 Integration of User Behavior Studies into Thesis

- These insights into user behavior research are directly aligned with the thesis's aim to explore energy conservation behaviors specifically within the context of Saudi Arabia. By understanding the methodologies and themes prevalent in other regions, this research can adapt and innovate on these approaches to better suit local conditions.
- The disparity in focus between developed and developing countries, as highlighted in the reviews, justifies the need for your research to fill in the gaps in understanding and influencing energy behaviors in a region that is less studied.

The integrated review findings substantiate the thesis' focus on identifying effective energy conservation strategies through the lens of user behavior, especially in underrepresented regions like Saudi Arabia. The insights from these reviews guide the research questions and methodology of this thesis by providing a clear picture of where gaps exist and where further investigation is needed. By understanding the global landscape and regional specifics, this research aims to propose actionable strategies that are both culturally and technologically appropriate for enhancing energy conservation efforts in Saudi Arabia and similar contexts.

This synthesis of bibliometric and systematic reviews not only highlights the existing knowledge on energy efficiency and conservation but also paves the way for targeted research on user behavior in energy conservation. It underscores the necessity for a balanced research approach that integrates both global perspectives and local realities to foster sustainable energy practices worldwide.

2.6 Research Gaps and Future Directions

The comprehensive reviews conducted within this thesis have unveiled significant gaps in the current literature concerning energy conservation, particularly pertinent to Saudi Arabia and similar developing regions:

1. **Lack of Focus on Behavioral Interventions:** The existing literature is extensively saturated with studies on technological advancements in energy efficiency, with a noticeable paucity in research directed towards behavioral interventions in energy conservation. This area, especially crucial in developing countries, remains underexplored despite its potential for cost-effective energy consumption reduction.
2. **Underrepresentation of Developing Regions:** Predominantly, the focus of existing research is skewed towards developed regions equipped with advanced technological infrastructures. There is a glaring underrepresentation of developing regions, such as the GCC countries including Saudi Arabia, which restricts the universal applicability and effectiveness of the generalized conservation strategies derived from the current literature.
3. **Integration of Cultural and Socio-economic Factors:** There exists a significant void in studies that integrate cultural and socio-economic factors within energy conservation strategies. An understanding of these factors is essential for devising effective and sustainable energy policies tailored to the specific needs of diverse populations.

4. **Insufficiency of Cross-cultural and Longitudinal Studies:** The literature currently lacks adequate cross-cultural comparisons and longitudinal studies. These studies are crucial as they provide insights into the long-term effectiveness of energy conservation measures and the variability of user behavior across different cultural settings.
5. **Limited Application of Emerging Technologies in Behavioral Research:** There is a notable underutilization of technologies, such as the Internet of Things (IoT), in the exploration of energy usage behavior. More research is necessary to understand how these technologies can be employed to collect real-time data and effectively influence energy-saving behaviors.

This thesis aims to address some of these identified gaps by focusing on the following areas, thereby substantiating the necessity and relevance of this study:

- **Emphasis on Behavioral Interventions in Saudi Arabia:** This thesis will explore behavioral interventions for energy conservation that have not been adequately examined in the Saudi context. Previous studies have predominantly focused on demographics and building characteristics, overlooking the nuances of user behavior. By addressing this gap, this research aims to provide deep insights into behavioral patterns and develop localized strategies tailored to the cultural and socio-economic backdrop of Saudi Arabia. These strategies are expected to significantly enhance energy conservation efforts within the region.
- **Bridging the Research Divide:** By concentrating on an underrepresented region in global energy conservation research, this study aims to bridge the existing divide

between developed and developing countries' research outputs. This endeavor will not only enrich academic literature but also provide practical recommendations that are applicable across similar global contexts.

- **Integration of Advanced Technologies:** The research will explore how technologies, particularly Machine Learning, can be integrated into studying and influencing energy conservation behaviors in residential settings. This approach aims to utilize data collected from residents to devise more dynamic and effective energy-saving strategies.

CHAPTER 3

METHODOLOGY

This chapter outlines the methodology employed to investigate the influence of user behavior on residential energy consumption within the Kingdom of Saudi Arabia (KSA), aiming to integrate artificial intelligence (AI) models to predict and manage this impact. The research is driven by a dual approach: quantitative analysis through surveys and data collection, and qualitative insights via semi-structured interviews and literature reviews. This mixed-methods strategy ensures a comprehensive understanding of the factors affecting energy usage in residential settings, thereby supporting the development of effective AI-driven predictive models. Specifically, the methodology, as visualized in Figure 22, is structured to capture a broad spectrum of user behaviors across different provinces, considering Saudi Arabia's diverse climatic and architectural contexts. By synthesizing behavioral data with advanced machine learning techniques, this research seeks to provide actionable insights that align with the nation's strategic energy efficiency goals under Saudi Vision 2030 and the 2060 carbon neutrality objective.

3.1 Research Design

This study employs a mixed-methods approach, combining quantitative surveys and qualitative interviews to comprehensively examine user behavior and its impact on energy consumption in residential buildings across Saudi Arabia Figure 22. The quantitative

component involves statistical and machine learning analysis of survey data to identify general patterns and trends, while the qualitative aspect includes semi-structured interviews to delve deeper into individual behaviors and perceptions. This dual approach allows for a robust analysis of both the measurable aspects of energy use and the subjective factors influencing those patterns, providing a holistic understanding of the dynamics at play.

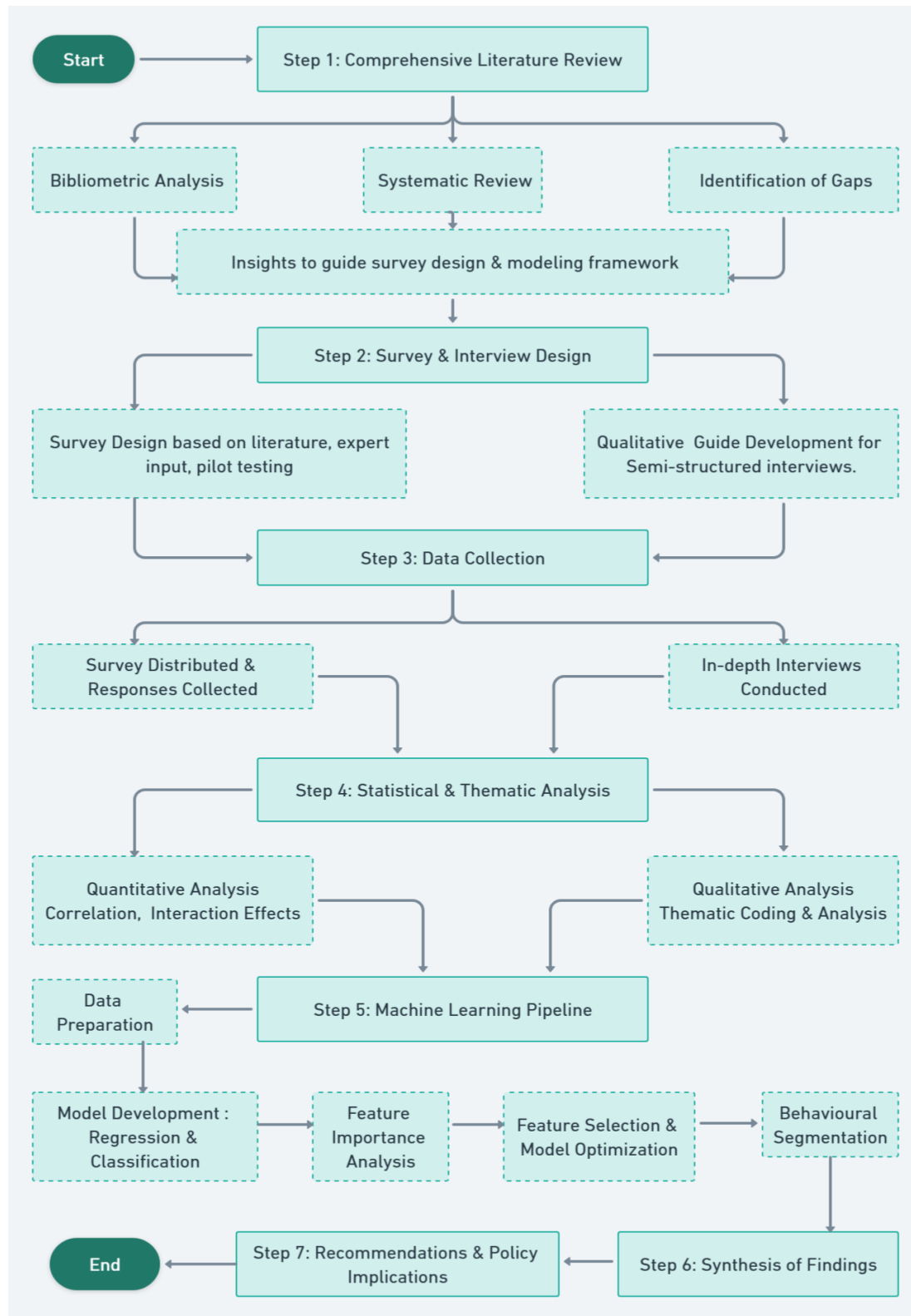


Figure 22: Methodology Flowchart

3.2 Data Collection

The data collection for this study was designed to capture a comprehensive understanding of the factors influencing residential energy consumption in Saudi Arabia. This process involved multiple methods, including surveys and semi-structured interviews, each contributing uniquely to the robust data set required to fulfill the research objectives. The survey was crafted, drawing upon extensive literature review and expert consultations to ensure its relevance and efficacy in gathering precise data on behaviors and practices affecting energy consumption. This section outlines the systematic approach undertaken in the development and implementation of the data collection instruments, ensuring that each step—from survey design to interview execution—was aligned with the goals of the thesis.

3.2.1 Survey Design

The construction of the survey was informed by a rigorous literature review and expert consultations to ensure its relevance and effectiveness in capturing the specific behaviors affecting energy consumption in residential settings across Saudi Arabia. Here's a detailed explanation of how the survey was designed:

3.2.1.1 Literature Guiding Survey Design

The survey's foundation was built on a comprehensive analysis of existing research within the domain of energy consumption behaviors. An extensive table listing previous studies was created, detailing the methods and key questions used in these studies to understand energy consumption patterns. This table served as a vital reference to identify proven survey techniques and effective questions that could be adapted for this study. Table 5

provides an overview of the studies that were instrumental in shaping the design and content of the questionnaire used in this research. Each entry in the table includes the reference to the study, the data collection technique used, and the key factors or questions that were explored in that research.

The studies reviewed covered a range of approaches from direct surveys to detailed case studies, each contributing unique insight into how residential energy consumption can be effectively measured and influenced by user behavior. For instance, the study in [6] utilized a survey method to gauge the impact of behavioral changes on energy savings, which highlighted the importance of including questions related to user habits and the physical home environment in our questionnaire.

Table 5: Literature Review guiding Survey Design

S. No.	Title	Data Collection/ Analysis	Data Points
1	A survey on energy consumption and energy usage behaviour of	Online questionnaire via smart devices, implemented by a professional company,	- Family: Family members, age, family form, daily routine, education, career, family income

	households and residential buildings in urban China. [117]	collecting data on family composition, building characteristics, energy use, conservation behaviors, and reactions to energy policies from 4964 households. Analysis included sample representativeness checks and quality control, with statistical methods like correlation and regression analysis proposed.	- Building: Unit size, building type, age of construction
			- Fuel and Energy: Fuel type, energy consumption, energy cost
			- End User and Behavior: Space heating, space cooling, domestic hot water, lighting, cooking, other home appliances
			- Satisfaction: Satisfaction on unit size, indoor comfort level
			- Attitude toward Energy Conservation Policy: Energy efficiency label of electrical appliances, attitude toward time-

			dependent electricity pricing scheme, attitude toward multi-step electricity pricing scheme
2	A statistical analysis of a residential energy consumption survey study in Hangzhou, China. [118]	Independent surveys conducted in Hangzhou, China during winter (March 2010, 642 participants) and summer (August 2010, 838 participants). The study focused on household characteristics, energy consumption, and occupant behavior. Data included dwelling area, family member ages, household income, appliance ownership, and cooling/heating methods. Analysis used path analysis, multiple linear	- Annual electricity consumption (kWh)
			- Annual electricity consumption for heating and cooling
			- Floor area (m ²)
			- Number of rooms
			- Number of household members
			- Total annual income (yuan)
			- Age of reference person in the household

		regression, and bivariate correlation, processed with SPSS.	- Number of air-conditioners installed in the household
			- Age of the respondent
			- Temperature setting of AC in winter
			- Daily number of hours using heating
			- Temperature setting of AC in summer
			- Daily number of hours using cooling
			- Thermal sensation vote at home in winter
			- Clothing level in winter

3	A decision tree method for explaining household gas consumption: The role of building characteristics, socio-demographic variables, psychological factors, and household behaviour. [119]	Questionnaire study conducted among Dutch households with smart meters, provided by Qurrent, in 2017. The analysis used a decision tree model to explore factors associated with gas consumption, focusing on building characteristics, socio-demographic variables, and psychological factors.	- Building Characteristics: House size, number of rooms, residence type, year built
			- Socio-Demographic Variables: Age, household type, education, occupation, income
			- Gas Use Behaviour: Room temperature
			- Psychological Variables: Biospheric values, egoistic values, hedonic values, altruistic values, corporate environmental responsibility, pro-environmental self-identity, personal norm, social norm

4	Exploring attitudes and behavioral patterns in residential energy consumption: Data-driven by a machine learning approach. [120]	Questionnaire survey conducted in Tehran, Iran, assessing residential energy consumption attitudes, behaviors, motivations, obstacles, and cognitive styles. Ethical approval and informed consent were obtained. Analysis employed machine learning techniques including Support Vector Regression (SVR) to examine relationships between variables, achieving high prediction accuracy for changes in behavior and attitudes.	- Attitudes Towards Energy Usage: Level of agreement on energy usage statements
			- Behavior Patterns: Habits like switching off lights, using energy-efficient appliances
			- Motivations for Energy Conservation: Intrinsic and extrinsic motivations like financial benefits, environmental consciousness
			- Cognitive Styles and Decision-Making: Insights into decision-making regarding energy use
			- Obstacles to Energy-Saving Practices:

			Challenges like insufficient information, budget limitations, comfort preferences
			- Demographic Information: Age, duration of residence, family size, employment, education
			- Behavioral Approach: How behavior influences energy consumption
			- Cognitive Approach: How knowledge and awareness affect energy use decisions
5	Buildings' energy consumption prediction models based on buildings'	The study reviews building characteristics as predictors of energy consumption using data-	- Relative Compactness
			- Surface Area
			- Wall Area

	characteristics: Research trends, taxonomy, and performance measures. [121]	driven models, including AI methods. The systematic literature review methodology was outlined but lacked specific details on analysis techniques. The focus was on the role of building features in predicting energy consumption.	- Roof Area
			- Overall Height
			- Orientation
			- Glazing Area
			- Glazing Area Distribution
			- Building Envelope Characteristics: Importance in energy consumption highlighted, focusing on design stage prioritization
			- Data Utilized: Benchmarked dataset by Tsanas and Xifara containing 768 instances of building characteristics

6	Effective Features to Predict Residential Energy Consumption Using Machine Learning. [122]	Data was collected through the Residential Energy Consumption Survey (RECS) by the DOE Energy Information Administration (EIA), including household characteristics, energy consumption, and expenditures from 5,686 households. Analysis involved feature selection using ML algorithms such as SVM regression, decision trees, random forest, and M5P Trees to identify key predictors of energy consumption.	- Appliance Data: Type, number, size, age, fuel type, and energy star status
			- Behavioral Data: Usage frequency, duration, temperature set-points for heating/cooling, appliance usage patterns
			- Technological Data: Building envelope characteristics, HVAC systems, water heaters, thermostat types, sensors, smart meter installation
			- Demographic Data: Occupant/family characteristics, who pays the bill, participation in energy assistance programs

			- Energy Consumption Data: Total electricity usage in kWh, heating and cooling energy consumption
			- Environmental Data: Climate zone, urban/rural classification
			- Building Data: Number of rooms and bathrooms, presence of swimming pools, types of heating and cooling equipment
7	Predicting Energy Consumption in Residential Buildings Using Advanced Machine	Data was collected from smart meters in residential buildings in Tomsk city, Russia, including sensor data, building attributes, and weather records over	- Smart Meter Data: Records of energy consumption, essential for analyzing usage patterns.
			- Weather Data: Daily outdoor temperatures,

	Learning Algorithms. [123]	five heating seasons. Analysis employed advanced machine learning algorithms such as a PSO-optimized random forest, LightGBM, Random Forest, and XGBoost for feature selection, dimensionality reduction, and classification.	aiding in understanding the environmental impact on energy consumption.
			- Building Attributes: Floor number, wall material, year of construction, influencing building energy efficiency.
			- Temperature Data: Temperature of water pipes and air temperature, used to study the causal relationships in energy consumption.
8	The role of socio-demographic and economic characteristics on energy-related occupant behavior. [124]	Data collected through surveys on Prolific from hotel guests in three-, four-, and five-star hotels in the United States, focusing on pre- and post-intervention energy behavior. Used	Focused on energy usage, attitudes towards energy saving, and the demographic profile of hotel guests
			- Survey Data: Age, gender, education level, ethnic

		machine learning techniques like linear regression, decision trees, random forest, and SVMs to analyze the data.	background, income, employment status
			- Energy Consumption Patterns: Assessed pre- and post-intervention to understand the impact of socio-demographic factors
9	Data Driven Based Prediction of the Energy Consumption of Residential Buildings in Oshawa. [125]	Data was collected using a combination of smart metering, phone surveys, and energy audits in 227 houses in Oshawa. This involved capturing actual electricity and gas consumption, along with detailed information on physical properties and mechanical systems of the buildings. Data analysis used MLR, SR, and SVM	- Energy Consumption Data: Actual electricity and gas consumption
			- Demographic and Social Info: Number of occupants, work status, housing situation, age of the homeowner, gross household income
			- Building Physical Properties: Outdoor air temperature, dew point, humidity, wind speed,

		to develop and evaluate prediction models.	number of rooms, floor area, type and age of the building, types of heating and cooling systems, building orientation and dimensions
			- Appliance and System Details: Number and type of bulbs, energy-saving appliances, fuel types for various utilities, air-conditioning and heating system details
			- Building Structural Details: Thermal resistance of windows, walls, ceilings, U-value of foundation and basement ceiling, air change rate

			- Survey-Specific Questions: Awareness of energy conservation, perceptions of government involvement, interest in energy-saving technologies
10	Reducing energy consumption in low income public housing - Interviewing residents about energy behaviors. [126]	Semi-structured interviews were conducted with residents of low-income public housing to explore their energy behaviors and perceptions. The study utilized both qualitative and quantitative analysis techniques, including a scoring procedure for interpreting interview responses. This method provided a comprehensive understanding of resident behaviors, perceptions,	- Resident Perceptions and Adaptations: Insights into how residents perceive and adapt to their household environment regarding energy use
			- Knowledge Gaps and Behavioral Interventions: Identification of knowledge gaps and potential areas for intervention
			- Resident Satisfaction and Maintenance Issues: Levels of satisfaction with housing

		and opportunities for behavioral interventions.	conditions, maintenance status
			- Energy Use Behaviors: Usage of thermostats, air conditioners, and window management in relation to heating
			- Attitudes Towards Energy Conservation: Differences in attitudes between bill payers and non-bill payers, willingness to adopt energy conservation measures (ECMs)
			- Interview Questions: Price concerns about energy, interest in energy-efficient appliances, humidity and comfort levels, attitudes

			towards cost and effectiveness of ECMs
11	Household Energy Conservation Behaviour: A Socio-Economic Perspective. [127]	A structured questionnaire was used to collect data from 329 households in Akure, Nigeria, focusing on the socioeconomic determinants of energy conservation behaviors. The study employed Partial Least Square Structural Equation Modeling (PLS-SEM) using Smart-PLS version 3.3.3 to analyze the data, reflecting both reflectively and formatively measured variables.	- Demographic Information: Gender, age distribution, educational background
			- Household Characteristics: Household size, family structure, number of dependents, marital status
			- Income and Expenditure: Monthly income levels, electricity bill amounts
			- Energy Consumption Behavior: Influencing factors like cost of electricity, number of rooms, number of

			appliances, weather conditions
			- Home and Appliance Details: Home ownership status, number of rooms, number of appliances
			- Socioeconomic Factors: Impact on energy conservation behavior, including specific questions to assess the influence of socioeconomic characteristics on energy-saving behaviors
12	Modeling Residential Energy Consumption Patterns with Machine Learning	Data was collected from 373 Brazilian households over the year 2022 to analyze monthly electricity consumption, capturing the	- Monthly Energy Consumption: History of energy usage expressed in kWh, capturing data from January to December 2022

	Methods Based on a Case-Study-in Brazil. [128]	dynamics of household energy usage in the context of post-COVID-19 changes. Various machine learning clustering methods such as agglomerative hierarchical clustering, k-means, self-organizing maps, along with principal component analysis and silhouette analysis were used for data analysis. Gradient boosting was also employed as a benchmarking tool.	- Data Dimensionality: Each of the twelve months represented a dimension in the analysis, reflecting detailed energy usage patterns
13	An investigation into factors influencing domestic energy consumption in an energy subsidized	Data was collected via an online questionnaire using SurveyMonkey from 622 participants through a snowball sampling technique. The survey	- Respondent Dwelling Types: Types and sizes of dwellings, number of bedrooms and toilets, presence of separate guest reception rooms

	developing economy . [129]	focused on public perception and knowledge of sustainable and low-energy homes, exploring cultural barriers and acceptance of energy retrofitting.	- Occupancy and Usage: Number of occupants, average daily occupancy, cooling system usage patterns, average AC usage - Knowledge and Perceptions: Public knowledge on sustainable/low-energy buildings, reasons for promoting sustainable homes - Cultural and Architectural Factors: Cultural barriers to sustainable homes, public evaluation of architectural designs contributing to high energy consumption - Future Perspectives: Public views on procedures
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			to establish sustainable homes and expectations for future sustainable housing in Saudi Arabia
14	Analysis of energy consumption pattern in Saudi Arabia's residential buildings with specific reference to Qassim region . [130]	Survey conducted with 191 participants, divided into two parts: general information about dwellings and data on electricity consuming items. The study detailed the types of appliances used and their energy consumption characteristics.	- Dwelling Information: Type of unit, unit area, occupancy status, number of occupants, age of occupants, insulation status of floor, outer walls, and roof
			- Appliance Usage: Types and usage of water heaters, air conditioners, washing machines, refrigerators, freezers, ovens, dishwashers, microwaves, water coolers, televisions, personal computers, vacuum machines

			- Energy Efficiency Measures: Use of energy-saving lighting, water filters, exhaust blowers, and other electrical devices
			- Construction Features: Material of window frames
			- Monthly Electricity Consumption: Recorded to assess the energy usage patterns across different household types and appliance setups
15	A regression-based model for estimating the energy consumption of school facilities	Utilized expert opinions, knowledgeable practitioners, and a review of previous research to identify key factors	- Location: City where the school is located
			- School Facility Details: AC capacity, number of floors, total building area,

	in Saudi Arabia . [131]	influencing energy consumption in 351 school facilities. The study specifically focused on actual energy consumption records from these facilities.	total roof area, total area being air conditioned
			- School Type and Demographics: Type of school, number of staff, building age, number of students, number of classrooms
16	Trends in Residential Energy Consumption in Saudi Arabia with Particular Reference to the Eastern Province . [132]	A questionnaire-based survey was conducted in Dhahran, gathering data from 128 randomly chosen dwellings, including 115 dwellings for which actual monthly electricity consumption data were specifically analyzed. The survey included in-person interviews, examination of building plans, and	- Dwelling Details: Type of dwelling (apartments, villas, traditional houses), dwelling age, area, and condition
			- Building Features: Type and age of air conditioning systems, thermal insulation, window glazing systems
			- Utility Usage: Fuel used for cooking

		analysis of electricity bills to assess energy usage across 62 apartments, 28 villas, and 25 traditional houses.	- Electricity Consumption Features: Main electricity consumption related features identified through direct assessment of electricity bills
17	Assessment of Current Energy Consumption in Residential Buildings in Jeddah, Saudi Arabia . [6]	Survey conducted using Google Forms, distributed via social media, with 396 completed responses. The survey collected data on energy costs and user behavior in response to the rise in energy prices, alongside detailed demographic information and residential energy consumption metrics.	- Demographic Information: Residency status, gender, marital status, age, educational status, occupation, household size, duration of living in Jeddah, monthly income
			- Housing Details: Housing type, proportion of income spent on rent
			- Energy Usage Details: Use of lighting appliances, thermal insulation, types of

			air conditioning, preferred indoor temperature, AC use in hours
			- Financial Impact: Increase in electricity bills post-2018 tariff changes, spending on electricity per square meter
			- Satisfaction Levels: Satisfaction concerning outdoor noise, window ratio, thermal comfort, daylight, electricity tariff, water/sewer tariff, water/sewer facility, room size
18	Estimating the energy consumption for residential	This study developed three predictive models to estimate residential energy	- Building Dimensions: Length, width, height in meters

	buildings in semiarid and arid desert climate using artificial intelligence . [133]	consumption based on structural and environmental variables. The models integrated building dimensions, orientation, envelope materials, window properties, and desired internal temperatures to determine energy consumption values.	- Building Orientation: Orientation with respect to north in degrees
			- Windows to Wall Ratio: Ratio for each façade
			- Thermal Properties: U-value of walls, roofs, and slab on grade
			- Window Glass Properties: U-value, Solar Heat Gain Coefficient (SHGC), and Visible Transmittance percent (VT)
			- Target Temperatures: Desired inside temperature in winter (Heat) and summer (Cool)

			- Energy Consumption (EC): Calculated energy consumption in Watts
19	The barriers to energy efficiency in China: Assessing household electricity savings and consumer behavior in Liaoning Province . [134]	This comprehensive study involved a survey with 615 responses, field research at government agencies, and interviews with officials to assess patterns of household electricity consumption, appliance ownership, and attitudes towards energy saving. The study aimed to identify effective policies for reducing electricity use and enhancing energy efficiency.	Data: Monthly household electricity bill knowledge, bill payment mode, electricity price awareness, payer of the bill, types of lighting used, reasons for not using energy-saving lamps - Appliance Use and Preferences: Type and number of appliances used, reasons for appliance choices (e.g., cost, design, function, energy efficiency), awareness and impact of energy-saving labels

			- Consumer Behavior: Energy-saving intentions, reasons for saving energy (cost, environmental protection), most active energy saver in the household
			- Demographic Information: Gender, age, location, role within the household
			- Energy Awareness: Knowledge about electricity saving, impact of devices left plugged in, reception of energy-saving brochures
20	The determinants of household electricity	The study utilized data from Taiwan's Family Income and Expenditure	- Demographic and Household Information: Age, gender, education,

	consumption in Taiwan: Evidence from quantile regression . [135]	Survey (FIES) to collect detailed household characteristics and demographic information. Quantile regression (QR) was employed as the primary analytical method to estimate the effects of various variables on the distribution of household electricity consumption across different quantiles, aiming to address sampling bias inherent in other methods.	household size, number of elderly members, number of workers
			- Economic Factors: Income, whether the property is owner-occupied
			- House and Facility Details: Floors, housing area, number of televisions, water heaters, air conditioners, washing machines, refrigerators
			- Location: Specific area within Taiwan where the data were collected
21	A Preliminary Assessment of Energy	The study conducted a survey with 158 responses from students to assess	- Demographic Information: Age, gender, student classification,

	Consumption Behaviour Pattern and Factors Influence Among Malaysian Higher Education Institutions Students . [136]	their energy consumption behavior. The questionnaire was structured into three sections covering demographic characteristics, internal behavior related to energy consumption, and daily energy consumption activities and device usage.	semester/year, religion, nationality, race
			- Economic Background: Family income per month
			- Energy Consumption Behavior: Internal behaviors related to energy usage and daily activities involving energy consumption and device usage
22	Energy use and saving in residential sector and occupant behavior: A case study in Athens . [137]	A structured questionnaire was administered to 451 residents to assess energy use and savings behaviors, including a detailed analysis of building characteristics, occupants' behavior on energy use,	- Socio-Demographic Profile: Gender, age, marital status, education level, household size, professional status, household income, type of occupancy (rental or owned)

		and their socio-demographic profiles. The survey included behavioral scales and questions on energy-saving practices.	- Building Characteristics: Size and type of dwelling, construction date, insulation type (walls, ceiling, and glazing), and energy systems for heating, cooling, and hot water
			- Beliefs and Values: Attitudes towards energy efficiency, environmental awareness, and reactions to economic changes impacting energy costs
			- Behavioral Aspects: Practices such as turning off appliances when leaving home, using natural cooling, consulting energy efficiency labels, and seeking information on energy savings

			- Energy Saving Trends: Influence of past economic crises on fuel wastage, state incentives for energy saving, and personal benefits from energy conservation
23	Characteristics or culture? Determinants of household energy use behaviour in Germany and the USA . [138]	An online survey was conducted with 1005 respondents in Germany and 1010 in the USA, cleaning the data to focus on 571 German households and 547 US households. The Oaxaca-Blinder decomposition was used to analyze the factors influencing differences in residential	- Household Characteristics: Education level, income, gender, household size, marital status, number of kids, number of cars, miles driven per year, occupant status (rent/owned) - Environmental Values and Attitudes: Views on human interaction with the environment, rights of plants and animals, and

		energy use behavior between the two countries.	perceptions of nature's resilience or fragility
			- Energy Efficiency Perceptions: Perceived financial benefits and effectiveness of energy use behaviors such as purchasing energy-efficient appliances, using energy conservation practices at home, and buying fuel- efficient cars
24	How do socio- demographic and psychological factors relate to households' direct and indirect energy	A questionnaire was administered to 314 respondents to monitor both direct and indirect energy use and savings over a period of five months. The study	- Socio-Demographic Variables: Income, household size, age
			- Attitudinal Measures: Attitudes towards energy conservation, including perceptions of hassle,

	use and savings? [139]	evaluated various socio-demographic variables and psychological factors influencing energy conservation behaviors.	comfort, quality of life, and time commitment
			- Perceived Behavioral Control: Respondents' perceived ability to conserve energy, including knowledge, difficulty, and ease of reducing energy use
			- Personal Norms: Moral obligations felt by individuals towards energy conservation, including feelings of guilt and pride associated with energy use
			- Awareness of Consequences: Beliefs about the impact of energy use on societal problems like the greenhouse effect and fossil fuel depletion

			- Ascription of Responsibility: Extent to which respondents felt responsible for dealing with energy-related environmental problems
25	Understanding the determinants on household electricity consumption in Korea: OLS regression and quantile regression . [140]	The study utilized data from the 2017 household energy consumption sample survey by the Korea Energy Economics Institute. It applied Ordinary Least Squares (OLS) and Quantile Regression to analyze electricity consumption patterns across various households in Korea. The OLS method estimated the conditional mean of annual power consumption, while Quantile Regression	- Socio-Demographic Characteristics: Age group of the household head, education level, monthly average household income, household size
			- Dwelling Characteristics: Housing area, type of cooling used
			- Power Consumption Characteristics: Number of household appliances, TV viewing time, washer usage time, air conditioner usage

		addressed the data's high variability and distribution skewness.	time, refrigerator usage time, rice cooker usage time
26	Household energy-saving behavior, its consumption, and life satisfaction in 37 countries . [141]	The study involved a large-scale, original, cross-sectional survey conducted between 2015 and 2017, gathering data from 37 countries with a total of 100,956 observations. Data collection methods included both internet-based and face-to-face approaches to ensure comprehensive coverage and reliability.	- Socioeconomic and Demographic Factors: Household income, education attainment, age, occupational status, household status, number of children, gender - Study Focus: Examined the impact of various socioeconomic and demographic factors on household energy consumption expenditure and related life satisfaction across multiple nations
27	Explaining household	The study utilized a dataset from a household	- Building Factors: Number of rooms, type of residence

	electricity consumption using quantile regression, decision tree, and artificial neural network . [142]	electricity consumption survey conducted in Cameroon. It employed quantile regression, decision tree, and artificial neural network (ANN) models to perform a comparative analysis to determine the effectiveness of these models in explaining electricity consumption patterns.	(urban), building materials (sheet metal, concrete slab, concrete block wall, wood wall), floor composition (cemented, tiled)
			- Sociodemographic Factors: Age of the head of household, household size, education level, employment status, monthly income
			- Appliance and Lighting Factors: Number and type of lamps, presence and usage frequency of appliances like fridges, washing machines, TVs, air conditioners, and irons
			- Energy Usage Behaviors: Frequency of using fans, air

			conditioners, and other appliances, energy-saving practices awareness, information-seeking on energy efficiency
			- Decision-Making in Appliance Purchase: Preferences for energy efficiency (e.g., class A appliances), price considerations, systematic habits like turning off lights and appliances when not in use

3.2.1.2 Expert Consultation

Field experts, including academicians and industry professionals were consulted to refine the survey questions. This step ensured that the survey was not only theoretically sound but also practically applicable and culturally sensitive to the Saudi Arabian context.

3.2.1.3 Pilot Study

A preliminary pilot study was conducted with a small, diverse group of participants to test the survey's effectiveness. The feedback from this pilot was crucial in identifying areas of improvement. Issues such as survey length and question clarity were addressed. Difficult questions were simplified, and visual aids, examples, and definitions were added to enhance understanding.

3.2.1.4 Survey Questionnaire Development

Based on the literature review, expert consultations, and pilot feedback, represented in Development of Survey Design , the survey was finalized to ensure clarity and relevance. It included a variety of questions designed to gather data on:

- **Demographics:** Professional industry, gender, educational background, and more, to understand the respondent's background.
- **Building Characteristics:** Details such as building type, age, and insulation to gauge physical factors affecting energy consumption.
- **Energy Consumption Details:** Information on electricity bills and payment modes to assess financial behaviors related to energy use.
- **Behavioral Patterns and Attitudes:** Frequency of energy-saving actions and attitudes towards energy efficiency to understand behavioral influences on energy consumption.

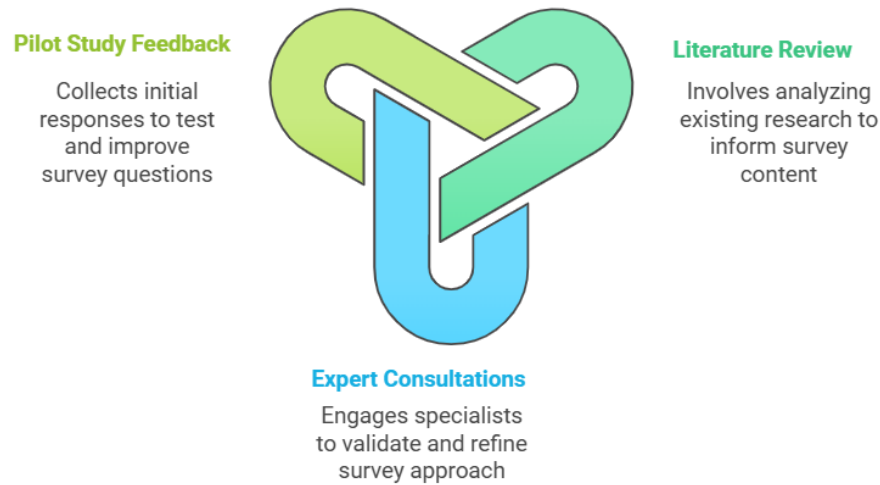


Figure 23: Development of Survey Design

3.2.1.4.1 Survey Design Alignment with Thesis Objectives

In designing the survey, specific attention was given to ensure that the questions not only gather comprehensive data but also align with and support the achievement of the thesis objectives. Each segment of the survey was crafted to address one or more research objectives, summarized in Table 6 , demonstrating a targeted approach to collecting relevant data. Below is a breakdown of how the survey questions align with the thesis objectives:

- **Demographic Information (Questions 1-9):** These questions aim to collect basic demographic data such as professional industry, gender, educational background, and nationality. This information is crucial to Objective 1, which is to analyze various aspects impacting energy consumption in residential buildings across Saudi Arabia.
- **Building Specifications and General Energy Usage (Questions 10-22):** This section delves into the physical characteristics of the buildings and general energy usage

patterns, including the types of air conditioning systems used and the building's insulation status. These details are pivotal for Objective 1, providing a foundational understanding of the structural and operational factors that influence energy consumption.

- **Behavioral Patterns and Attitudes Towards Energy Saving (Question 23):** This question assesses the frequency of energy-saving actions and attitudes towards energy efficiency. It addresses both Objective 1, by analyzing critical aspects of user behavior, and Objective 3, by identifying areas where behavior could be influenced to optimize energy consumption.
- **Perceptions on Energy Efficiency (Question 24) and Awareness on Various Environmental and Energy Topics (Question 25):** These questions gauge the participants' perceptions of and awareness about energy efficiency and environmental issues. They serve Objective 1 by analyzing how awareness and perceptions impact energy use behaviors.
- **Actions Taken and Reasons for Not Improving Energy Efficiency (Questions 26 and 27):** These are designed to explore the measures residents have taken to improve energy efficiency and the barriers they face. These insights are critical for Objective 3, which aims to craft actionable strategies based on identified behaviors.
- **Social Influence and Response to Economic Factors (Questions 28-30):** Questions in this segment investigate who in the household is more proactive about energy saving, how energy prices impact behavior, and the influence of energy rating labels on

purchase decisions. These directly support Objective 3 by identifying leverage points for behavioral interventions.

- **Awareness of Energy Efficiency Programs (Question 31):** This question assesses awareness of local or national programs aimed at improving energy efficiency, aligning with Objective 1 to analyze the contextual factors impacting energy consumption behaviors.

Table 6: Survey Design Alignment with Thesis Objectives

Objective of Thesis	Relevant Survey Questions	Significance of the Question
Identify and analyze critical aspects of user behavior that impact energy consumption.	22) Frequency of energy-saving actions like switching off AC, adjusting thermostats, etc.	These questions identify specific user behaviors and modifications in household energy usage, crucial for understanding patterns and potential areas of intervention.
	23) Frequency of using energy-efficient appliances.	
	26) Measures taken to improve energy efficiency at home.	
Develop an AI-driven predictive model to forecast energy consumption	6) Number of People in Household.	Collecting detailed data on living conditions and appliance usage allows for robust modeling of energy consumption predictors based
	12) Total floor area of the house.	
	13) Number of floors.	
	14) Age of building.	

based on analyzed behaviors.	15) Type of window glass.	on user behavior and household characteristics. Including EUI as a variable provides a standardized way to compare energy efficiency across different units.
	16) Building insulation.	
	17) Types of air-conditioning systems and usage.	
	19) Operational hours of AC daily.	
	20) Typical Thermostat setpoint in summer.	
	21) Annual average electricity bill.	
	EUI Calculation: Utilizing Questions 12, 13, and 21.	
Craft actionable strategies and recommendations to improve user behavior towards optimizing energy consumption.	23) Perceived need for energy efficiency improvements.	Understanding attitudes, awareness, and barriers provides insights into where interventions may be most needed and accepted, informing strategic recommendations.
	24) Agreement with statements about energy efficiency and user behavior importance.	
	27) Barriers to adopting energy-efficient technologies.	
	28) Influence on household energy decisions.	

3.2.1.5 Survey Implementation

The comprehensive survey, provided in ANNEX, was distributed across various regions in Saudi Arabia. It was structured to gather both quantitative and qualitative data, providing a robust dataset for analysing energy consumption behaviors in residential buildings. Figure 22 in the thesis visually details this methodological approach from the initial literature review through to the final survey deployment, underscoring the systematic effort to ensure the survey's validity and comprehensiveness.

3.2.2 Survey Distribution and Administration

3.2.2.1 Distribution Methods

The survey was distributed using Google Forms, a convenient and accessible platform that facilitated widespread dissemination. To reach a broad audience across different provinces in Saudi Arabia, the survey link was initially shared with personal contacts, including family, friends, and colleagues, who were then requested to further distribute it within their networks. This approach, known as snowball sampling, helped to capture a diverse set of respondents from various demographic backgrounds and residential sectors across the country.

3.2.2.2 Strategies to Enhance Reach

To ensure the survey reached participants across different provinces effectively, efforts were made to leverage a wide network of contacts. These included:

- **Professional Networks:** Utilizing connections from the workplace and professional circles to share the survey link widely.
- **Social Media Channels:** Posting the survey link on personal social media accounts with encouragement for others to share, enhancing the survey's visibility and reach.
- **Community Groups:** Engaging with local community groups and forums, particularly those focused on residential living and energy conservation, to distribute the survey link.

3.2.2.3 Measures to Ensure High Response Rate

To maximize the response rate and ensure robust data collection, several strategies were employed:

- **Regular Reminders:** Sending out periodic reminders via email and social media posts to encourage participation. These reminders highlighted the importance of the survey in contributing to meaningful research on energy conservation.
- **Ease of Access:** Ensuring that the survey was mobile-friendly and could be easily accessed on various devices, reducing barriers to participation.

- **Clear Communication:** Providing clear instructions and support for any questions or technical issues participants might encounter, thereby reducing the dropout rate among respondents.

3.2.3 Semi-Structured Interviews

The interviews were designed to be semi-structured, allowing for flexibility in the discussion while ensuring all relevant topics were covered. This format facilitated an in-depth exploration of personal behaviors, technological adoptions, and the cultural context of energy use within residential settings. The core questions were developed to align closely with the research objectives, ensuring that the discussions would yield data pertinent to understanding and improving energy consumption patterns. Guided by literature [143], [144], data from the interviews will be analyzed qualitatively to extract themes and patterns that complement the quantitative survey data. This integration will enrich the thesis's findings by providing nuanced insights into the motivations, barriers, and effects of behavioral and technological interventions on energy consumption. The qualitative data will also help validate and expand upon the quantitative results, offering a more comprehensive understanding of the factors influencing energy consumption in Saudi Arabian residential buildings.

3.2.3.1 Selection of Participants

Participants for the interviews were selected using a purposive sampling method to ensure a diverse representation of the residential population in Saudi Arabia. This included 6 individuals from various demographic backgrounds and professional sectors who exhibited high engagement in the preliminary survey. The sample included individuals from different

genders, age, education, income, and nationality backgrounds, and varied housing statuses (renter, owner). Professions among participants included an academic professor, a healthcare doctor, a bus driver, a university staff member, a master's student in engineering, and housewife. This diverse participant pool was intended to enrich the study with a wide range of perspectives on energy use behaviors in Saudi Arabia.

3.2.3.2 Interview Process

Each interview lasted between 40 to 60 minutes, with most approaching the 50-minute mark. Interviews were conducted in person, audio-recorded, and transcribed verbatim. Non-English-speaking participants were assisted by a translator to ensure accuracy in capturing their responses. The interview questions were largely derived from and expanded upon the questions used in the quantitative survey portion of the research, enabling a deeper exploration of topics already identified as significant. The interviews were conducted with the utmost respect for the participants' privacy and confidentiality. Participants were informed that their participation was voluntary and that they could withdraw at any time. All data were anonymized in the dissemination of research findings to protect participants' identities and ensure candidness in their responses.

3.2.4 Survey Data Collection Tools and Technologies

3.2.4.1 Tools for Data Collection and Management

The primary tool used for the distribution and collection of the survey was Google Forms. This platform was chosen for its user-friendly interface, ease of access, and robust functionality which allowed for the creation of a structured questionnaire accessible to a

broad demographic across various regions of Saudi Arabia. Google Forms also supports real-time data collection and automatic organization of data into spreadsheets, facilitating efficient data management and preliminary analysis.

3.2.4.2 Ensuring Security and Confidentiality of Data

To ensure the security and confidentiality of the data collected, several measures were implemented:

- **Anonymity:** The survey was designed to be anonymous, not requiring participants to provide any identifiable information such as names or email addresses. This approach helped in minimizing any potential privacy concerns and made it easier for respondents to provide honest answers.
- **Data Protection:** As the data was collected and stored via Google Forms, it was protected under Google's robust security protocols, which include secure data centers and encryption of data transmissions.
- **Access Control:** Access to the collected data was restricted to the research team only. Each member of the team was required to adhere to strict data handling and confidentiality protocols to ensure that all information remained secure.
- **Ethical Considerations:** Before participating, respondents were informed about the purpose of the research, how their data would be used, and reassured about their privacy and data security. This transparency helped in building trust and ensuring ethical compliance.

3.2.4.3 Ethical Approvals

To conduct this research ethically and responsibly, formal ethical approval was secured from the Office of the Vice President for Scientific Research and Innovation, Ministry Of Education Saudi Arabia. The approval process required a comprehensive submission of the research proposal, along with supporting documents that detailed the study's methodology, potential risks, and benefits to participants. Additionally, the research team was mandated to undertake a series of educational modules on ethical research practices. Upon successful completion of these modules, a certificate was issued as a part of the requirement to commence the study. This rigorous process ensured that all aspects of the research adhered to the highest ethical standards as mandated by the institutional review board (IRB).

3.3 Data Analysis

This study employs a multi-dimensional analytical approach to explore the relationship between user behavior and residential energy consumption in Saudi Arabia. Three distinct forms of analysis are utilized to address the research objectives comprehensively: statistical analysis, thematic analysis, and machine learning analysis. Statistical analysis is used to quantify relationships between behavioral, sociodemographic, and building-related variables and energy usage. Thematic analysis provides qualitative insights derived from open-ended survey responses, offering a deeper understanding of user perceptions and contextual influences on energy behavior. Finally, machine learning analysis is conducted to develop predictive models and identify key features influencing energy consumption patterns, with a focus on interpretability and segmentation.

3.3.1 Statistical Analysis

The statistical analysis in this study was conducted to uncover key patterns, relationships, and influencing factors related to residential energy consumption in Saudi Arabia. Given the complexity of energy use behaviors and their interactions with demographic, structural, and behavioral factors, a comprehensive statistical approach was applied. This section outlines the key steps undertaken in the statistical analysis .

1. **Descriptive Statistics:** The analysis began with descriptive statistics to summarize and understand the dataset's key characteristics. This included calculating means, medians, standard deviations, and frequency distributions . This step helped identify trends and anomalies in the dataset, providing an initial understanding of how different variables relate to energy consumption.

2. **Correlation Analysis:** To identify pairwise relationships, Pearson and Spearman correlation analyses were performed. This step examined the strength and direction of relationships between energy consumption (EUI) and behavioral, demographic, and structural factors. It also examined the association between behavioral variables (e.g., AC usage, thermostat adjustments, and energy-saving habits). Correlation analysis provided insights into which factors might play a significant role in energy consumption and guided further statistical modeling.

3. **Interaction Analysis:** To explore how two variables jointly impact energy-related behaviors and consumption, interaction analysis was performed on key relationships. This allowed for a more nuanced understanding of combined effects that might not be evident from simple correlations.

3.3.2 Data Analysis for Interviews

The interviews transcribed were subjected to content analysis as shown in, Figure 24 to aid in systematic interpretation. The analysis involved several steps to ensure a thorough examination of the data:

1. **Familiarization with Data:** Multiple readings of the transcriptions were conducted to become intimately familiar with the content, noting initial ideas and impressions.
2. **Generating Initial Codes:** Codes were generated by identifying significant phrases or sentences that encapsulated key aspects of the participants' responses related to energy use behaviors.
3. **Searching for Themes:** Codes were reviewed and grouped into potential themes that represented broader patterns in the data.
4. **Reviewing Themes:** Themes were refined to ensure they accurately represented the coded extracts and were coherent, distinct, and meaningful within the context of the entire dataset.
5. **Defining and Naming Themes:** Detailed definitions were developed for each theme, specifying the aspect of the data each captured and their relevance to the research questions.
6. **Writing Up:** The final step involved integrating the analytic narratives with direct quotes from the interviews and contextualizing these within the broader literature on energy consumption behaviors.

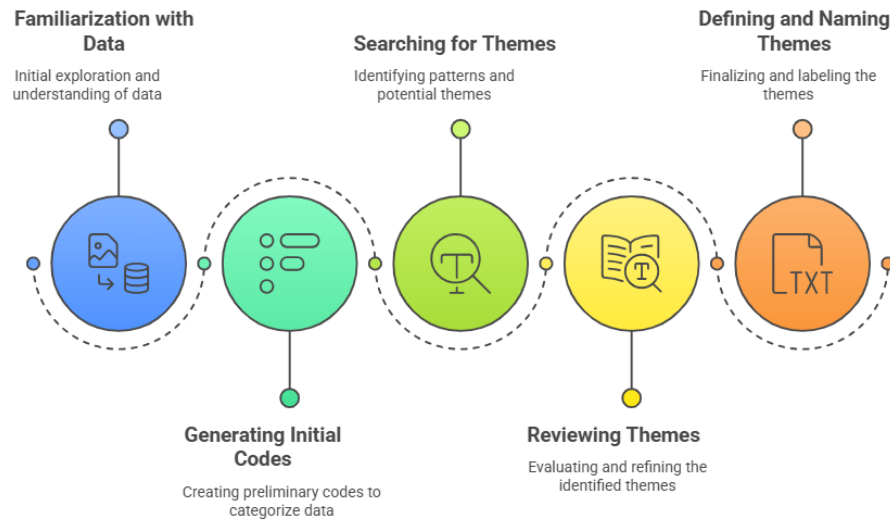


Figure 24: Data Analysis Process for Interviews.

3.3.3 Machine Learning Analysis

To complement the statistical and qualitative findings, machine learning (ML) techniques were employed to model and predict residential energy consumption based on the survey data. The objective of this analysis was twofold: (1) to evaluate the predictive power of various algorithms using behavioral, building, and sociodemographic features, and (2) to identify the most influential factors shaping energy use through model interpretability techniques. Supervised learning algorithms including Ridge Regression, Lasso Regression, Random Forest, and Gradient Boosting were implemented to perform both regression and classification tasks. Regression models aimed to predict the actual energy consumption (measured in kilowatt-hours), while classification models aimed to categorize households into low or high energy usage groups based on defined thresholds. Model performance was

evaluated using standard metrics such as R^2 for regression and Area Under the Curve (AUC) for classification.

Feature importance analysis was conducted using permutation importance and SHAP values. Additionally, unsupervised learning via K-Means clustering was applied for behavioral segmentation, enabling the identification of distinct household archetypes with similar energy use patterns. These archetypes provide actionable insights for designing targeted behavioral interventions and policy strategies. Data preprocessing steps such as missing value imputation, feature encoding, and normalization were carried out prior to model training. Cross-validation was used to ensure model generalizability and reduce the risk of overfitting.

3.4 Sampling Method

3.4.1 Sample Selection Criteria

Participants were selected based on the criteria that they must reside in residential buildings within Saudi Arabia. The study did not target specific demographic groups within the residential sector; rather, it aimed to gather a broad perspective from various inhabitants, whether renters or homeowners, to encompass diverse experiences and insights on energy consumption.

3.4.2 Inclusion and Exclusion Criteria

The inclusion criterion for participants was straightforward: individuals had to be living in residential units within Saudi Arabia, irrespective of whether these were owned or rented.

The sole exclusion criterion was non-residence in a Saudi Arabian residential unit, ensuring that all data collected pertained directly to the residential energy context within the country.

3.4.3 Sampling Method

The study employed a non-probabilistic sampling method, which leaned towards convenience and snowball sampling techniques. Initial participants were primarily recruited from the university community at King Fahd University of Petroleum and Minerals (KFUPM) in Dhahran, where the researcher is a master's student. The survey was further disseminated through social media and personal contacts, including family and friends residing within Saudi Arabia. Participants were encouraged to share the survey link, facilitating a wider reach across various provinces through snowball sampling.

3.4.4 Rationale for Sampling Strategy

The chosen sampling method was dictated by accessibility and the potential to reach a broad and diverse participant pool quickly. While convenience sampling allowed for quick distribution within familiar and readily accessible groups, snowball sampling helped extend the reach, capturing a wider array of experiences from residents across different regions of Saudi Arabia. This method was particularly useful in a country where regional differences can significantly influence residential energy behaviors and where personal networks play a crucial role in information dissemination.

3.4.5 Representation of the Sample

Although non-probabilistic, the combination of convenience and snowball sampling methods leveraged in this study aimed to capture a broad cross-section of Saudi Arabia's

residential population. Notably, 80% of Saudis live in ten major urban centers: Riyadh, Jeddah, Mecca, Medina, Hofuf, Ta'if, Buraydah, Khobar, Yanbu, Dhahran, and Dammam [145]. The majority of the 425 participants come from these areas, providing a robust perspective from regions with significant energy consumption and diverse residential dynamics. This geographic concentration ensures that the study reflects the energy consumption behaviors and patterns within diverse residential settings across the major urban centers, contributing to a richer understanding of the residential energy landscape in Saudi Arabia.

In conducting survey research, the representativeness of the sample is crucial for the reliability and validity of the results. To ensure a representative sample of the target population, the sample size for this study was determined using a formula that considers the desired confidence level and margin of error. Following the methodology from study in [117], and to achieve a 95% confidence level, the formula used was:

$$Sample\ size = \frac{z^2 \times p(1 - p)/e^2}{1 + (z^2 \times \frac{p(1 - p)}{e^2 N})}$$

where:

- N is the total population size, which for this study is 34.3 million representing the population of Saudi Arabia.
- e is the margin of error, set at 0.05 for this study.
- z is the z-score, which corresponds to 1.96 for a 95% confidence level.

- p is the estimated proportion of the attribute present in the population, assumed to be 0.5, which maximizes the required sample size under the assumption of maximum variability.

Based on these parameters, the calculated minimum sample size required is 385. The actual sample size obtained for the study was 425, which is above the minimum requirement. This ensures that the survey sample is statistically significant and representative enough to infer conclusions about the entire population with a high degree of confidence. This adequacy in sample size supports the robustness of the survey findings and their generalizability to the broader population of Saudi Arabia.

3.5 Research Tools and Instruments

The study utilized a range of research tools and instruments to ensure the systematic collection, organization, and analysis of data. A structured questionnaire comprising only closed-ended questions was developed to capture a comprehensive set of variables related to user behavior, sociodemographic characteristics, and building attributes. The questionnaire was administered using Google Forms, enabling efficient dissemination and real-time data collection across diverse respondent groups.

Data analysis was conducted primarily using the Python programming language, which facilitated both statistical and machine learning analyses. Statistical procedures such as correlation testing, descriptive analysis, and regression modeling were carried out using libraries like Pandas, NumPy, and SciPy. For predictive modeling and feature importance evaluation, additional Python libraries such as Scikit-learn and Matplotlib were employed.

Jupyter Notebooks served as the development environment, allowing for transparent and reproducible workflows.

In addition to Python, RapidMiner software was also explored during the predictive modeling phase. Its visual workflow interface provided an alternative environment to validate model performance and experiment with different algorithmic configurations, enhancing the robustness of the machine learning component.

3.6 Limitations

The rigor of any study is not only determined by its strengths but also by the acknowledgment and understanding of its limitations. This research, while comprehensive in its approach, encounters several limitations that might influence the findings and their applicability:

- **Self-Reported Data:** A significant portion of the data collected in this study is self-reported, primarily gathered through surveys and interviews. While measures were taken to ensure the reliability and validity of the questions, self-reported data can be subject to biases such as over-reporting or under-reporting of behaviors, especially in areas sensitive to social desirability bias. Participants might have provided answers they perceived as socially acceptable rather than those that accurately reflect their true behaviors or energy consumption patterns.
- **Sample Size and Generalizability:** Although efforts were made to distribute the survey widely, the final sample size of 425 may not fully represent the diverse demographic and geographic landscape of Saudi Arabia. The majority of responses

were concentrated in urban centres such as Riyadh, Jeddah, and the Eastern Province, which may not accurately represent rural or less populated regions. As such, the findings might not be generalizable to all residential settings across the country, particularly those with distinct socioeconomic or cultural characteristics.

- **Sampling Method:** The study employed a convenience and snowball sampling method, primarily due to accessibility and resource constraints. While this method facilitated data collection across a broad network of contacts, it might have introduced selection bias, as participants who share similar characteristics or social circles are more likely to be included. This could affect the diversity of the sample and potentially limit the study's findings to specific social groups.
- **Technological Constraints:** The use of digital tools like Google Forms , while effective, may also limit participation to individuals who have access to and are comfortable using these technologies. This could exclude segments of the population who are either not technologically adept or do not have consistent access to the internet, thus skewing the data towards a more tech-savvy demographic.
- **Longitudinal Changes:** The study's cross-sectional design provides a snapshot of behaviors and energy consumption patterns at a specific point in time. It does not account for changes over time or seasonal variations, which can be significant given the varying climate conditions in Saudi Arabia. Longitudinal studies would be required to understand the dynamics of energy consumption behaviors over different seasons and years.

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Introduction to Data Analysis and Results

This section provides an overview of the methods and processes used to analyze the data collected from various sources throughout the course of this study. The data comprise both quantitative and qualitative elements that offer a comprehensive view of the energy consumption behaviors and the factors influencing these behaviors in Saudi Arabian households. The research utilized a mixed-methods approach to gather both quantitative and qualitative data, ensuring a robust analysis of energy consumption patterns and the underlying factors affecting these patterns [146]. Quantitative data were primarily derived from structured surveys that collected information on annual energy bills and floor area, alongside other variables. This data was used to calculate the Energy Use Intensity (EUI), providing a standardized measure of energy consumption relative to the building area. The surveys also gathered comprehensive data on household demographics, energy use habits, and awareness of energy conservation measures. Qualitative data were obtained through semi-structured interviews with a diverse group of participants. These interviews were aimed at uncovering deeper insights into the personal and cultural factors that influence energy behaviors.

The data collected were subjected to three primary methods of analysis to address the research questions from multiple angles as shown in Figure 25 and ensure a comprehensive understanding of the phenomena under study:

- **Statistical Analysis:** This method focuses on the quantitative aspects of the data, employing statistical tests to identify significant patterns and relationships. Techniques such as correlation, will be used to draw conclusions from the survey data, particularly in calculating and interpreting the EUI and behaviour interaction.
- **Thematic Analysis:** For the qualitative data from interviews, thematic analysis will be employed to identify and analyse patterns or themes across the data set. This approach allows for the interpretation of various aspects of the energy use behavior as expressed directly by the participants, providing context to the quantitative findings.
- **Machine Learning Techniques:** Advanced machine learning algorithms will be applied to model and predict behaviors and trends in energy consumption. These techniques will help in identifying non-obvious patterns and can provide forecasts that are essential for planning and implementing targeted energy conservation programs.

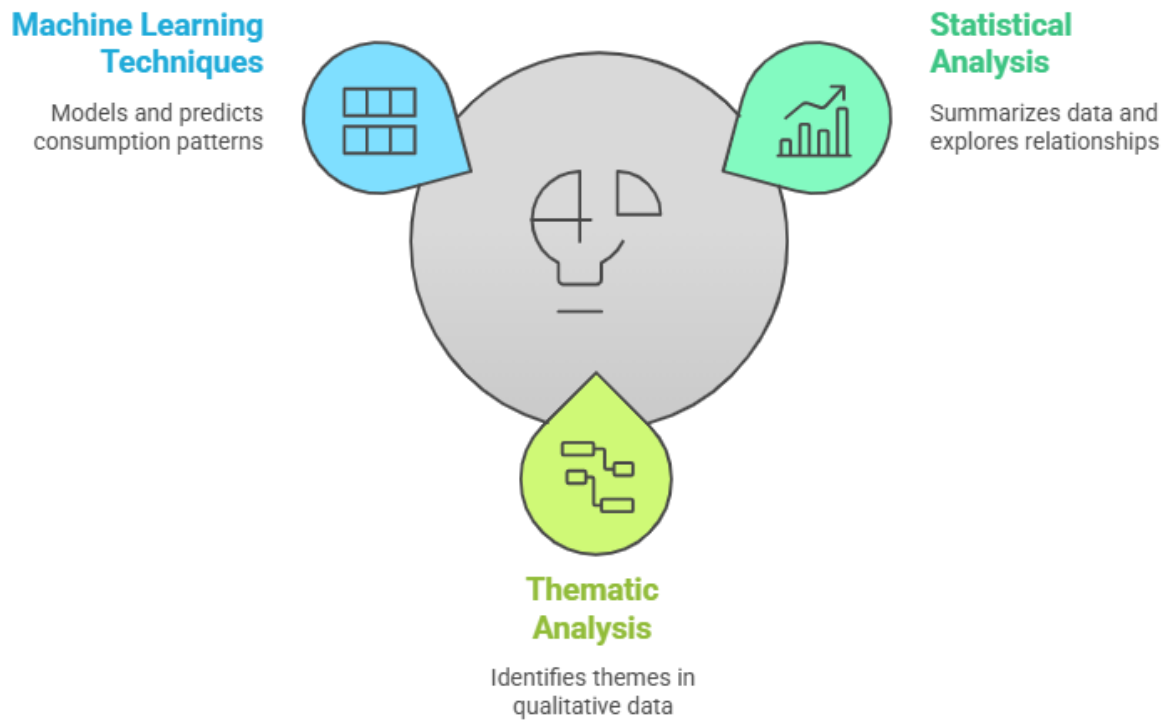


Figure 25: Analytical Approaches to Understand Energy Consumption.

4.2 Statistical Analysis and Findings

Statistical analysis is a fundamental component of this research, aimed at identifying user behavior trends and their impact on residential energy consumption in Saudi Arabia. Given the self-reported nature of the survey data, statistical methods are used to uncover meaningful patterns, relationships, and trends that would otherwise remain hidden. This analysis provides a data-driven foundation for subsequent machine learning models by ensuring that key behavioral factors influencing energy consumption are well understood.

The primary objectives of statistical analysis in this study are:

- To explore and summarize the dataset through descriptive statistics.

- To identify significant relationships between household characteristics, user behaviors, and energy consumption.
- To perform inferential analysis that helps validate observed trends and assess their broader implications.
- To inform predictive modelling by highlighting the most influential variables for energy forecasting models.

The statistical methods applied in this study follow a structured approach, progressing from descriptive statistics to inferential analysis. The techniques used include:

➤ **Descriptive Statistics**

Descriptive statistics were employed to summarize key variables, including energy consumption, household characteristics, and behaviors. Measures of central tendency, such as the mean, median, and mode, were used to provide an overall understanding of the data, while measures of dispersion, including standard deviation and variance, captured the variability within the dataset. Additionally, distribution analysis was conducted using histograms and heat maps to visualize patterns and detect potential anomalies in energy usage.

➤ **Correlation Analysis**

Correlation analysis was used to assess the strength and direction of relationships between variables, particularly energy use intensity (EUI) and behavioral or demographic factors. Pearson correlation coefficients were applied to examine associations between continuous variables, such as AC usage hours and EUI, while Spearman correlation was utilized for

ordinal variables, such as income levels and energy efficiency awareness. These analyses provided insights into how specific factors relate to energy consumption, helping to identify key drivers of variation.

➤ **Interaction Analysis**

Interaction analysis explored how different factors combined to influence energy consumption and efficiency behaviors. Interaction terms in regression models were used to examine combined effects, such as how insulation influences thermostat usage. This approach helped uncover nuanced relationships that might not be evident when examining individual factors in isolation.

4.2.1 Descriptive Statistics

In this section, as shown in Figure 26 the foundational elements of the data are delved into, with the diverse characteristics of the respondents and their environments, as well as their behaviors and attitudes towards energy consumption and efficiency, being highlighted. Through a detailed examination of demographic and building characteristics, the context in which energy usage patterns emerge is established. The specifics of energy consumption details are also explored to understand the financial and operational aspects of energy use within households. Behavioral patterns are analyzed to discern prevalent energy-saving practices and the social dynamics that influence these behaviors. Additionally, the adoption of energy efficiency measures is assessed to gauge the acceptance and resistance towards energy conservation technologies and strategies. Furthermore, the attitudes and awareness surrounding energy issues are dissected, shedding light on the community's perception of energy efficiency programs and their readiness to engage in energy-saving actions. This

comprehensive descriptive analysis sets the stage for more intricate inferential statistics, providing a robust basis for understanding the nuances of energy use behavior in Saudi Arabian households.

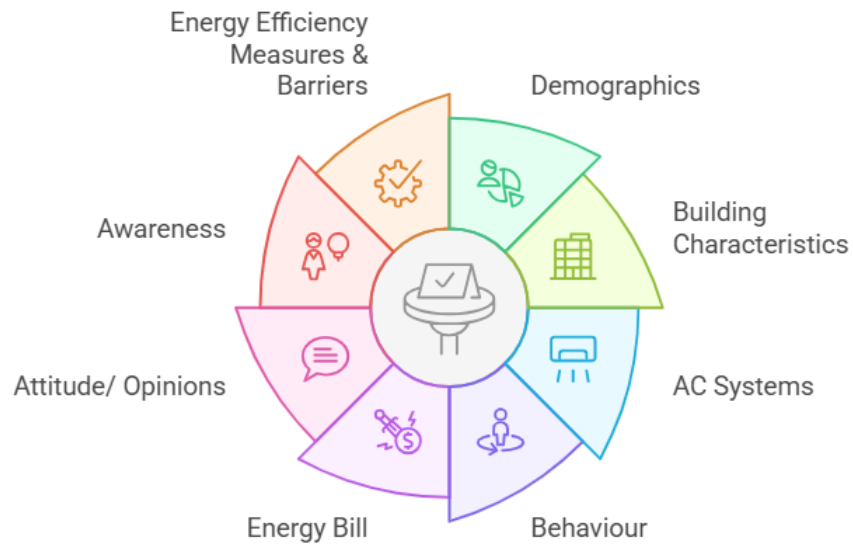


Figure 26: Elements of Data.

4.2.1.1 Demographics

The survey sampled a diverse cross-section of residents across various regions of Saudi Arabia, providing a comprehensive overview of demographic and building characteristics influential in residential energy consumption patterns.

- **Professional Industry:** The distribution of respondents by professional industry reveals significant representation from the private sector, comprising 45.8% of the total responses (194 respondents). This is followed by individuals employed in the public or government sector, accounting for 23.6% of responses (100 respondents). Students formed 12.7% of the sample (54 respondents), indicating a good mix of young adults

likely residing in shared or rental housing. Other categories included housewives (6.1%), self-employed (5.2%), retired (3.8%), and others (2.8%), reflecting a varied demographic that could influence differing energy usage patterns due to their diverse daily routines and residential needs. Figure 27 shows the distribution of respondents by professional industry.

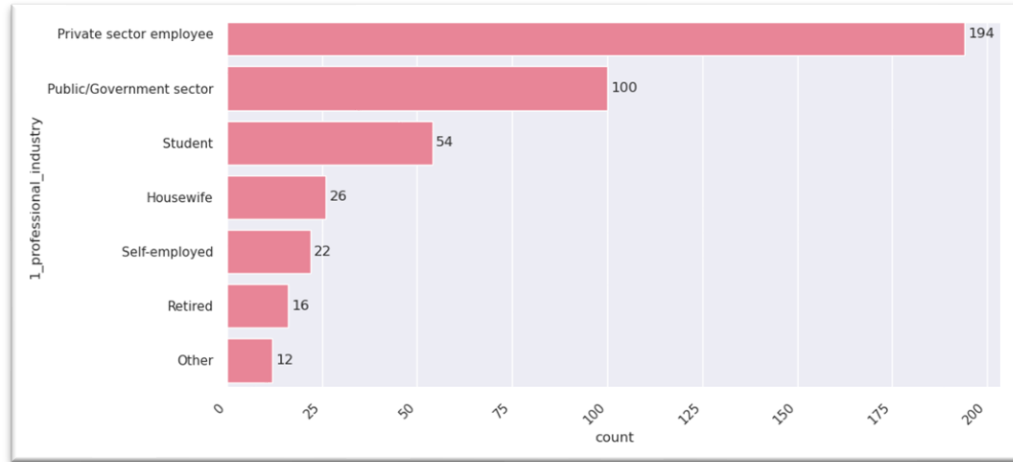


Figure 27: Distribution of Professional Industry

- Gender Distribution :** The survey participants consisted predominantly of males, making up 67.7% of the responses (287 respondents), while females accounted for 32.3% (137 respondents). This distribution highlights a gender disparity that could influence the analysis of energy consumption behaviors. Figure 28 shows the gender distribution in survey.

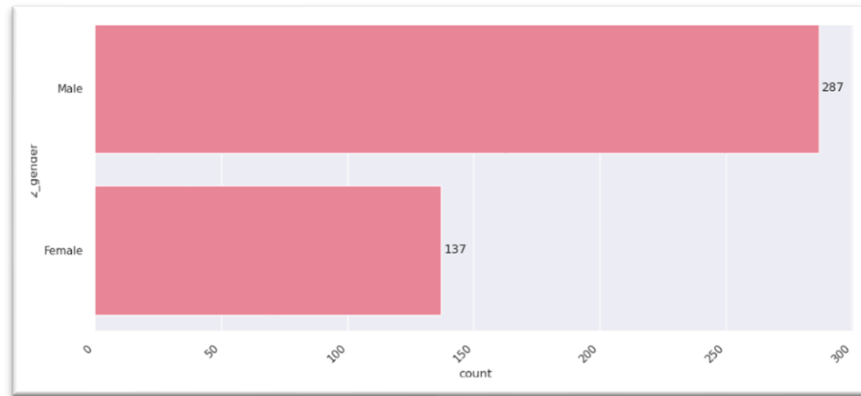


Figure 28: Gender Distribution in Survey

- Education Level Distribution:** Educational background of respondents varied, with a significant majority holding higher education degrees, accounting for 66.7% of the sample (283 respondents). Undergraduate respondents represented 21.2% (90 respondents), followed by high school graduates at 8.3% (35 respondents), and other educational qualifications at 3.8% (16 respondents). This educational diversity is crucial in understanding energy use behavior as it often correlates with awareness and implementation of energy-saving measures. Figure 29 shows education level distribution in survey.

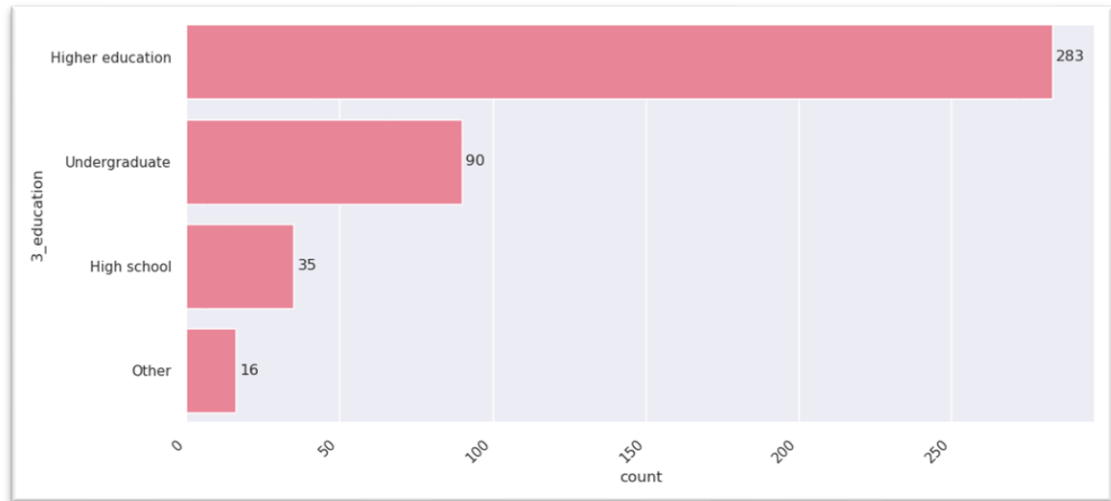


Figure 29: Education Level Distribution in Survey.

- Nationality Distribution:** The demographic breakdown by nationality showed a nearly even split with non-Saudi nationals making up 52.1% of the sample (221 respondents) and Saudi nationals 47.9% (203 respondents). This mix provides a comprehensive insight into residential energy behaviors across different cultural backgrounds. Figure 30 shows Nationality Distribution in Survey.

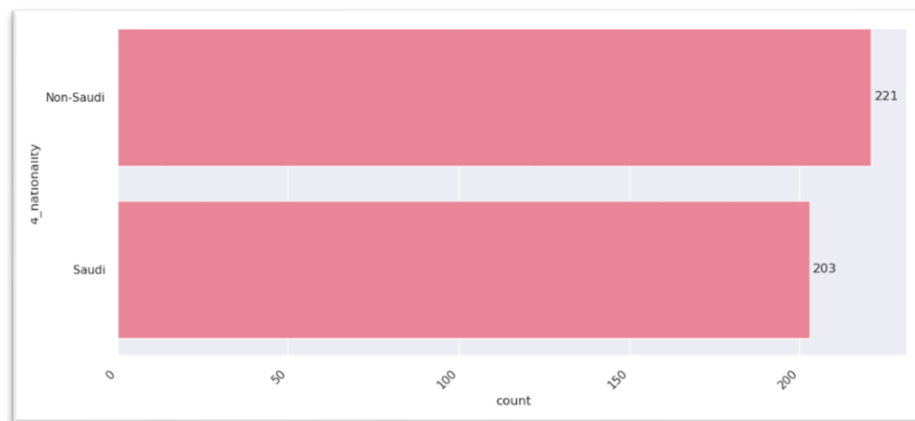


Figure 30: Nationality Distribution in Survey.

- Age Group Distribution:** Age distribution among the participants varied, with the largest group being those aged 31-40 years, representing 30.0% of the sample (127

respondents). This was followed closely by the 41-50 age group at 25.2% (107 respondents), and the 21-30 age group at 23.6% (100 respondents). Older age groups were less represented, which may impact insights into the energy behaviors typical of senior demographics. Figure 31 shows the Age Group Distribution in Survey.

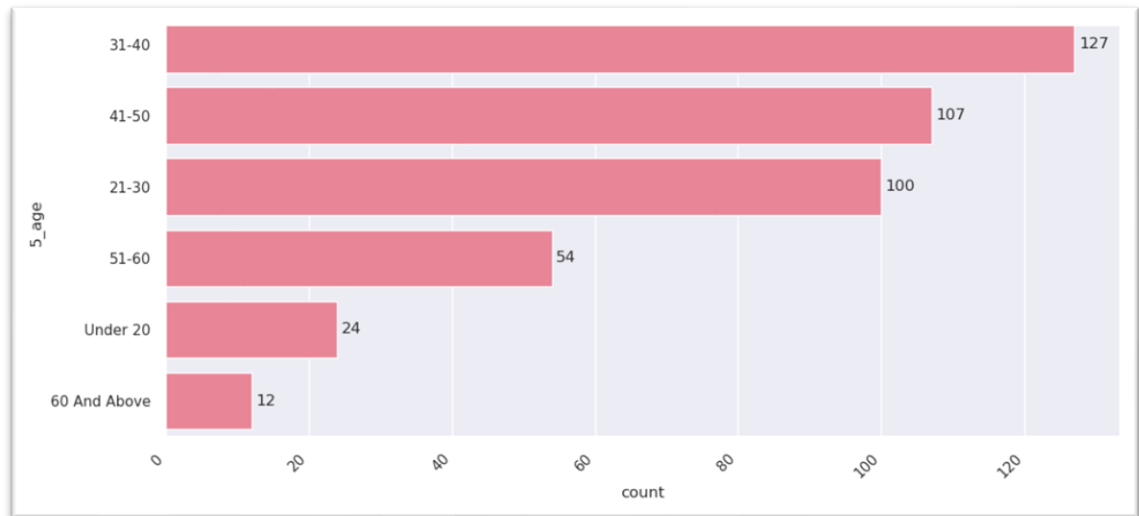


Figure 31: Age Group Distribution in Survey.

- Household Size Distribution:** Household sizes ranged broadly, with the majority falling within the 3-4 members category, representing 37.5% of the responses (159 respondents). The next largest group, 5-6 members, comprised 32.5% of the sample (138 respondents). Smaller (1-2 members) and larger households (more than 10 members) were less common, indicating typical Saudi family sizes which influence energy usage patterns. Figure 32 shows Household Size Distribution in survey.

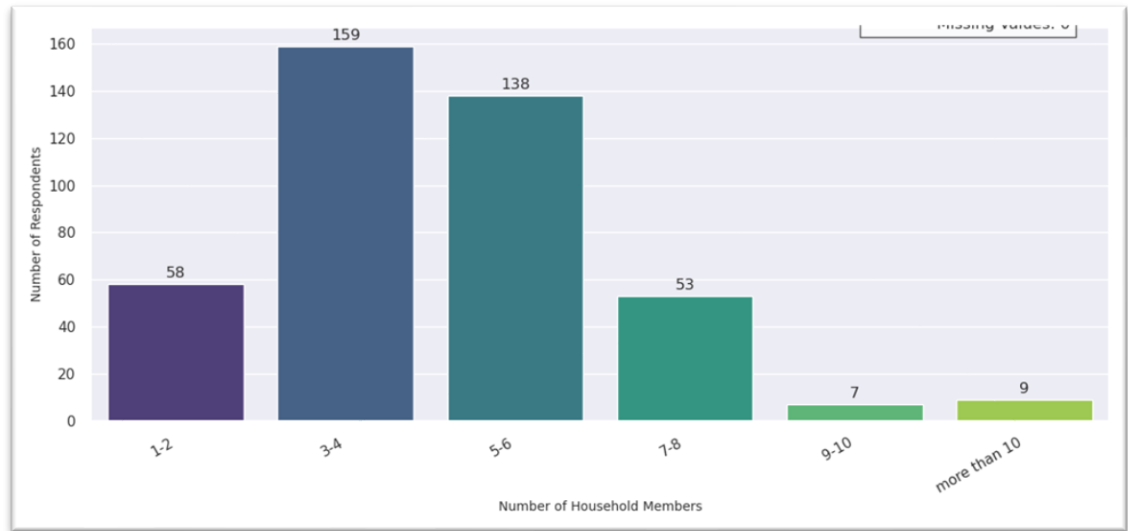


Figure 32: Household Size Distribution in Survey.

- Monthly Income Distribution:** Income levels among respondents also varied, with 27.6% earning between 10,001-20,000 SAR (117 respondents), and a similar proportion (26.9%) earning between 5,001-10,000 SAR (114 respondents). The income distribution is a critical factor in assessing energy consumption as it influences the ability to invest in energy-efficient technologies. Figure 33 shows Monthly Income Distribution in Survey.



Figure 33: Monthly Income Distribution in Survey

- Bill Payer Distribution:** Most respondents reported that they are responsible for paying their own electricity bills (59.2%, 251 respondents), with a significant portion stating that a family member handles the bill payments (35.1%, 149 respondents). This indicates who makes decisions about energy use at the household level. Figure 34 shows Bill Payer Distribution in Survey.

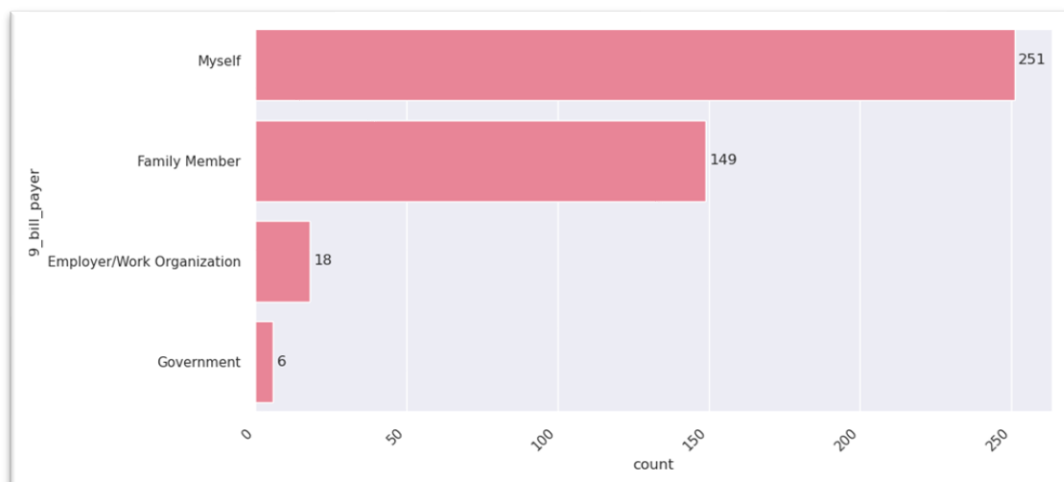


Figure 34: Bill Payer Distribution in Survey.

- Regional Distribution:** The survey responses were predominantly from the Eastern Province (44.8%, 190 respondents), followed by the Makkah Region (25.7%, 109 respondents), and the Riyadh Region (18.2%, 77 respondents). The regional spread is essential for understanding localized energy usage behaviors and the impact of regional energy policies. Figure 35 shows the Survey Responses Distribution by Region in Saudi Arabia.

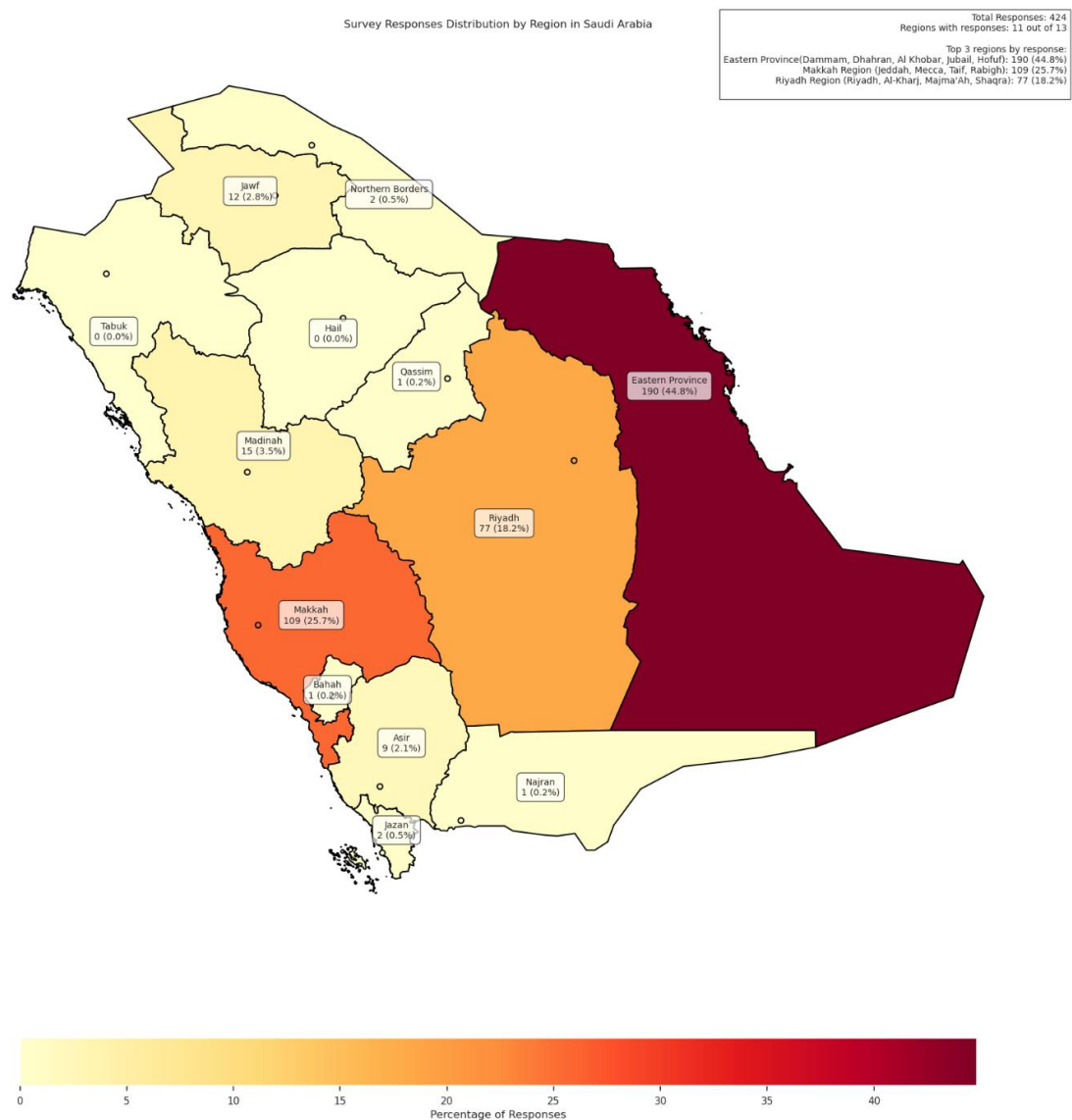


Figure 35: Survey Responses Distribution by Region in Saudi Arabia.

4.2.1.2 Building Characteristics

- **Building Type Distribution:** The majority of the survey respondents reside in apartments, representing 62.5% of the total (265 responses), followed by villas at 21.9% (93 responses), duplexes at 9.2% (39 responses), traditional houses at 4.0% (17 responses), and other types of housing at 2.4% (10 responses). This variety in building types suggests diverse energy usage patterns attributable to different living spaces and associated lifestyle factors. Figure 36 shows the Building Type Distribution in Survey Data.

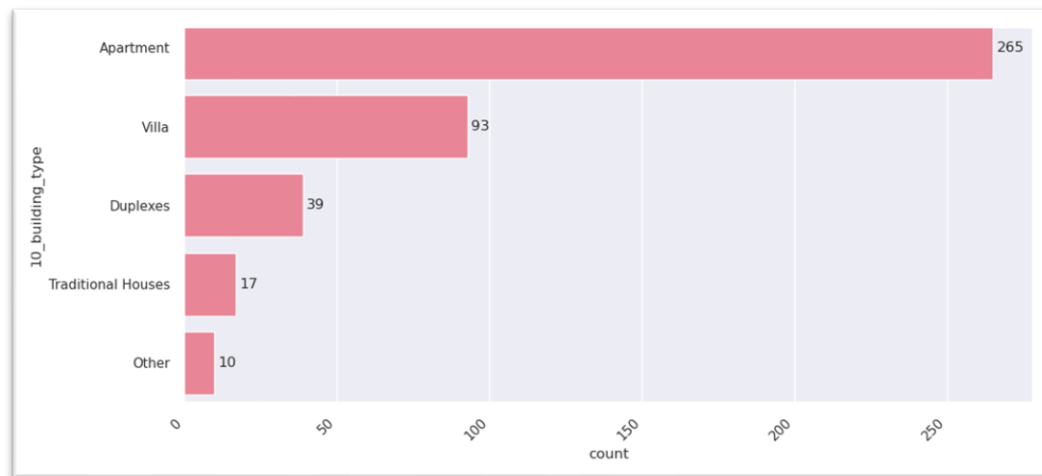


Figure 36: Building Type Distribution in Survey Data

- **Building Ownership Distribution:** Regarding ownership, 59.0% of the buildings are rented (250 responses), while 37.0% are owned (157 responses). The remaining 4.0% fall into other categories of ownership status (17 responses). Ownership status can significantly influence the implementation of energy-saving measures, as renters may

have different incentives or abilities to invest in such technologies compared to owners. Figure 37 shows the Building Ownership Distribution in survey.

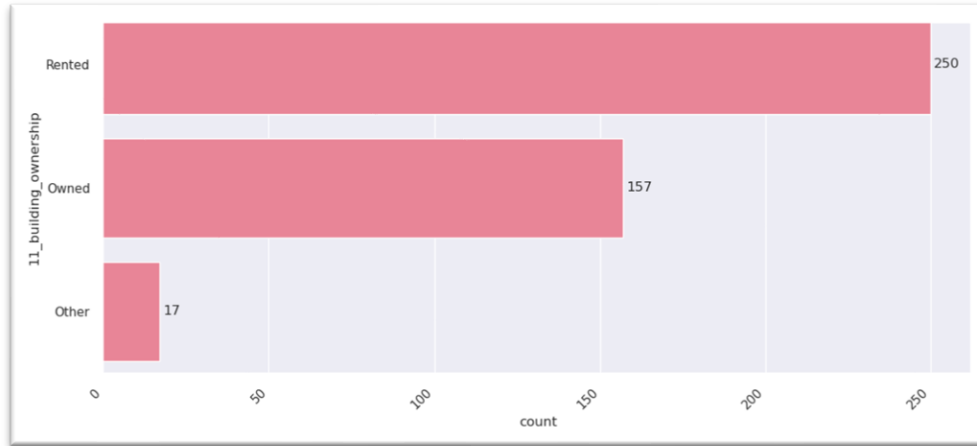


Figure 37: Building Ownership Distribution in Survey.

- Floor Area Distribution:** The average floor area reported by respondents is approximately 258.44 square meters, with a standard deviation of 178.02 square meters. The floor areas ranged from as small as 18 square meters to as large as 1000 square meters, indicating a wide variety of living spaces that can affect energy consumption levels. Figure 38 shows the Floor Area Distribution in Survey data. Table 7 lists the detailed floor area statistics.

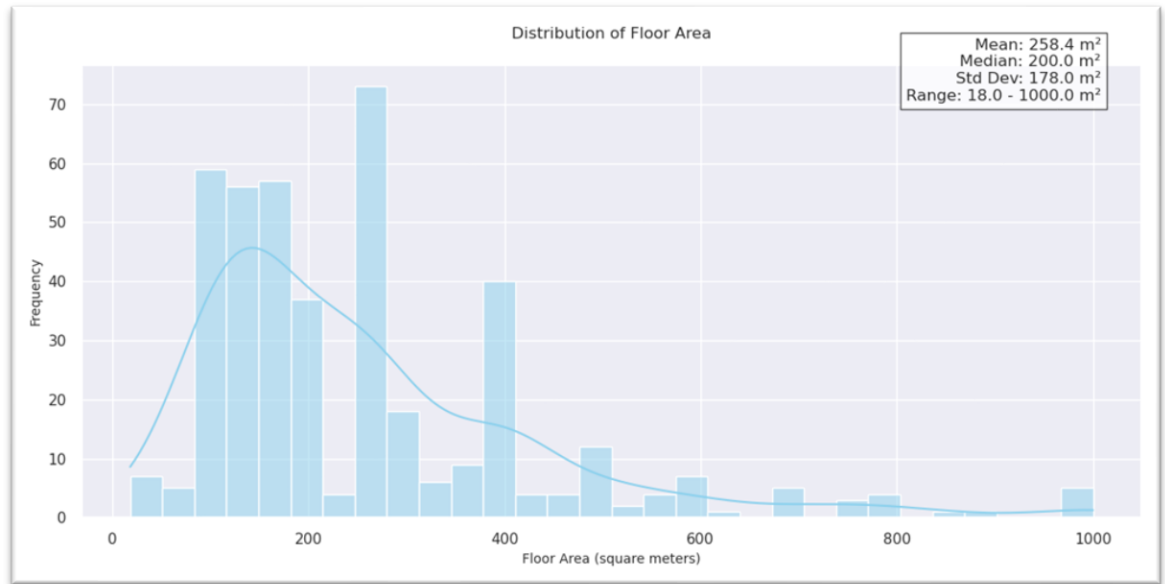


Figure 38:Floor Area Distribution in Survey data.

Table 7:Distribution of Floor Areas Across the Sampled Buildings.

Statistic	Value
Count	424
Mean	258.44
Std Dev	178.02
Min	18.00
25% (First Quartile)	130.00
50% (Median)	200.00
75% (Third Quartile)	321.25

Max	1000.00
-----	---------

- Number of Floors Distribution:** Responses indicate a balanced distribution in the number of floors: 31.1% of buildings have one floor (132 responses), 31.8% have three floors (135 responses), 21.7% have two floors (92 responses), and 15.3% have more than three floors (65 responses). The number of floors is an essential factor in energy use, particularly in heating and cooling requirements. Figure 39 shows the Number of Floors Distribution in survey.

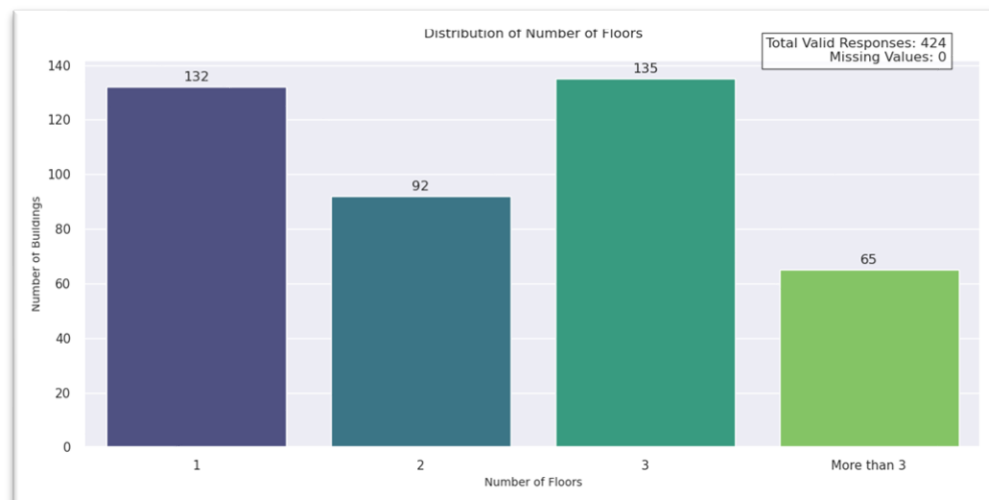


Figure 39: Number of Floors Distribution in Survey.

- Building Age Distribution:** Building age also varies widely, with 36.1% of buildings being less than 10 years old (153 responses) and another 36.1% between 11-20 years old (153 responses). Older buildings, those aged 21-30 years and more than 30 years, constitute 10.6% (45 responses) and 10.4% (44 responses) respectively, with 6.8% not known (29 responses). Figure 40 shows the Building Age Distribution in Survey Data.

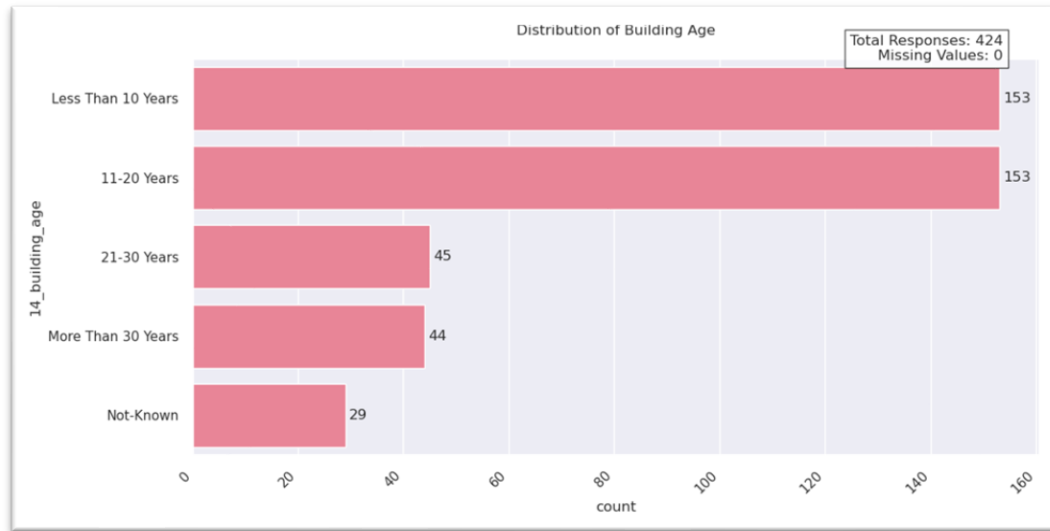


Figure 40: Building Age Distribution in Survey Data.

- Window Type Distribution:** The types of window glass used also vary, with 52.6% of respondents having single-pane glass (223 responses) and 34.2% having double panes of glass (145 responses). The remaining 13.2% were not known (56 responses). Window type is crucial for thermal insulation and energy loss. Figure 41 shows the Window Type Distribution in Survey Data.

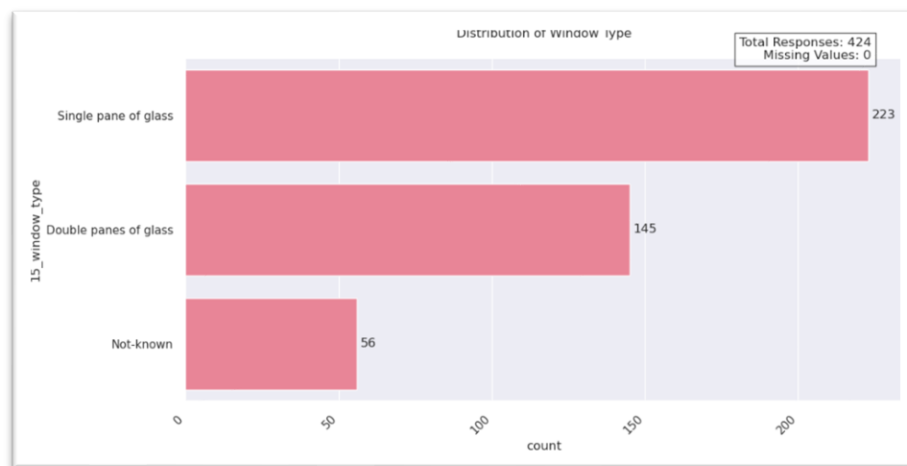


Figure 41: Window Type Distribution in Survey Data.

- **Wall Insulation Distribution:** Wall insulation presence is reported as follows: 40.3% have no insulation (171 responses), 26.7% have insulation (113 responses), and 33.0% do not know (140 responses). Insulation plays a significant role in energy efficiency, affecting heating and cooling loads. Figure 42 shows the Wall Insulation Distribution in Survey Data.

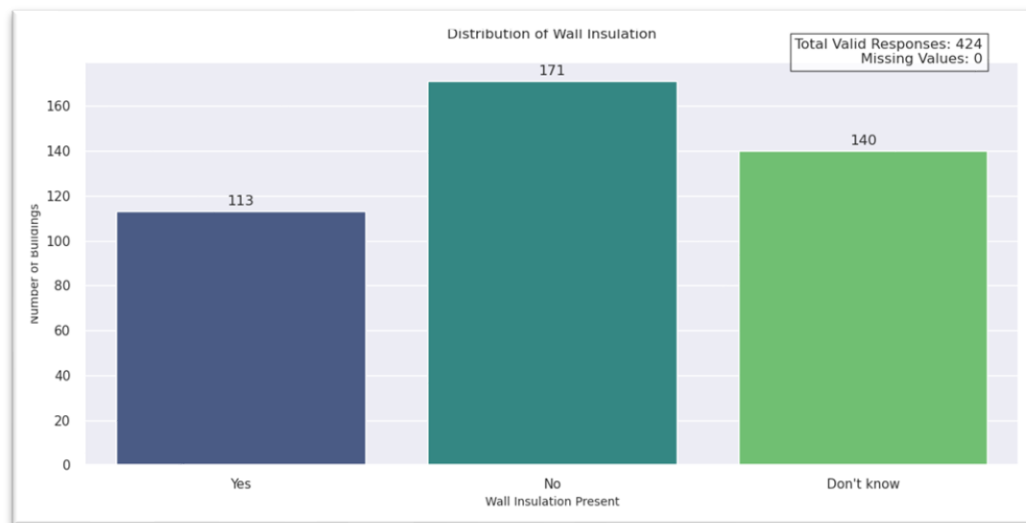


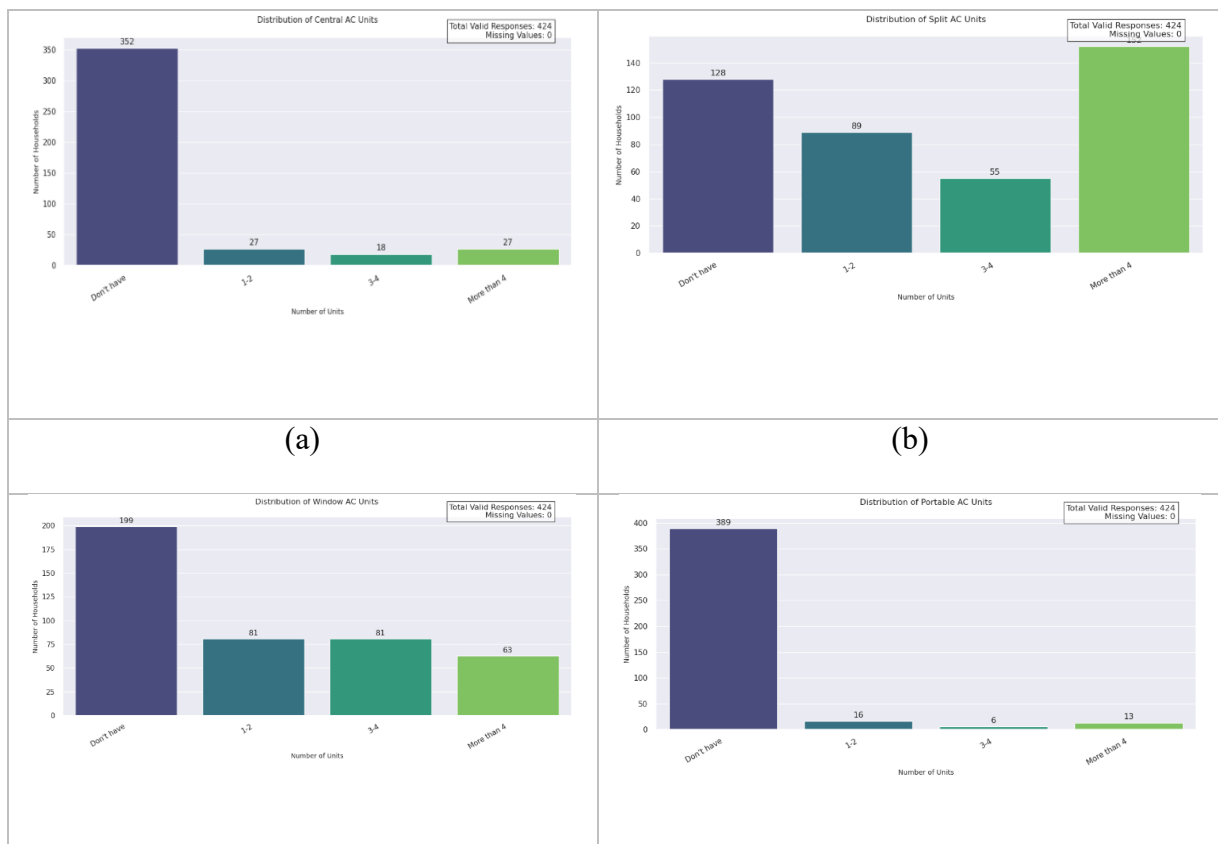
Figure 42: Wall Insulation Distribution in Survey Data

4.2.1.3 AC Systems

- **Air Conditioning Systems Distribution:** Air conditioning systems vary widely among surveyed households, reflecting different preferences and needs based on the building type and size:
 - **Central AC Units:** Predominantly absent in most households with 83.0% not having any (352 households). Where present, 1-2 units are found in 6.4% of

households, and another 6.4% have more than 4 units, with 4.2% having 3-4 units.

- **Split AC Units:** More common than central systems, with 35.8% of households having more than 4 units. No units are reported in 30.2% of households, 21.0% have 1-2 units, and 13.0% have 3-4 units.
 - **Window AC Units:** Absent in 46.9% of households, with 19.1% having 1-2 units, another 19.1% having 3-4 units, and 14.9% having more than 4 units.
 - **Portable AC Units:** Least common, with 91.7% of households not having any; 3.8% have 1-2 units, 3.1% have more than 4 units, and 1.4% have 3-4 units.
- Figure 43 shows the Air Conditioning Systems Distribution in Survey Data.



(c)	(d)
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Figure 43: Air Conditioning Systems Distribution in Survey Data. (a):Distribution of Central AC units. (b): Distribution of Split AC Units (c): Distribution of Window AC Units (d):Distribution of Potable AC Units.

4.2.1.4 Behaviour

- **AC Monthly Usage (Usage Periods) :** Households reported varying lengths of AC usage throughout the year, categorized into four periods. The duration of AC usage offers insight into seasonal operation patterns and likely energy consumption:
 - **1-3 months:** 50 households, indicating minimal usage typically in milder weather.
 - **4-6 months:** 63 households, suggesting moderate usage possibly during warmer months.
 - **7-9 months:** 167 households, reflecting extended usage that spans the majority of the year, highlighting the reliance on air conditioning in warmer climates.
 - **10-12 months:** 144 households, demonstrating year-round usage due to extreme climate conditions prevalent in many regions of Saudi Arabia.

Figure 44 shows the AC Monthly Usage Patterns in Saudi Arabia.

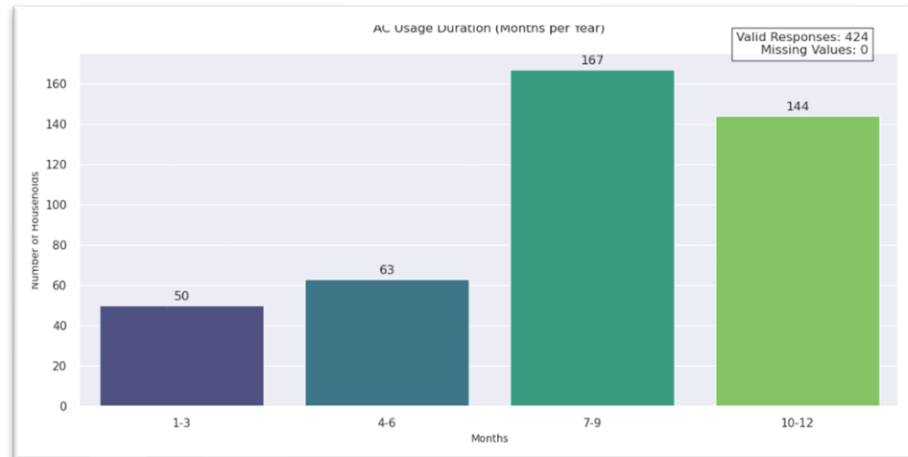


Figure 44: AC Monthly Usage Patterns in Saudi Arabia.

- **AC Daily Usage (Operation Intensity):** The daily operation intensity of air conditioning systems shows a significant variance, reflecting diverse usage habits among households:
 - **Less or Equal to 8 Hours:** A smaller segment of the population, with 74 households, uses air conditioning sparingly, likely during cooler parts of the day or in milder weather.
 - **9-12 Hours:** The largest group, comprising 133 households, indicates moderate use, which could be consistent during the day or primarily in daytime to evening hours.
 - **13-16 Hours:** A substantial number, 106 households, extend their AC usage well into the evening, likely reflecting higher temperature conditions or preference for constant climate control indoors.

- **17-20 Hours:** 64 households report near-continuous operation, suggesting very high dependence on air conditioning possibly due to extreme external temperatures or specific household needs.
- **Over 20 Hours:** 47 households operate their AC systems almost continuously, indicative of extremely hot climates and/or high comfort requirements.

Figure 45 shows the AC Daily Usage Hours Patterns in Saudi Arabia.

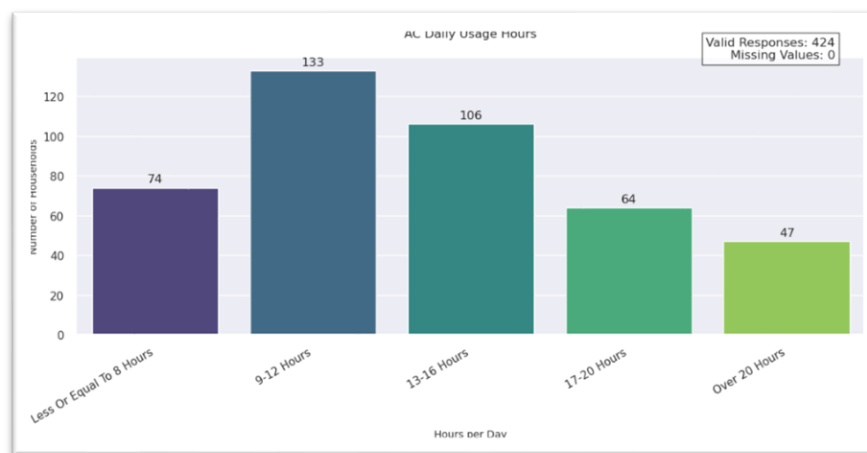


Figure 45: AC Daily Usage Hours Patterns in Saudi Arabia.

- **Thermostat Settings (Temperature Preferences) :** The range of thermostat settings varied significantly among households, indicating different comfort preferences and potential impacts on energy consumption.
 - The most common settings fall between 20°C and 24°C, reflecting a preference for moderate indoor temperatures.

- The mean thermostat setting is 21.3°C, with a median of 22.0°C, and the settings range from 16.0°C to 27.0°C.
- The spread of setpoints, with a standard deviation of 2.4°C, indicates varied comfort levels and potential implications for energy efficiency strategies.

Figure 46 shows the Thermostat Settings Distribution in Saudi Arabia.

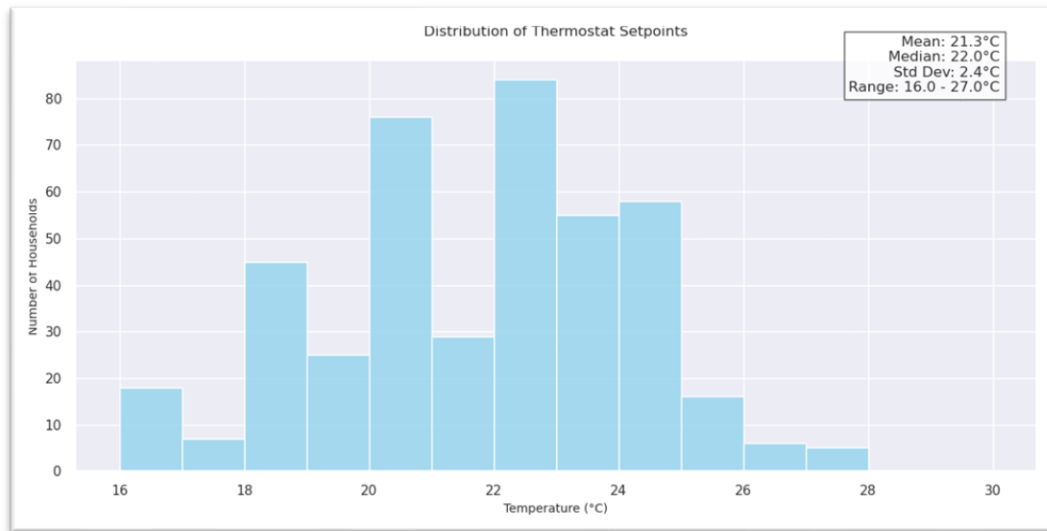


Figure 46:Thermostat Settings Distribution in Saudi Arabia.

- **Energy-Saving Habits:** The analysis of energy-saving habits among surveyed households reveals a varied adherence to behaviors that can significantly reduce energy consumption:
 - **AC Management:**
 - **Switching off AC when not needed** is widely practiced, with a substantial number of respondents indicating they always or often do so.

- **Adjusting thermostat settings** is less common, suggesting a potential area for increased energy savings.
 - **Using fans instead of AC** and **regular AC maintenance** show moderate adherence, indicating room for improvement in these practices.
- **Lighting Control:**
 - **Turning off unused lights** and **utilizing natural daylight** are highly adopted practices.
 - **Use of LED lighting** is also quite prevalent, reflecting a shift towards more energy-efficient lighting solutions.
- **Natural Ventilation:**
 - **Opening windows for ventilation** is a moderately common practice, which can significantly reduce the need for mechanical cooling.
- The distribution and mean response data from the survey are illustrated in the Figure 47 and Figure 48 and listed in Table 8, showcasing the percentage of households engaging in each behavior and the average response rating on a scale from 1 (Never/Strongly Disagree) to 5 (Always/Strongly Agree). The mean responses, as shown in Figure 48 highlight that while some energy-saving behaviors are well integrated into daily routines, others, particularly related to air conditioning management, could be emphasized more in public awareness campaigns or energy conservation initiatives.

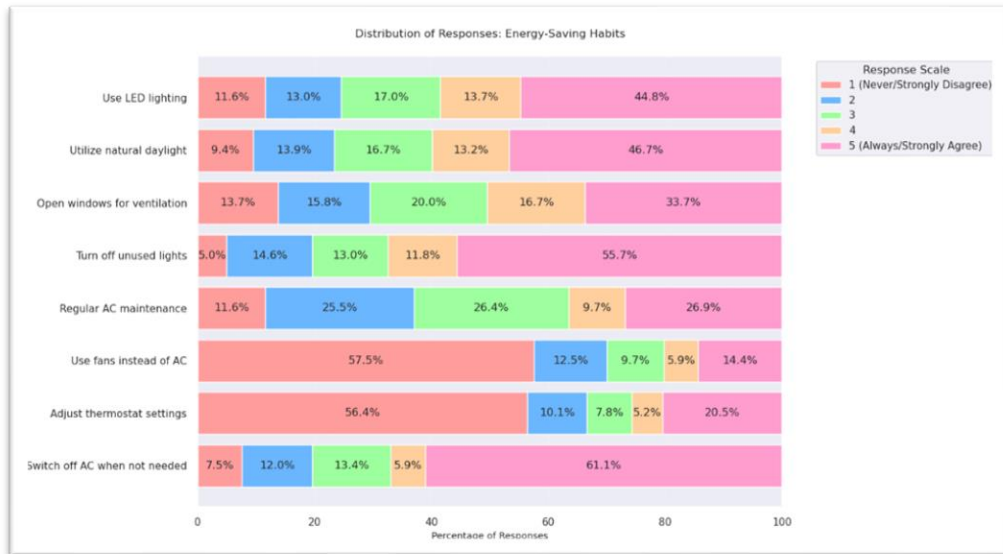


Figure 47: Distribution of Responses for Energy-Saving Habits

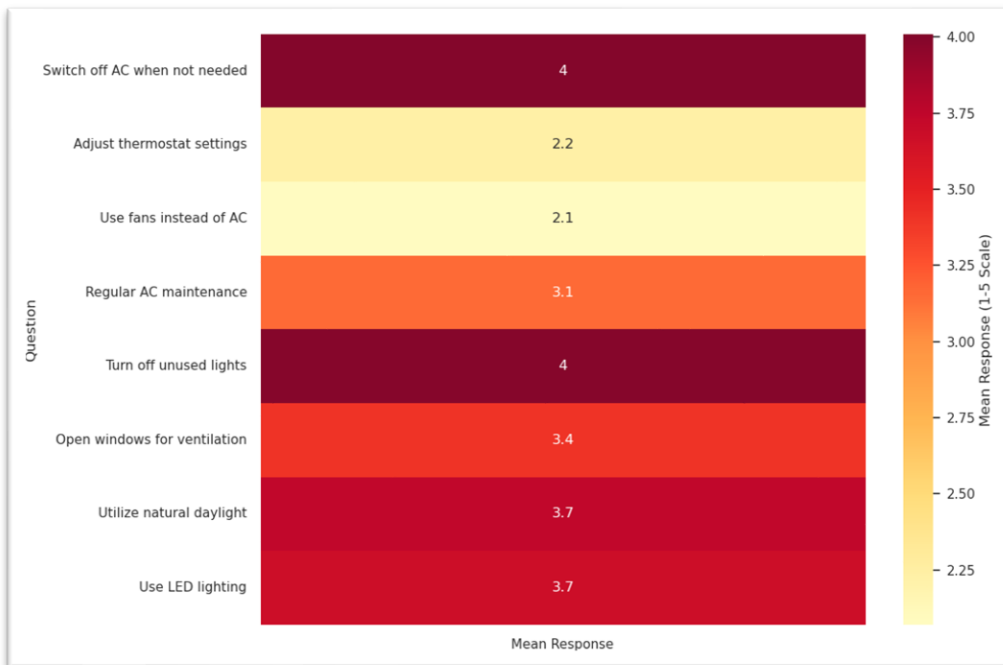


Figure 48: Mean Responses for Energy Saving Habits.

Table 8: Summary of Energy-Saving Habits Responses.

Energy-Saving Habit	Response 1	Response 2	Response 3	Response 4	Response 5	Mean	Std Dev
Switch off AC when not needed	32	51	57	25	259	4.01	1.38
Adjust thermostat at settings	239	43	33	22	87	2.23	1.63
Use fans instead of AC	244	53	41	25	61	2.07	1.48
Regular AC maintenance	49	108	112	41	114	3.15	1.37
Turn off unused lights	21	62	55	50	236	3.99	1.31

Open windows for ventilation	58	67	85	71	143	3.41	1.43
Utilize natural daylight	40	59	71	56	198	3.74	1.41
Use LED lighting	49	55	72	58	190	3.67	1.44

4.2.1.5 Energy Bill

- **Annual Electricity Bills:** Households exhibit varied annual electricity spending patterns, categorized into different cost brackets. This analysis helps identify typical expenditure ranges and consumption patterns.
 - A significant number of households (126) spend less than 1,000 SAR annually, suggesting either minimal energy usage, smaller living spaces, or highly efficient energy practices.
 - The majority of households have bills that range from 1,000 SAR to 6,000 SAR, with numbers gradually decreasing as the bill amounts increase. This typical

pattern indicates a standard variation in energy consumption related to differing household sizes, appliance use, and air conditioning habits.

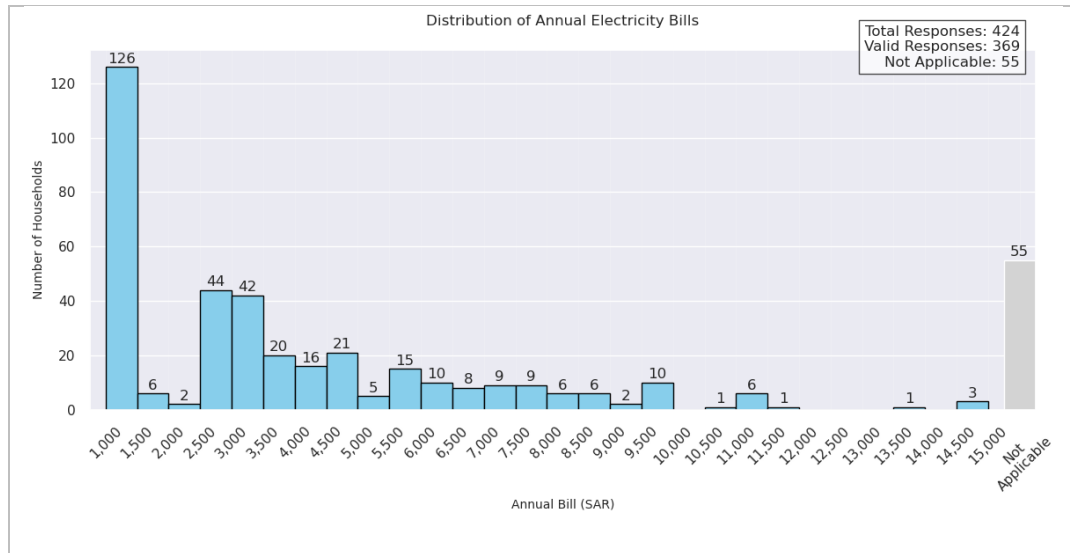
- A small number of households (1-10) report very high electricity bills, ranging from 10,000 SAR to over 15,000 SAR annually, which may reflect larger homes, extensive use of air conditioning, or less efficient energy systems.
 - Additionally, 55 responses were categorized as 'Not Applicable', which could include various scenarios such as respondents not being responsible for paying the bill directly or living in accommodations where utilities are included.
- (Figure: Distribution of Annual Electricity Bills)

Figure 49 (a) shows the Annual Electricity Bills Distribution in Saudi Arabia.

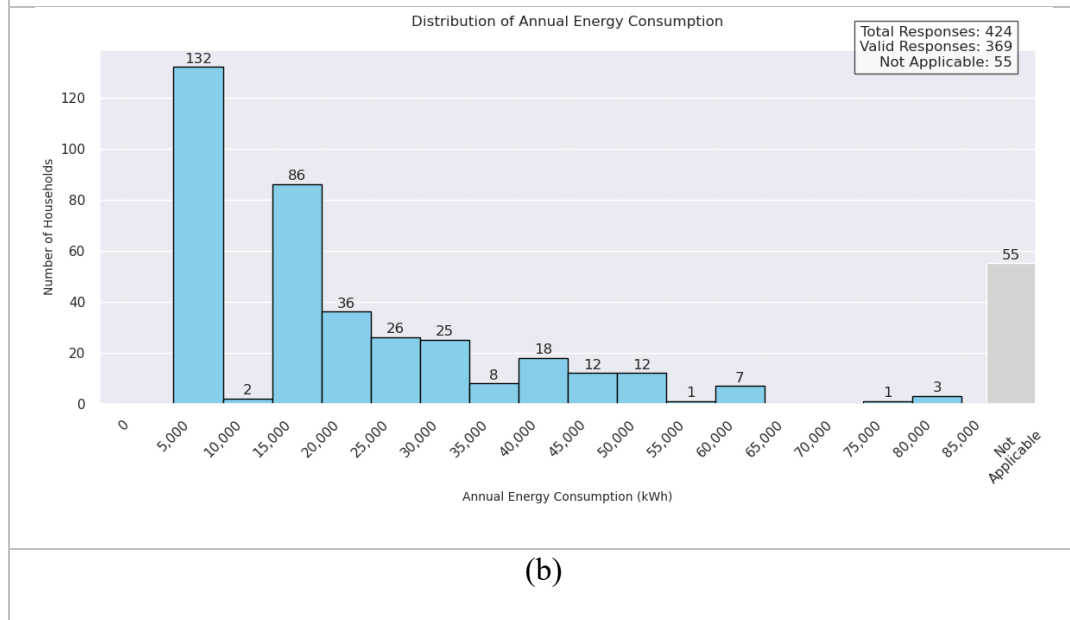
- **Energy Consumption Analysis:** The Energy Use Intensity (EUI), measured in kWh/m²/year, is calculated and analyzed to understand energy efficiency patterns across different building types and sizes. The examination of both annual energy consumption and Energy Use Intensity (EUI) provides a comprehensive view of energy usage patterns and efficiencies across surveyed households:
 - **Annual Energy Consumption:** The distribution of annual energy consumption in kWh shows that a large number of households (132) consume very low amounts of energy, potentially reflecting efficient energy usage or minimal use of high-consumption appliances. Most households fall within the range of 0 to 30,000 kWh, with numbers tapering off as consumption increases beyond this range. This distribution pattern is crucial for identifying households with unusually high energy consumption, which might benefit from targeted energy-

saving interventions. Figure 49 (b) shows the Distribution of Annual Energy Consumption (kWh)

- **Energy Use Intensity (EUI):** Calculated as kWh/m²/year, EUI normalizes energy consumption by floor area, offering a metric to compare energy efficiency across different building sizes and types. The majority of buildings have an EUI less than 200 kWh/m²/year, indicating efficient energy usage. There are, however, a few buildings with an EUI as high as 450 to 500 kWh/m²/year, highlighting areas where significant improvements in energy efficiency could be made. Figure 49 (c) shows the Distribution of Energy Use Intensity based on annual energy consumption, floor area and base tariff in Saudi Arabia. The data on EUI is derived from the annual energy consumption figures adjusted for building floor area and the base tariff rates in Saudi Arabia, thus providing a detailed insight into how energy is consumed relative to the space used. This combined analysis helps in understanding the broader implications of energy use practices, aiding in the development of more effective energy conservation strategies



(a)



(b)

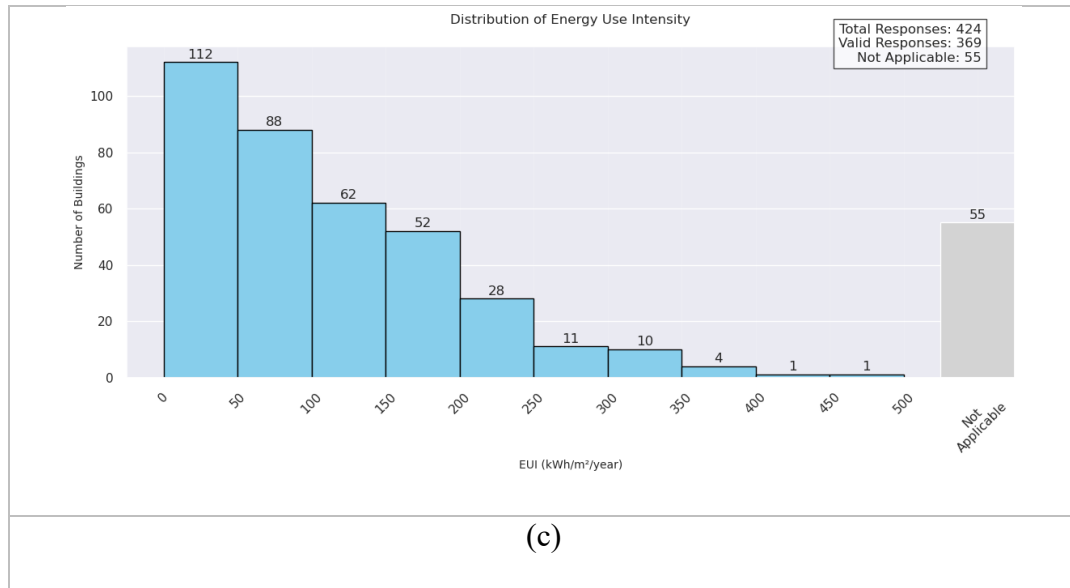


Figure 49: Energy Costs and Consumption Analysis. (a) Annual Electricity Bills Distribution . (a) Annual Electricity Bills Distribution , (b) Distribution of Annual Energy Consumption, (c) Distribution of Energy Use Intensity.

- Bill Payment Mode: Payment Methods:** The distribution of bill payment modes is largely skewed towards postpaid systems, comprising 84.7% of responses (359 households). Prepaid systems account for 5.9% (25 households), and 9.4% were categorized as not applicable (40 responses). Figure 50 shows this distribution.

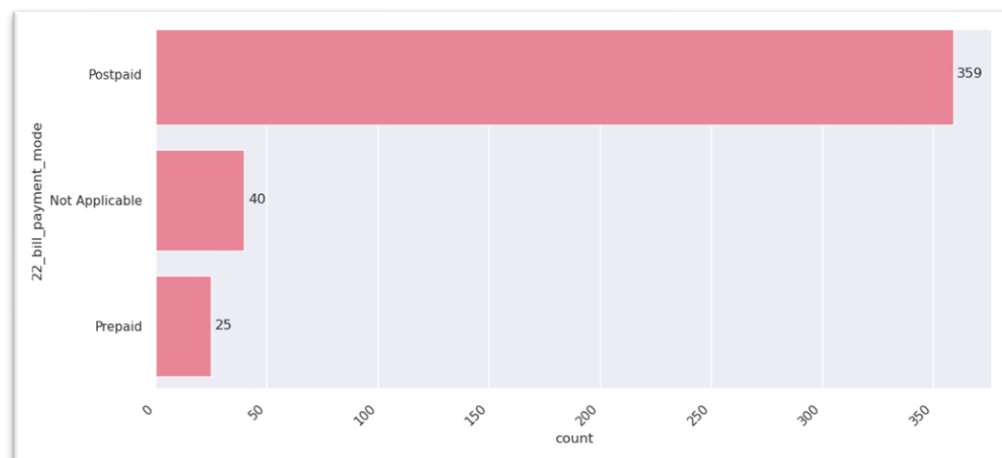


Figure 50: Bill Payment Mode Distribution in Saudi Arabia)

4.2.1.6 Attitude/ Opinions

- **Energy Conservation Opinions**

The survey of energy conservation opinions unveils diverse attitudes towards various facets of energy efficiency, reflecting the complexity of societal, technological, and individual factors influencing energy conservation behaviors:

1. **Need for Improvement:** This opinion scores high, reflecting a strong consensus on the necessity to enhance energy conservation measures within homes, indicating widespread recognition of potential improvements.
2. **Social Circle Influence:** Opinions vary, with a moderate consensus that social interactions can influence personal energy-saving behaviors, highlighting the social component of energy conservation.
3. **Technology Sufficiency:** Responses suggest skepticism about the adequacy of current technologies in achieving energy conservation goals, pointing to a gap between existing solutions and perceived needs.
4. **Behavior Importance:** Strongly emphasized, indicating that respondents see significant value in individual actions for effective energy conservation.
5. **Awareness Levels:** There is a broad acknowledgment of varying levels of awareness about energy conservation, suggesting room for enhanced educational initiatives.
6. **Society-wide Attitudes:** Mixed responses indicate diverse societal attitudes towards energy efficiency, reflecting varying cultural and societal norms.

7. **Need for Incentives:** Many respondents support the idea that incentives are crucial for encouraging energy-efficient behaviors, suggesting a role for policy in energy conservation.
8. **Home Energy Waste:** Perceptions of energy waste at home vary, with many indicating moderate to significant waste, underscoring the need for better energy management practices in households.

The graphical representations in Figure 51 and Figure 52 provide a visual summary of the distribution of these opinions and the average responses. Distribution of Responses illustrates the varied responses across different aspects of energy conservation, providing a clear view of areas where there is strong agreement or disagreement among participants. Mean Responses for Energy Conservation Opinions highlights the average scores for each opinion, helping to pinpoint areas where interventions could be most impactful. Table 9 summarizes these opinions.



Figure 51: Distribution of Responses for Energy Conservation Opinions

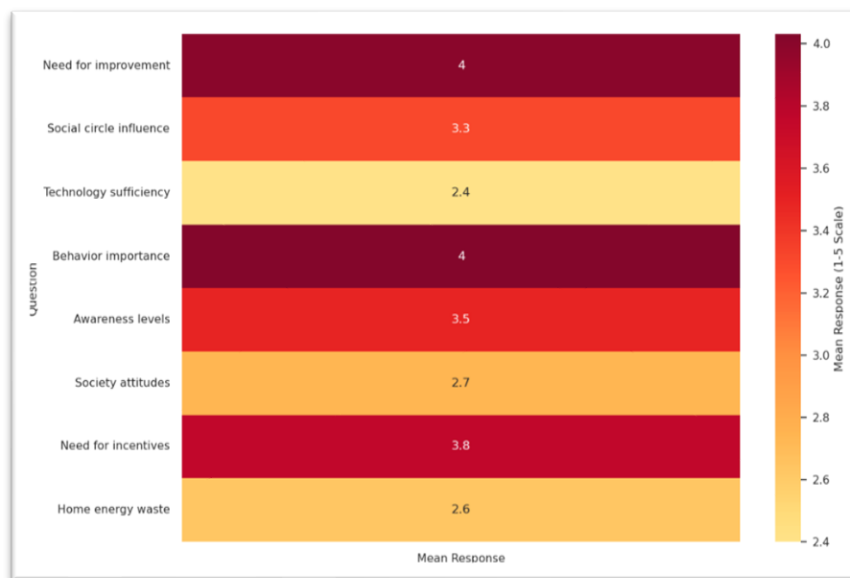


Figure 52: Mean Responses for Energy Conservation Opinions

Table 9: Summary of Energy Conservation Opinions.

Question	Response 1	Response 2	Response 3	Response 4	Response 5	Mean	Std Dev
	1	2	3	4	5		

Need for improvement	22	41	86	39	236	4.00	1.27
Social circle influence	57	70	106	68	123	3.31	1.39
Technology sufficiency	149	96	93	32	54	2.40	1.36
Behavior importance	17	46	77	53	231	4.03	1.23
Awareness levels	35	59	122	80	128	3.49	1.28
Society attitudes	80	102	144	45	53	2.74	1.24
Need for incentives	20	53	95	95	161	3.76	1.21
Home energy waste	107	97	112	60	48	2.63	1.30

- **Energy Saving Responsibility**

The survey investigated who in the household is perceived to be more keen on saving energy. The results demonstrate a diverse range of responsibility:

- **Main earner** takes the lead with 233 responses, representing 40.7% of the total, showing a significant inclination towards managing energy usage.
- **Male members** of the household are also notably active, with 205 responses or 35.8%.
- **Female members** are engaged as well, with 134 responses or 23.4%.

These distributions are illustrated in Figure 53, which highlights the energy-saving initiatives within households by different members.

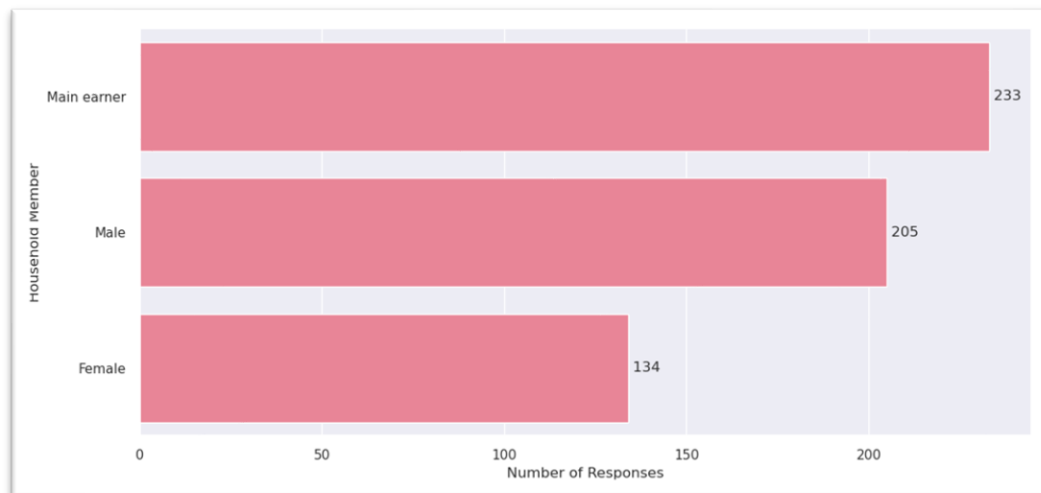


Figure 53: Who is More Keen About Saving Energy

- **Energy Price Impact**

Responses to how much pressure from energy prices impacts their lives were captured on a Likert scale from 1 (no pressure) to 5 (high pressure):

- A significant portion, 212 respondents or 50%, feel a high level of pressure due to energy prices.

- Middle ranges (2-4) collectively have 187 responses, indicating varying degrees of impact across the population.

The pressure from energy prices seems to be linked with a readiness among respondents to adjust their lifestyles in response to or to alleviate energy costs. A total of 140 respondents, representing 33%, indicated the highest willingness to make lifestyle changes. Figure 54 and Figure 55 illustrate the Distribution of Responses for Pressure from Energy Prices and the Distribution of Responses for Willingness to Change Lifestyle. **Tables** provide a summary of the Response Statistics for Pressure from Energy Prices and Response Statistics for Willingness to Change Lifestyle, respectively.

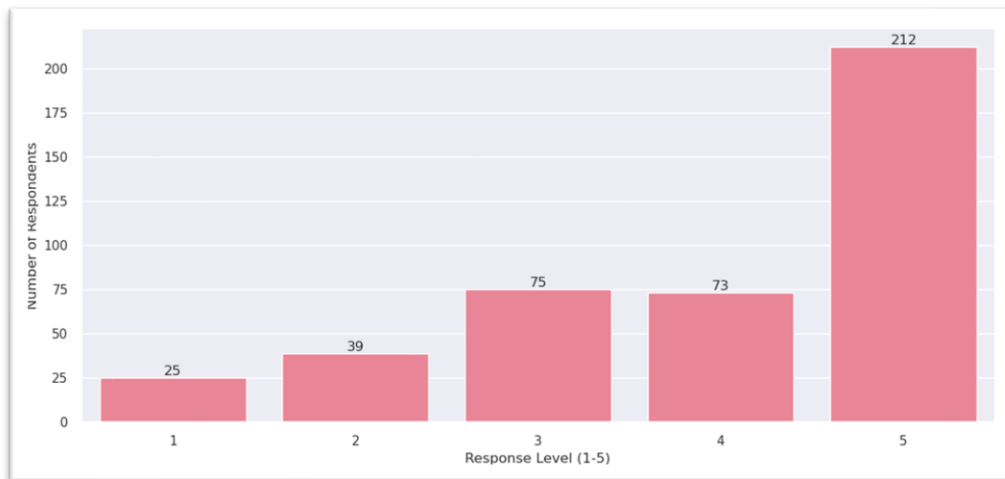


Figure 54: Distribution of Responses for Pressure from Energy Prices.

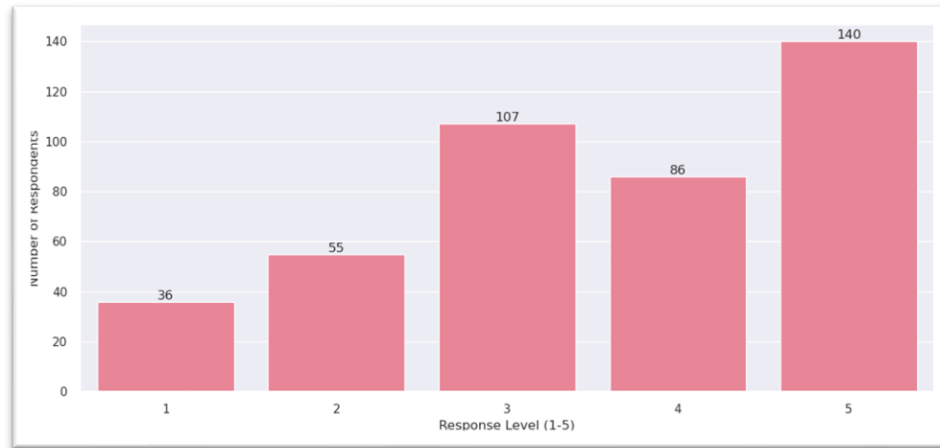


Figure 55: Distribution of Responses for Willingness to Change Lifestyle

4.2.1.7 Awareness

- **Energy Awareness**

The survey on energy awareness assesses the knowledge and attitudes towards various sustainability and energy efficiency topics:

1. **Climate Change:** Strong awareness, with a significant portion of respondents acknowledging the importance and impact of climate change.
2. **Green Buildings:** Good awareness levels, indicating familiarity with green building concepts among participants.
3. **Efficiency Management:** A high level of awareness, reflecting understanding of the importance of energy efficiency management in buildings.
4. **Carbon Neutrality by 2060:** Moderate awareness, suggesting that while some are informed about carbon neutrality goals, there is room for broader dissemination of this information.

5. **Building Codes:** Varying levels of awareness, with a need to enhance understanding of building codes related to energy efficiency.
6. **Renewable Technology:** Reasonable awareness, indicating familiarity with renewable energy technologies among the surveyed population.
7. **Sustainable Development:** Moderate awareness, showing some understanding of sustainable development practices but also indicating potential for increased education.

Figure 56 and Figure 57 visualize the distribution of responses and the mean responses, providing a clear graphical representation of how well these topics are understood across the survey population. Table 10 summarizes these responses. Figure 56 displays the varied levels of agreement or awareness among respondents for each energy awareness topic, highlighting areas where awareness is strong and others where it could be improved. Figure 57 averages the responses, giving a straightforward measure of the overall awareness levels across different key topics in energy and sustainability.

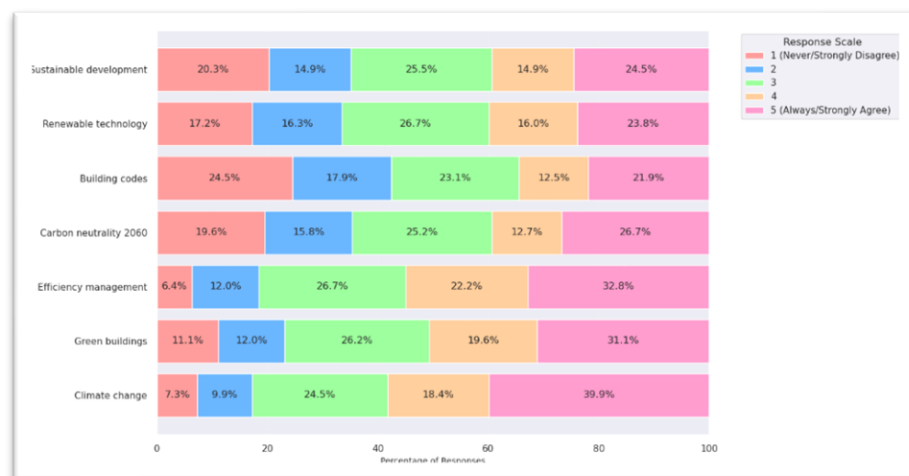


Figure 56: Distribution of Responses for Energy Awareness

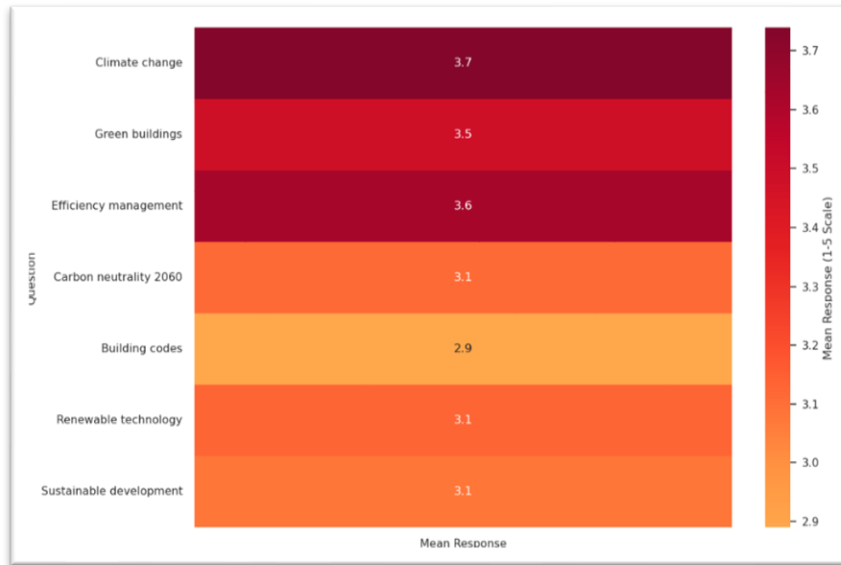


Figure 57: Mean Responses for Energy Awareness.

Table 10: Summary of Energy Awareness Responses.

Question	Response 1	Response 2	Response 3	Response 4	Response 5	Mean	Std Dev
Climate Change	31	42	104	78	169	3.74	1.28
Green Buildings	47	51	111	83	132	3.48	1.33

Efficiency Management	27	51	113	94	139	3.63	1.23
Carbon Neutrality 2060	83	67	107	54	113	3.11	1.46
Building Codes	104	76	98	53	93	2.89	1.47
Renewable Technology	73	69	113	68	101	3.13	1.40
Sustainable Development	86	63	108	63	104	3.08	1.44

- **Energy Efficiency Program Awareness**

Awareness of energy efficiency programs among respondents is notably low, with 286 participants, or 67.5%, indicating they are not aware of such initiatives. In contrast, 138 respondents, or 32.5%, have acknowledged awareness. Figure 58 provides a visual representation of survey response distribution for the Awareness of Energy Efficiency Programs, and the Table 11 offers a detailed summary of the data on Energy Efficiency Program Awareness.

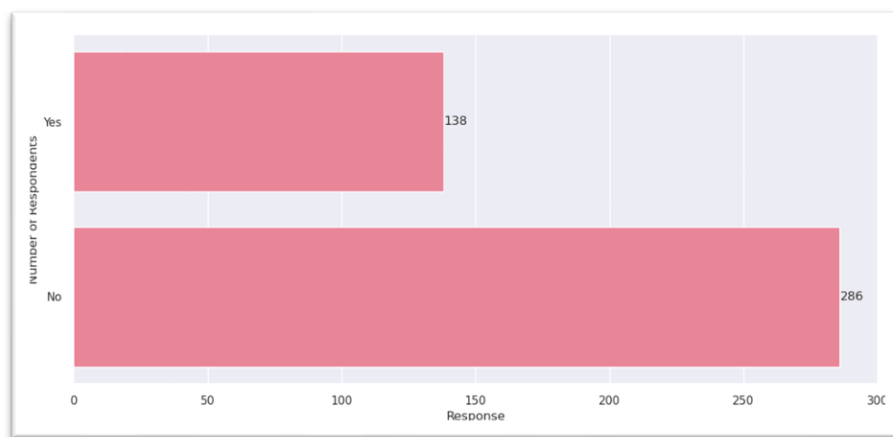


Figure 58: Awareness of Energy Efficiency Programs.

Table 11: Energy Efficiency Program Awareness

Awareness Level	Number of Responses	Percentage
Yes	138	32.5%
No	286	67.5%

4.2.1.8 Energy Efficiency Measures & Barriers

- **Adoption Rates-** The survey data illustrate significant engagement with energy efficiency measures among the respondents:
 - **Adoption Status:**
 - **Yes:** A substantial majority, 303 respondents or 71.5%, have adopted energy efficiency measures, which reflects a proactive approach towards energy conservation within the community.
 - **No:** 97 respondents or 22.9% have not adopted these measures, indicating areas where further outreach and education could be impactful.
 - **Don't think needed:** 24 respondents or 5.6%, do not perceive a need for such measures, possibly due to satisfactory energy usage levels or lack of awareness of potential benefits.

This distribution is detailed in Figure 59, providing a visual representation of the adoption rates, underscoring the widespread acceptance and areas for potential growth in adoption.

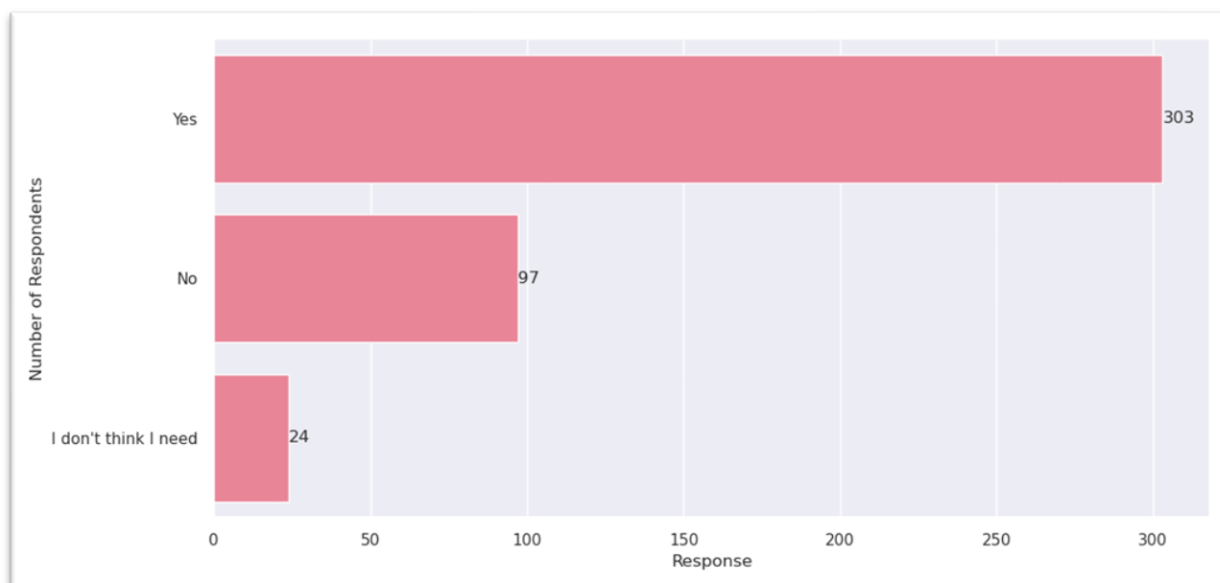


Figure 59: Adoption of Energy Efficiency Measures

- **Reasons for Non-Adoption**

Major barriers of why some respondents have not adopted energy efficiency measures reveals several barriers:

- **Lack of Information** and **High Capital Costs** are prominent reasons, each cited by 52 respondents, suggesting significant opportunities for interventions that lower financial barriers and enhance informational outreach.
- **Lack of Motivation:** Indicated by 39 respondents, pointing to a need for motivational campaigns and possibly incentives to foster a shift towards energy-efficient practices.

Additional barriers such as Low Energy Prices, Lack of Technology Providers, and Fear of Lifestyle Changes further elaborate on the challenges faced by respondents in adopting energy efficiency measures. These reasons are depicted in Figure 60, highlighting the relative frequency of each barrier, providing insights into targeted areas for policy and

programmatic interventions. Table 12 and Table 13 offers a detailed summary of the reported reasons.

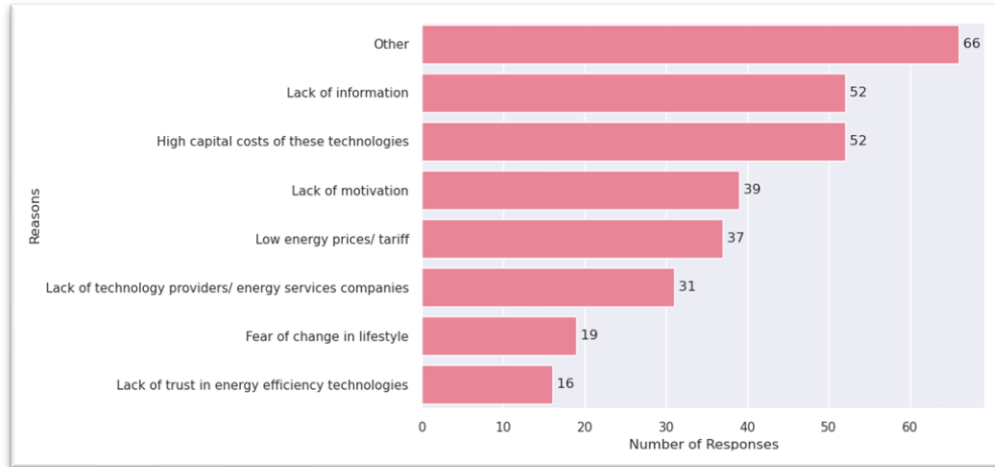


Figure 60: Reasons for Not Adopting Energy Efficiency Measures

Table 12: Summary of Energy Efficiency Measures Adoption.

Response Category	Number of Respondents	Percentage
Yes (have adopted)	303	71.5%
No (haven't adopted)	97	22.9%
Don't think needed	24	5.6%

Table 13: Summary of Reasons for Non-Adoption.

Reason	No. of Responses	% of Non-Adopters
Lack of information	52	16.7%

High capital costs	52	16.7%
Lack of motivation	39	12.5%
Low energy prices/tariff	37	11.9%
Lack of technology providers/energy services	31	9.9%
Other	66	21.2%
Fear of change in lifestyle	19	6.1%
Lack of trust in energy efficiency technologies	16	5.1%

4.2.2 Correlation Analysis

Correlation analysis was conducted to examine the associations between key survey variables and Energy Use Intensity (EUI). Given the nature of the dataset, both Pearson correlation (for continuous variables) and Spearman correlation (for ordinal and categorical variables) were applied. The significance of the correlations was determined using p-values, with a threshold of $p < 0.05$ considered statistically significant. The analysis aimed to identify the strongest predictors of energy consumption patterns among residential users in Saudi Arabia. The correlation results were ranked based on the absolute value of the

correlation coefficient ($|r|$) to highlight the most influential factors. The findings are summarized in Table 14 and visually represented in Figure 61.

Table 14: Correlation of Variables with Energy Use Intensity (EUI)

Variable	Corrtype	r-value	p-value
12_floor_area	Pearson	-0.389	0
10_building_type	Spearman	-0.231	0
11_building_ownership	Spearman	-0.215	0
1_professional_industry	Spearman	-0.205	0
2_gender	Spearman	-0.19	0.0001
15_window_type	Spearman	-0.181	0.0002
29.1_energy_price_impact_pressure	Spearman	0.178	0.0002
4_nationality	Spearman	0.175	0.0003
24.1_energy_opinions_need_improvement	Spearman	0.172	0.0004
17.1_ac_systems_central	Spearman	-0.165	0.0006
23.1_energy_habits_switch_off_ac	Spearman	0.164	0.0007
17.2_ac_systems_split	Spearman	-0.163	0.0007
22_bill_payment_mode	Spearman	-0.161	0.0009
17.4_ac_systems_portable	Spearman	-0.154	0.0014
9_bill_payer	Spearman	0.147	0.0024
17.3_ac_systems_window	Spearman	0.129	0.0077
25.3_energy_awareness_efficiency_management	Spearman	0.126	0.0095

30_energy_rating_influence	Spearman	0.123	0.0112
29.2_energy_price_impact_lifestyle_change	Spearman	0.121	0.0124
25.1_energy_awareness_climate_change	Spearman	0.112	0.0207
7_region	Spearman	-0.111	0.0217
24.7_energy_opinions_incentives_needed	Spearman	0.108	0.0266
24.2_energy_opinions_social_circle	Spearman	0.105	0.0302
27_reason_no_measures_Other	Spearman	-0.105	0.0305
23.2_energy_habits_adjust_thermostat	Spearman	-0.098	0.043
25.2_energy_awareness_green_buildings	Spearman	0.089	0.0661
23.5_energy_habits_turn_off_lights	Spearman	0.08	0.0987
5_age	Spearman	0.079	0.1031
16_wall_insulation	Spearman	-0.079	0.1055
23.6_energy_habits_open_windows	Spearman	0.073	0.1339
24.4_energy_opinions_behavior_important	Spearman	0.07	0.1488
23.3_energy_habits_use_fans	Spearman	0.063	0.1957
23.4_energy_habits_ac_maintenance	Spearman	0.062	0.2036
19_ac_daily_hours	Pearson	0.061	0.2124
8_monthly_income	Spearman	0.053	0.2727
23.7_energy_habits_daylight_use	Spearman	-0.052	0.2826
24.5_energy_opinions_awareness_lack	Spearman	0.052	0.2891
25.7_energy_awareness_sdgs	Spearman	0.048	0.3247
27_reason_no_measures_Low_energy_prices_tariff	Spearman	-0.047	0.3358

27_reason_no_measures_Lack_of_motivation	Spearman	0.041	0.4034
24.3_energy_opinions_tech_sufficient	Spearman	-0.041	0.4054
25.6_energy_awareness_renewable_tech	Spearman	0.039	0.4246
27_reason_no_measures_Lack_of_information	Spearman	0.038	0.4363
27_reason_no_measures_High_capital_costs_of_these_technologies	Spearman	0.037	0.4525
23.8_energy_habits_use_led	Spearman	0.035	0.4679
18_ac_months_used	Spearman	0.032	0.5061
13_num_floors	Pearson	-0.03	0.5346
24.8_energy_opinions_home_wastage	Spearman	0.03	0.542
3_education	Spearman	0.024	0.6276
27_reason_no_measures_Lack_of_technology_providers__energy_services_companies	Spearman	0.023	0.6328
26_energy_efficiency_measures	Spearman	0.023	0.6354
14_building_age	Spearman	-0.02	0.6794
20_thermostat_setpoint	Spearman	-0.019	0.7003
31_awareness_efficiency_programs	Spearman	0.015	0.7647
25.5_energy_awareness_building_code	Spearman	0.014	0.7728
27_reason_no_measures_Fear_of_change_in_lifestyle	Spearman	-0.009	0.8579
28_energy_saver	Spearman	-0.008	0.8721

25.4_energy_awareness_carbon_neutral_2060	Spearman	0.008	0.8771
27_reason_no_measures_Lack_of_trust_in_energy_efficiency_technologies	Spearman	0.005	0.9106
27_reason_no_measures_count	Spearman	-0.003	0.9563
6_household_size	Pearson	0.002	0.9743
24.6_energy_opinions_saudi_society	Spearman	0.002	0.9754

4.2.2.1 Key Correlations with Energy Use Intensity (EUI)

To better understand the factors influencing residential Energy Use Intensity (EUI) in Saudi Arabia, correlation analysis was conducted across various demographic, building, behavioral, and attitudinal variables. The results revealed several statistically significant associations, with both positive and negative correlations observed. Top 5 Strongest Correlations with EUI:

1. Floor Area ($r = -0.389$, $p < 0.0001$, Pearson): Larger homes tend to have lower EUI, possibly due to better energy efficiency per square meter or differences in occupancy patterns.
2. Building Type ($r = -0.231$, $p < 0.0001$, Spearman): Apartments exhibit higher EUI compared to villas and traditional houses, likely due to smaller living spaces with intensive cooling needs or lower insulation quality.

3. Building Ownership ($r = -0.215$, $p < 0.0001$, Spearman): Rented homes show higher EUI than owned homes, possibly indicating lower investment in energy efficiency by tenants.
4. Professional Industry ($r = -0.205$, $p < 0.0001$, Spearman): Employment sector influences energy consumption patterns, with potential differences in working hours and time spent at home. This suggests that private-sector workers may leave cooling systems running while they are away, leading to higher overall energy consumption. Government employees and retirees may have lower EUI due to more flexible schedules, subsidized housing, or better energy management practices.
5. Gender ($r = -0.190$, $p = 0.0001$, Spearman): Male-headed households have higher EUI, potentially due to higher occupancy rates or different cooling preferences.

Beyond these top correlations, several other variables exhibited statistically significant relationships with EUI:

1. Window Type ($r = -0.181$, $p = 0.0002$, Spearman) : Double-pane windows correlate with lower EUI, reinforcing the importance of insulation.
2. Energy Price Pressure ($r = 0.178$, $p = 0.0002$, Spearman) : Households experiencing higher price pressure tend to have higher EUI, indicating that affordability constraints may affect energy-saving efforts.
3. Nationality ($r = 0.175$, $p = 0.0003$, Spearman) : Non-Saudi residents tend to have higher EUI, potentially reflecting different lifestyle preferences and home energy consumption habits.

4. Central AC Usage ($r = -0.165$, $p = 0.0006$, Spearman) : Households using centralized cooling systems tend to have lower EUI, highlighting the efficiency of central AC over individual split units.
5. Energy-Saving Habits (Switching Off AC) ($r = 0.164$, $p = 0.0007$, Spearman) : Households with higher EUI are more likely to turn off AC frequently, suggesting that high-energy consumers attempt to manage their usage actively.

These findings underscore the complex interplay between building characteristics, household behaviors, and socioeconomic factors in shaping residential energy consumption patterns. The results of the correlation analysis are visually summarized in Figure X, where a horizontal bar chart displays the correlation coefficients for all survey variables against EUI, sorted by absolute value to highlight the most influential predictors.

4.2.2.1.1 Interpretation and Implications

The correlation analysis provides valuable insights into residential energy consumption drivers, revealing the importance of structural, behavioral, and socioeconomic factors in shaping Energy Use Intensity (EUI).

- **Structural Factors Matter:** Larger floor areas, well-insulated windows, and central AC systems are linked to lower EUI, underscoring the importance of energy-efficient building design.
- **Behavioral Awareness vs. Action Gap:** Notably, households with higher EUI tend to have greater awareness of energy efficiency. However, this does not necessarily mean that energy-conscious households consume more energy. Rather, it suggests that high-

consuming households are more aware of their energy use and recognize the need for efficiency improvements, even if these behaviors have not yet been fully implemented. This finding underscores the potential gap between awareness and action in energy-saving practices, a pattern that has also been observed in previous research [147].

- Socioeconomic Considerations: Rented properties show higher EUI, highlighting the split-incentive problem where landlords may not invest in efficiency upgrades. Price sensitivity is a significant driver, implying that financial incentives (e.g., tiered pricing structures) could help encourage conservation behaviors.

These findings support the need for targeted energy efficiency policies, including incentives for renters, insulation standards, and awareness campaigns tailored to high-EUI households. Overall, these findings serve as a foundation for further analysis, including interaction effects and regression models, to better understand relationships and predictive factors for energy consumption Figure 62.



Figure 61: Correlation of Variables with Energy Use Intensity (EUI).

4.2.2.2 Correlation of Behavioral Variables with Other Factors

Beyond overall correlations with Energy Use Intensity (EUI), an additional layer of analysis was conducted to examine how key energy-related behaviors correlate with demographic, structural, awareness, and attitudinal factors. This analysis provides deeper insights into the drivers of occupant behavior and how they interact with external influences. Using Pearson or Spearman correlation, as appropriate, the study explored relationships between:

- AC usage patterns and income, awareness, and household demographics.
- Thermostat settings and insulation quality, income, and attitudes.
- Energy-saving behaviors (e.g., AC usage, switching off AC, using fans, or turning off lights) and awareness levels, bill payment responsibility, and perceived barriers to efficiency.

The results are summarized in Table 15 and visualized in Figure 62, highlighting the strongest behavioral correlations.

Table 15: Correlations: Behavior vs. Other Variables

Varibale_Name_1	Varibale_Name_2	Correlation Type	r-value	p-value
Turn Off Lights	Attitude: Behavior Important	spearman	0.319	0
Use LED Lighting	Awareness of Efficiency	spearman	0.296	0
Switch Off AC	Awareness of Efficiency	spearman	0.282	0

Daylight Use	Attitude: Behavior Important	spearman	0.256	0
Open Windows	Awareness of Efficiency	spearman	0.251	0
AC Maintenance	Awareness of Efficiency	spearman	0.25	0
Turn Off Lights	Awareness of Efficiency	spearman	0.246	0
Daylight Use	Awareness of Efficiency	spearman	0.209	0
AC Maintenance	Attitude: Behavior Important	spearman	0.201	0
AC Usage (Months/Year)	Age	spearman	- 0.198	0
Adjust Thermostat	Awareness of Efficiency	spearman	0.139	0.0041
Switch Off AC	Barrier (Low energy prices/tariff)	spearman	- 0.122	0.012
Use LED Lighting	Education Level	spearman	0.121	0.0124
Thermostat Setpoint	Monthly Income	spearman	0.11	0.0234
Use Fans	Wall Insulation	spearman	- 0.109	0.0255
Daily AC Hours	Monthly Income	pearson	0.108	0.0261
AC Usage (Months/Year)	Awareness of Efficiency Management	spearman	- 0.091	0.06
Open Windows	Region	spearman	0.089	0.0661
Switch Off AC	Who Pays the Bill	spearman	0.087	0.0733

AC Usage (Months/Year)	Monthly Income	spearman	0.085	0.0815
Open Windows	Wall Insulation	spearman	0.078	0.1101
AC Maintenance	Monthly Income	spearman	- 0.075	0.1223
Switch Off AC	Monthly Income	spearman	- 0.075	0.1252
Use Fans	Awareness of Efficiency	spearman	0.063	0.1938
Adjust Thermostat	Region	spearman	0.058	0.2322
Use Fans	Household Size	pearson	- 0.058	0.233
Use LED Lighting	Monthly Income	spearman	0.052	0.2858
AC Usage (Months/Year)	Building Type	spearman	- 0.051	0.2932
Turn Off Lights	Education Level	spearman	- 0.051	0.2976
Daily AC Hours	Awareness of Efficiency Management	spearman	0.045	0.3593
Thermostat Setpoint	Attitude: Behavior Important	spearman	0.037	0.4522
Thermostat Setpoint	Awareness of Efficiency	spearman	0.029	0.5498
Daily AC Hours	Energy Price Pressure	pearson	- 0.017	0.7285

Thermostat Setpoint	Wall Insulation	spearman	0.016	0.7395
Daily AC Hours	Region	spearman	0.011	0.8231
Adjust Thermostat	Attitude: Behavior Important	spearman	0.008	0.8725
Daylight Use	Monthly Income	spearman	0.004	0.9268

The analysis identified 16 statistically significant correlations ($p < 0.05$), highlighting the interplay between energy-saving habits, awareness, financial incentives, and building characteristics. The top Five Strongest Behavioral Correlations are as follows ($(|r| > 0.25)$):

1. Turning Off Lights vs. Attitude: "Behavior is Important" ($r = 0.319$, $p < 0.0001$, Spearman): Individuals who strongly agree that behavior plays a critical role in energy efficiency are more likely to consistently turn off lights when not in use. This finding underscores the role of attitudes in shaping energy-conscious behaviors and suggests that targeted awareness campaigns emphasizing behavioral responsibility could enhance household energy savings.
2. Using LED Lighting vs. Awareness of Energy Efficiency ($r = 0.296$, $p < 0.0001$, Spearman): Households that are more aware of energy efficiency concepts are significantly more likely to use LED lighting. This finding supports the positive impact of awareness on sustainable technology adoption, reinforcing the need for educational programs and financial incentives to promote LED lighting as an energy-saving measure.

3. Switching Off AC vs. Awareness of Energy Efficiency ($r = 0.282$, $p < 0.0001$, Spearman): A strong positive correlation was observed between awareness of energy efficiency and the habit of switching off AC when not in use. This suggests that while awareness influences conservation behaviors, external factors—such as financial incentives, automation, or smart cooling systems—may be needed to further reinforce and sustain these energy-saving habits.
4. Daylight Use vs. Attitude: "Behavior is Important" ($r = 0.256$, $p < 0.0001$, Spearman): Households that perceive behavior as essential for energy efficiency are more likely to use natural daylight instead of artificial lighting. This finding highlights how attitudinal factors drive conscious energy decisions and suggests that promoting passive lighting strategies (e.g., architectural design improvements, daylighting techniques) can support household energy efficiency.
5. Opening Windows vs. Awareness of Energy Efficiency ($r = 0.251$, $p < 0.0001$, Spearman): Respondents who are aware of energy efficiency measures are more likely to use windows for ventilation instead of relying on air conditioning. This correlation indicates that knowledge about energy conservation encourages behavioral adjustments, particularly in terms of reducing AC dependency through natural cooling strategies.

Beyond the top five, several other relationships offer insights into how behaviors are shaped by demographics, financial factors, and home characteristics.

1. AC Usage (Months per Year) vs. Age ($r = -0.198$, $p < 0.0001$, Spearman): Older individuals tend to use air conditioning for fewer months per year, possibly due to lower cooling preferences or different lifestyle patterns. This suggests that cooling needs and

- energy-saving behaviors vary across age groups, which can inform age-targeted energy efficiency programs.
2. Daily AC Hours vs. Monthly Income ($r = 0.108$, $p = 0.0261$, Pearson): Higher-income households tend to run AC for longer hours daily, suggesting that financial capacity influences cooling behavior. This reinforces the need for incentive programs targeting high-income consumers, promoting energy-efficient cooling appliances and smart AC usage.
 3. Switching Off AC vs. Barrier: "Low Energy Prices/Tariff" ($r = -0.122$, $p = 0.0120$, Spearman): Households that cite low electricity costs as a barrier to adopting energy-saving measures are less likely to switch off AC when not in use. This suggests that subsidized electricity prices reduce the financial motivation to conserve energy, reinforcing the need for policy interventions such as tiered pricing structures.
 4. Thermostat Setpoint vs. Monthly Income ($r = 0.110$, $p = 0.0234$, Spearman): Higher-income households tend to set their thermostats at slightly higher temperatures, possibly due to increased comfort preferences. This suggests that wealthier households may prioritize thermal comfort over energy efficiency, highlighting the potential for incentive-based behavioral interventions to encourage optimal thermostat settings.
 5. Use LED Lighting vs. Education Level ($r = 0.121$, $p = 0.0124$, Spearman): Households with higher education levels are more likely to adopt LED lighting, reinforcing the idea that access to information plays a significant role in technology adoption. This finding suggests that expanding educational outreach efforts—particularly targeting lower-education households—could increase LED adoption rates.

The results of the behavioral correlation analysis are visually represented in Figure 62, where each behavior is compared against its strongest influencing factor. The variables are sorted by absolute correlation values to highlight the most influential relationships.

4.2.2.2.1 Interpretation and Policy Implications

The findings from this analysis emphasize the strong influence of awareness and attitudes on energy-saving behaviors, highlighting key policy implications:

- **Awareness Campaigns Are Effective but Need Reinforcement:** Households with greater awareness of energy efficiency are more likely to adopt energy-saving behaviors (e.g., turning off lights, using LED bulbs, switching off AC). However, awareness alone is not always sufficient—financial incentives, automation (e.g., smart thermostats), and structural improvements can further reinforce energy-saving habits.
- **Financial Factors Play a Crucial Role in Energy Use Decisions:** Higher-income households tend to consume more energy, particularly in terms of longer AC usage hours and thermostat settings. Subsidized electricity prices discourage conservation, highlighting the potential need for tiered electricity pricing or incentive-based reductions to promote efficient energy use.
- **Targeted Behavioral Interventions Can Enhance Energy Savings:** Older individuals use AC for fewer months, suggesting different cooling needs across age groups. Attitudes strongly influence behavior—households that recognize the importance of behavior in energy efficiency are more likely to engage in sustainable habits. Encouraging passive cooling strategies (e.g., using windows, daylighting techniques) through awareness and structural incentives can help reduce reliance on air conditioning Figure 62.

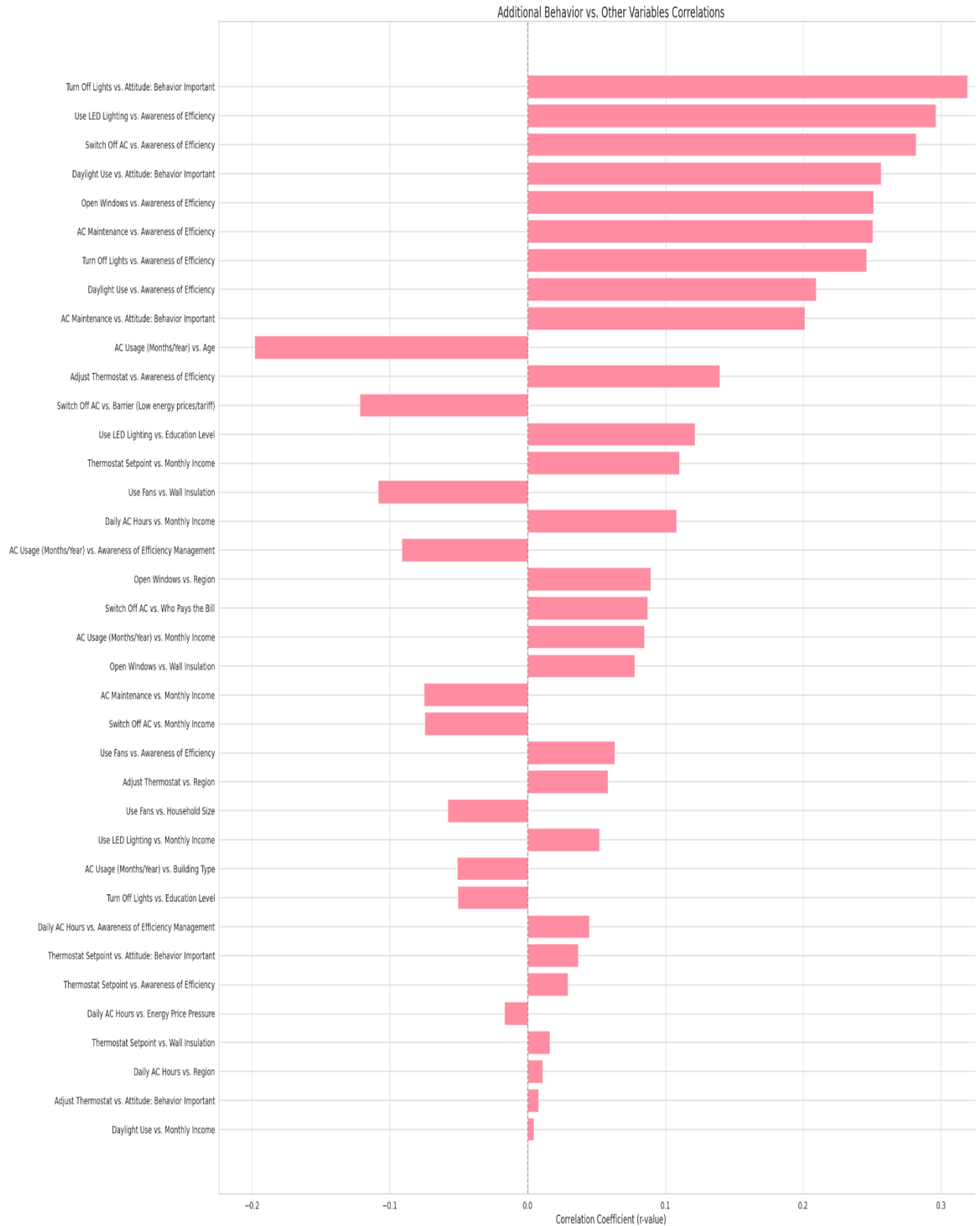


Figure 62: Correlations : Behavior vs. Other Variables

4.2.3 Interaction Analysis: Understanding Combined Effects

While previous sections examined individual correlations between variables and Energy Use Intensity (EUI), interaction analysis explores how two factors work together to influence energy consumption. Unlike simple correlations that evaluate direct relationships, interaction effects reveal how the impact of one variable changes depending on another factor. In residential energy consumption, various factors do not act independently. By studying interactions, we gain deeper insights into complex dynamics that one-dimensional analyses may overlook. Understanding these effects can identify targeted intervention opportunities and inform better energy management strategies. To assess interaction effects, two complementary approaches were used:

- **Stratified Correlation Analysis:** Examining how the correlation between two variables differs across levels of a moderator variable (e.g., how wall insulation affects EUI under different AC usage habits).
- **Visual Interaction Assessment:** Creating conditional plots to illustrate how relationships vary across different categories.

Additionally, Statistical interaction testing was performed using regression models with interaction terms. A significant interaction indicates that the effect of one variable on EUI depends on the level of another variable.

4.2.3.1 Interaction Between Building Size and LED Usage Frequency

This section examines the interaction between building size (floor area) and LED usage frequency in influencing Energy Use Intensity (EUI). While LED lighting is widely

recognized as an energy-efficient solution, its effectiveness may be influenced by home size, as larger buildings have different lighting requirements, distribution efficiencies, and overall energy demand compared to smaller residences. This analysis investigates whether the energy-saving benefits of LED lighting vary with home dimensions, which could inform targeted efficiency recommendations. Table 16 presents the correlation results, illustrating how the relationship between floor area and EUI changes based on LED usage frequency.

Table 16: Stratified Correlations Between Floor Area and EUI by LED Usage Frequency.

LED Usage Frequency Level (Moderator Variable)	N (Sample Size)	Correlation (r)	p-value	Correlation Type
Always (5)	190	-0.43	0.00	Pearson
Often (4)	58	-0.42	0.00	Pearson
Sometimes (3)	72	-0.37	0.00	Pearson
Rarely (2)	55	-0.30	0.03	Pearson
Never (1)	49	-0.33	0.02	Pearson

4.2.3.1.1 Key Findings and Interpretation

- A consistent negative correlation is observed across all LED usage levels, indicating that larger homes tend to have lower EUI per square meter, likely due to improved spatial energy efficiency in bigger residences.
- The strongest negative correlation is found among households that "always" use LED lighting ($r = -0.43$, $p = 0.00$), suggesting that frequent LED adoption further enhances the energy efficiency gains associated with larger homes.
- Among those who "never" or "rarely" use LED lighting, the negative correlation is weaker ($r = -0.33$, $p = 0.02$ and $r = -0.30$, $p = 0.03$, respectively), indicating that infrequent LED use limits the efficiency benefits of larger spaces.
- Households that use LED lighting "often" ($r = -0.42$, $p = 0.00$) or "sometimes" ($r = -0.37$, $p = 0.00$) also exhibit strong negative correlations, reinforcing the trend that higher LED adoption is associated with enhanced energy efficiency across different home sizes.

These findings suggest that LED lighting plays a complementary role in reducing energy intensity, particularly in larger homes. Figure 63 presents a scatter plot with regression lines, illustrating how the relationship between floor area and EUI varies across different levels of LED usage frequency.

4.2.3.1.2 Key Observations from the Visualization

- All groups show a negative slope, confirming that larger homes tend to have lower EUI.

- The steepest downward trends are seen among frequent LED users (yellow, purple), confirming the interaction effect.
- Households that rarely or never use LED lighting (teal, blue) tend to have more scattered, higher EUI values, particularly in smaller homes.
- For larger homes (above ~500 m²), the effect of LED usage becomes less pronounced, suggesting that lighting efficiency plays a bigger role in smaller homes.

4.2.3.1.3 Implications of the Findings

- LED adoption is most beneficial in smaller homes, where lighting represents a larger share of total energy consumption.
- In larger homes, additional energy-saving measures beyond LED adoption are necessary, such as better insulation, AC efficiency improvements, or passive cooling strategies.
- Energy efficiency programs should prioritize LED adoption campaigns for smaller residential units, where the impact on EUI is more significant.
- For larger homes, a more comprehensive energy strategy is needed, incorporating multiple interventions beyond lighting improvements.

These findings highlight the importance of integrating lighting efficiency into broader energy management strategies, demonstrating that both structural and behavioral factors shape residential energy consumption patterns Figure 63.

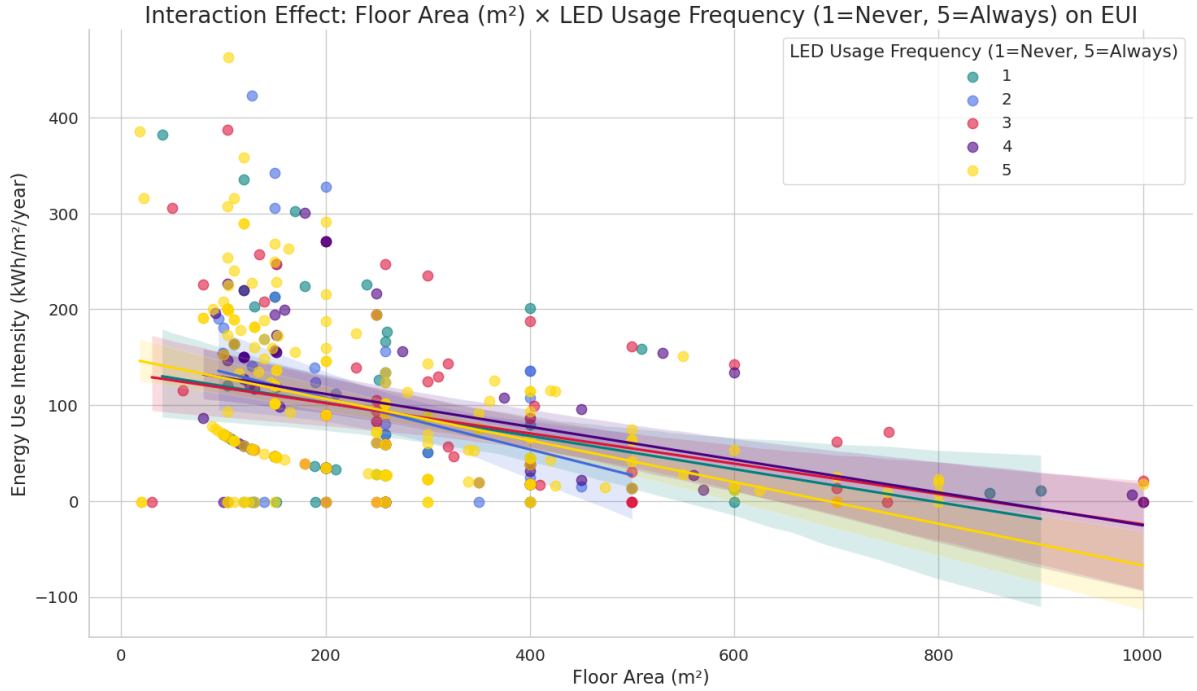


Figure 63: Interaction Effect of Floor Area and LED Usage Frequency on EUI

4.2.3.2 Interaction Between Education Level and Energy Efficiency Adoption

This section explores how education level interacts with energy efficiency adoption in influencing Energy Use Intensity (EUI). Higher education may be associated with greater awareness of energy efficiency benefits, better implementation of energy-saving technologies, or more effective usage of installed systems. This analysis examines whether individuals with higher education levels experience greater energy savings from efficiency measures, providing insights into how educational background influences energy consumption behaviors. Table 17 presents the correlation results, illustrating how the relationship between education level and EUI varies based on efficiency measure adoption status.

Table 17: Stratified Correlations Between Education Level and EUI by Efficiency Measure Adoption Status.

Efficiency Measure Adoption	n	Correlation (r)	p-value	Correlation Type
No	121	-0.01	0.95	Spearman
Yes	303	0.03	0.58	Spearman

4.2.3.2.1 Key Findings and Interpretation

- No strong relationship between education level and EUI. The correlation results suggest that education alone does not have a meaningful impact on household energy consumption.
- Energy efficiency adoption does not significantly lower EUI. The median EUI values for those who adopted efficiency measures and those who did not are similar, indicating that simply adopting energy-saving measures does not guarantee reduced energy consumption.
- Higher education does not amplify the impact of efficiency adoption. If education were a strong determinant of energy savings, we would expect a noticeable gap between adopters and non-adopters in the higher education category. However, this pattern is absent, suggesting that awareness alone does not drive energy conservation—effective implementation and behavior modification are crucial.
- High variability in EUI within each education group. Figure 64 shows that EUI varies widely across all education levels, with no clear trend. This suggests that other factors (such as building characteristics, household size, or appliance usage) play a stronger role in determining energy consumption than education level alone.

These results suggest that while education may influence awareness and attitudes toward energy efficiency, its direct impact on EUI is limited when accounting for efficiency measure adoption. Figure 64 illustrates the interaction between education level and energy efficiency adoption on EUI. The x-axis represents education levels (High School, Undergraduate, Higher Education, Other), while the color-coded graph correspond to different levels of efficiency measure adoption (Yes, No). The y-axis denotes EUI (kWh/m²/year), providing a visual representation of energy consumption across these categories.

4.2.3.2.2 Key Observations from the Visualization

- Energy efficiency adoption does not show a clear reduction in EUI for any education level. In some cases, those who adopted measures even exhibit slightly higher energy use, suggesting that additional behavioral factors or structural inefficiencies may offset the benefits of efficiency adoption.
- The presence of high-EUI outliers in all education groups suggests that extreme energy consumption cases are not limited to specific education levels.
- The variation within each education category indicates that education alone is not a sufficient predictor of energy use, reinforcing the need for targeted behavioral interventions alongside efficiency measures.

4.2.3.2.3 Implications of the Findings

- Awareness campaigns alone may not be enough to drive energy savings—policy interventions should focus on behavioral reinforcement and practical implementation rather than relying solely on education-based awareness programs.

- Efficiency programs should be tailored to encourage not just the adoption but also the correct use of energy-saving technologies.
- Further investigation is needed to explore why efficiency adoption does not translate into significantly lower EUI. Future research could examine factors such as behavioral habits, home occupancy patterns, and appliance efficiency.

These findings highlight the complex interplay between education, energy efficiency adoption, and actual energy consumption, emphasizing the need for holistic approaches that combine awareness, behavioral interventions, and technical improvements to achieve meaningful energy savings Figure 64.

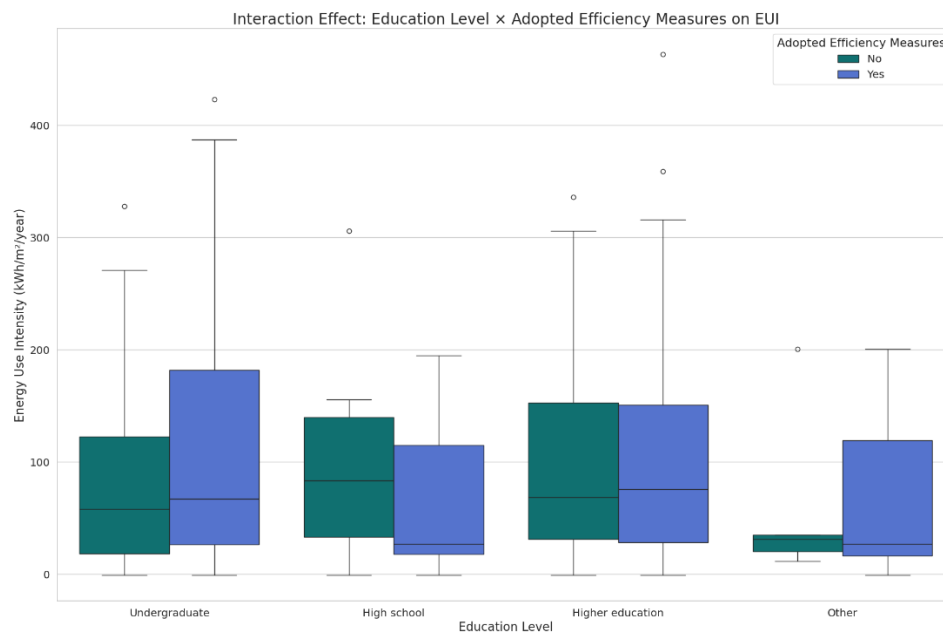


Figure 64: Interaction Effect of Education Level and Efficiency Adoption on EUI.

4.2.3.3 Interaction Between Income Level and AC Usage Discipline

This section examines how household income interacts with AC usage discipline in influencing Energy Use Intensity (EUI). While higher-income households may have access

to more energy-efficient cooling technologies, they may also exhibit different behavioral patterns in air conditioning usage. This analysis investigates whether higher-income households engage in more disciplined AC usage and whether this behavior translates into lower energy consumption. Stratified Correlations Between AC Usage Discipline and EUI Across Building Types. presents the correlation results, illustrating how the relationship between income level and EUI varies based on AC switch-off discipline.

Table 18: Stratified Correlations Between AC Usage Discipline and EUI Across Building Types.

AC Switch-Off Discipline	n	Correlation (r)	p-value	Correlation Type
Never (1)	32	0.10	0.58	Spearman
Rarely (2)	51	0.09	0.54	Spearman
Sometimes (3)	57	-0.05	0.73	Spearman
Often (4)	25	0.33	0.11	Spearman
Always (5)	259	0.06	0.34	Spearman

4.2.3.3.1 Key Findings and Interpretation

- Weak and inconsistent correlations between income and EUI were observed across all AC switch-off discipline levels, indicating that income alone is not a strong determinant of energy consumption efficiency.
- No clear trend was observed where lower-income households benefitted more from switching off AC compared to higher-income households.

- Households that always switch off AC (discipline level 5) did not show a significantly lower EUI than those who rarely or never switch off AC. This contradicts the expectation that more disciplined AC management would strongly reduce energy use.
- Variability in EUI exists across all income levels, suggesting that external factors such as home insulation, cooling system efficiency, and lifestyle habits might overshadow income-driven differences in energy-saving practices.

Figure 65 illustrates the interaction between income level and AC switch-off discipline on EUI. The x-axis represents monthly income categories (Less than 5000, 5001–10,000, 10,001–20,000, 20,001–30,000, Over 30,000, Not Applicable), while the color-coded graph correspond to different AC switch-off habits (1 = Never, 5 = Always). The y-axis denotes EUI (kWh/m²/year), showing variations in energy consumption across income and behavioral categories.

4.2.3.3.2 Key Observations from the Visualization

- High variability within income groups: Across all income levels, EUI distributions remain broad, indicating that income alone does not strongly dictate energy efficiency. The lowest-income households ("Less than 5000 SAR") display both low and high EUI values, suggesting a mix of energy-efficient and inefficient homes. Higher-income households ("Over 30,000 SAR") exhibit somewhat lower variability in EUI, indicating potentially better energy management, but the trend is weak.
- AC switch-off discipline does not consistently reduce EUI: The "Always switch off AC" (5) group (yellow) does not exhibit significantly lower EUI than less disciplined groups, suggesting that merely turning off AC does not guarantee substantial energy

savings. Inconsistent effects across income levels: In some income brackets, disciplined AC use correlates with lower EUI, while in others, the effect is negligible.

4.2.3.3.3 Implications of the Findings

- Income alone is not a strong predictor of energy efficiency. Other structural and behavioral factors (such as home insulation and appliance efficiency) likely play a more dominant role.
- Financial incentives alone may not drive lower-income households toward better energy efficiency. Additional interventions, such as awareness programs or energy-efficient appliance subsidies, may be necessary.
- AC switch-off habits do not show a significant energy-saving impact. This suggests that cooling efficiency may depend more on AC system type, thermostat settings, and insulation quality rather than just turning AC on and off.
- Policy Recommendations: Targeted efficiency retrofits (e.g., improved insulation and smart thermostats) may be more effective than behavioral interventions alone. Higher-income households may have greater access to energy-efficient appliances, but the impact on EUI remains moderate. Expanding incentives for efficiency upgrades could help optimize cooling energy use.

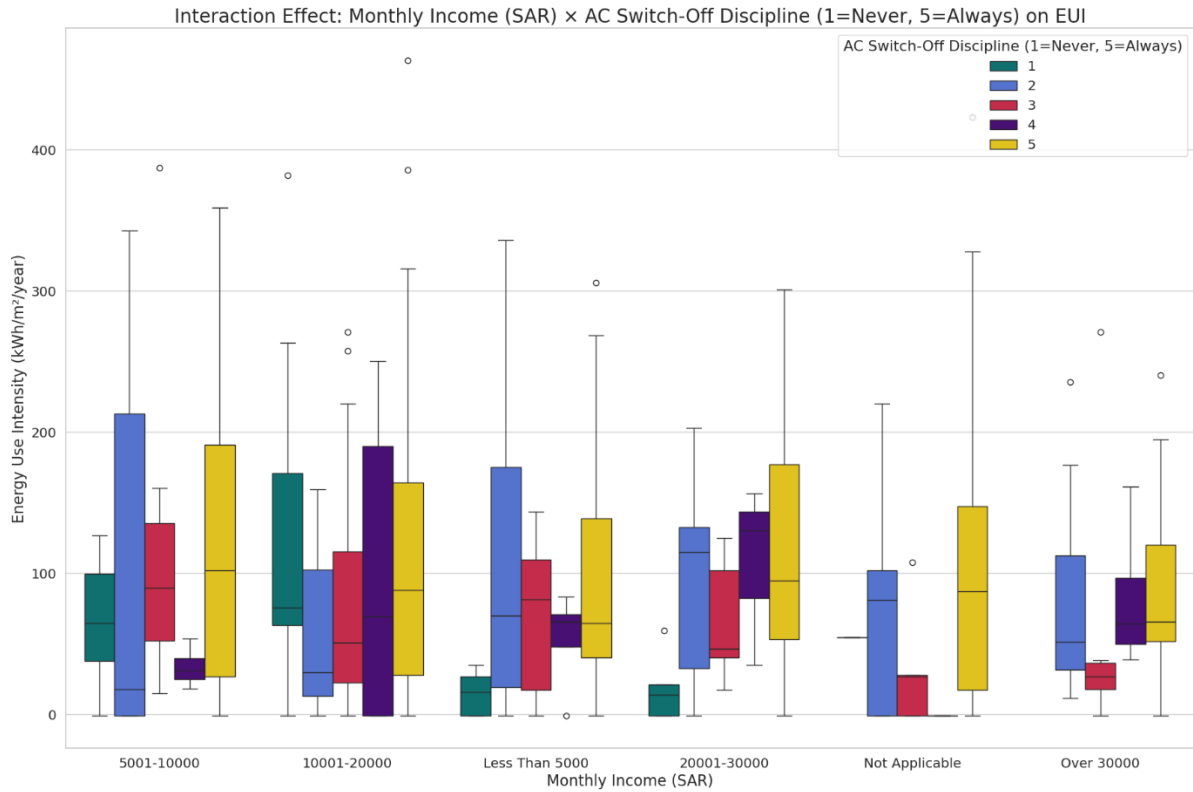


Figure 65: Interaction Effect of Income Level and AC Switch-Off Discipline on EUI.

4.2.3.4 Interaction Between Building Ownership and Energy Efficiency

Adoption

This section investigates how building ownership status interacts with the adoption of energy efficiency measures in influencing Energy Use Intensity (EUI). Homeownership status can impact energy consumption decisions, as owners may be more inclined to invest in energy-saving measures, while renters might have limited control over structural modifications. This analysis explores whether efficiency adoption has a differential impact on EUI depending on ownership status. Table 19 presents the correlation results,

illustrating how the relationship between building ownership and EUI varies based on whether energy efficiency measures have been adopted.

Table 19: Correlation Between Building Ownership and EUI, Stratified by Efficiency Measure Adoption.

Efficiency Measure Adoption	n	Correlation (r)	p-value	Correlation Type
No	121	-0.05	0.61	Spearman
Yes	303	-0.28	0.00	Spearman

4.2.3.4.1 Key Findings and Interpretation

- **No Clear Reduction in EUI with Efficiency Adoption.** The median EUI for households that adopted efficiency measures is similar to or slightly higher than those who did not adopt them in both owners and renters. This suggests that simply adopting efficient measures does not automatically lead to lower energy consumption. Other factors, such as how these measures are used, building conditions, or occupant behavior, may play a more significant role in energy savings.
- **Renters Exhibit Higher Variability in EUI, Regardless of Efficiency Adoption.** Renters show a wider spread of EUI values, indicating more inconsistency in energy consumption. This suggests that other uncontrolled factors—such as landlord decisions, building conditions, or occupant energy use behaviors—may impact EUI more strongly in rented homes than in owned properties.
- **Owners Show a More Consistent Reduction in EUI When Adopting Efficiency Measures.** Among homeowners, efficiency adoption appears to have a more consistent

impact on reducing EUI, as evidenced by fewer extreme values (outliers). This may indicate that homeowners are more likely to implement efficiency measures effectively, possibly due to better maintenance, control over energy upgrades, or long-term investment in energy-saving practices.

Figure 66 illustrates the interaction between building ownership and energy efficiency adoption on EUI. The x-axis represents ownership categories (Rented, Owned), while the color-coded graph corresponds to different efficiency adoption statuses (Yes, No). The y-axis denotes EUI (kWh/m²/year), highlighting energy consumption variations across these groups.

4.2.3.4.2 Key Observations from the Visualization

- EUI distributions for renters are more dispersed, with high variability in both those who adopted and those who did not adopt efficiency measures. This reflects greater inconsistency in energy savings for rented properties.
- Homeowners have a more stable pattern, suggesting that renters may have limited ability to implement impactful energy-saving modifications.
- Efficiency adoption appears to correlate with slightly lower EUI in owned properties. However, this effect is not as pronounced as expected.
- The overlap in distributions between adopters and non-adopters across both groups suggests that efficiency measures alone are not the primary driver of EUI differences.

4.2.3.4.3 Implications of the Findings

- Efficiency adoption does not automatically reduce energy use—effective implementation and complementary behavioral changes are necessary.
- Renters experience greater variability in EUI, highlighting the need for policy interventions that encourage landlords to implement energy efficiency improvements.
- Homeowners appear to benefit more from efficiency measures, suggesting that targeted incentives for energy-saving upgrades in owned properties could enhance the effectiveness of efficiency adoption.
- Future research should explore why efficiency adoption does not lead to a stronger reduction in EUI, investigating factors such as appliance efficiency, HVAC usage patterns, and insulation quality.

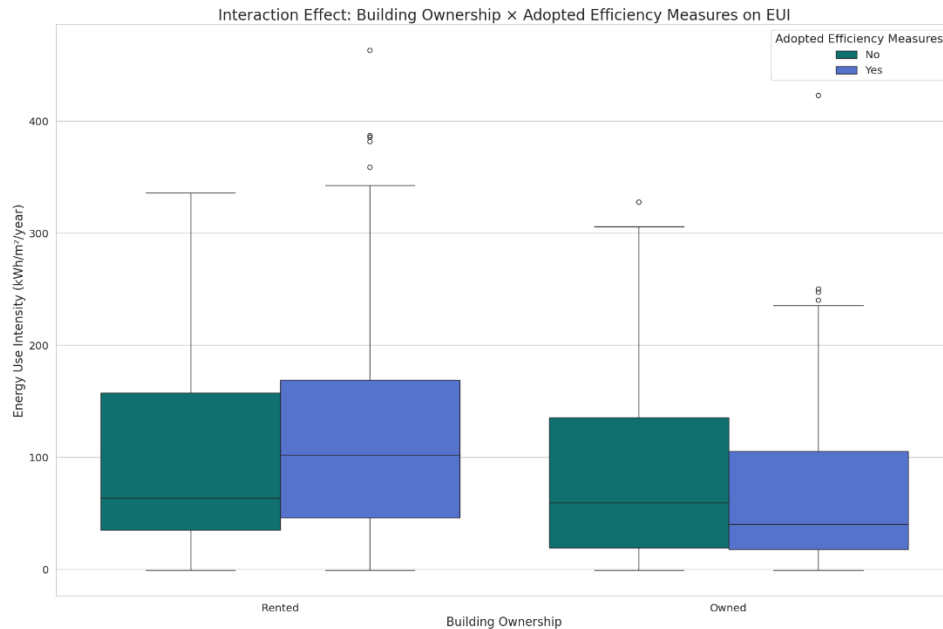


Figure 66: Interaction Effect of Building Ownership and Efficiency Measure Adoption on EUI.

4.2.3.5 Interaction Between Building Size and AC Usage Discipline

This section examines how building size (floor area) interacts with AC usage discipline in influencing Energy Use Intensity (EUI). Larger buildings may exhibit different energy consumption patterns depending on how frequently occupants switch off air conditioning when leaving. The analysis aims to determine whether disciplined AC usage has a stronger impact on reducing EUI in larger or smaller homes. Table 20 presents the correlation results, illustrating how the relationship between floor area and EUI varies across different levels of AC switch-off discipline.

Table 20: Correlation Between Floor Area and EUI, Stratified by AC Switch-Off Discipline.

AC Switch-Off Discipline	n	Correlation (r)	p-value	Correlation Type
Always (5)	259	-0.40	0.00	Pearson
Never (1)	32	-0.37	0.04	Pearson
Rarely (2)	51	-0.39	0.00	Pearson
Sometimes (3)	57	-0.32	0.02	Pearson
Often (4)	25	-0.30	0.05	Pearson

4.2.3.5.1 Key Findings and Interpretation

- For smaller homes (below ~300m²), AC switch-off discipline does not guarantee lower EUI. Households that always switch off AC (level 5, yellow line) do not consistently show the lowest EUI in this range. This suggests that in smaller homes, other factors

- (e.g., poor insulation, cooling demand per square meter, inefficient appliances) may overshadow the benefits of disciplined AC use.
- For larger homes (above $\sim 400\text{m}^2$), disciplined AC usage has a stronger effect in reducing EUI. The yellow regression line (AC discipline = 5) has the steepest decline, indicating that switching off AC consistently leads to significantly lower EUI in bigger homes. This suggests that in large homes, where cooling accounts for a substantial portion of energy use, turning off AC when not needed plays a crucial role in improving efficiency.
 - All AC discipline levels show a negative correlation between floor area and EUI, reinforcing that larger homes tend to be more energy efficient per square meter.

These findings suggest that AC usage discipline plays a crucial role in energy conservation across different building sizes, with particularly strong effects in larger homes.

4.2.3.5.2 Key Observations from the Visualization

Figure 67 presents a scatterplot illustrating the interaction between building size and AC switch-off discipline on EUI. The x-axis represents floor area (m^2), while the y-axis denotes EUI ($\text{kWh}/\text{m}^2/\text{year}$). Color-coded trend lines correspond to different levels of AC switch-off discipline (1 = Never, 5 = Always).

- Large homes with disciplined AC use (yellow and blue dots) show consistently lower EUI.
- In smaller homes, EUI remains high across all AC usage levels, indicating that AC discipline alone is not enough to drive energy savings.

- Variability in EUI is highest in smaller homes, possibly due to differences in insulation, cooling habits, or appliance efficiency.

4.2.3.5.3 Implications of the Findings

- AC switch-off discipline is most effective in larger homes. Energy efficiency programs should emphasize behavioral interventions (e.g., AC management awareness campaigns) in large homes where cooling represents a dominant energy load.
- For smaller homes, energy-saving efforts should focus on structural improvements. Encouraging insulation upgrades, efficient cooling technologies, and behavioral awareness programs can complement AC switch-off habits.
- Policymakers should tailor energy-saving recommendations based on home size. AC discipline strategies should be prioritized for larger homes, while smaller homes may require broader efficiency upgrades to achieve meaningful reductions in EUI.

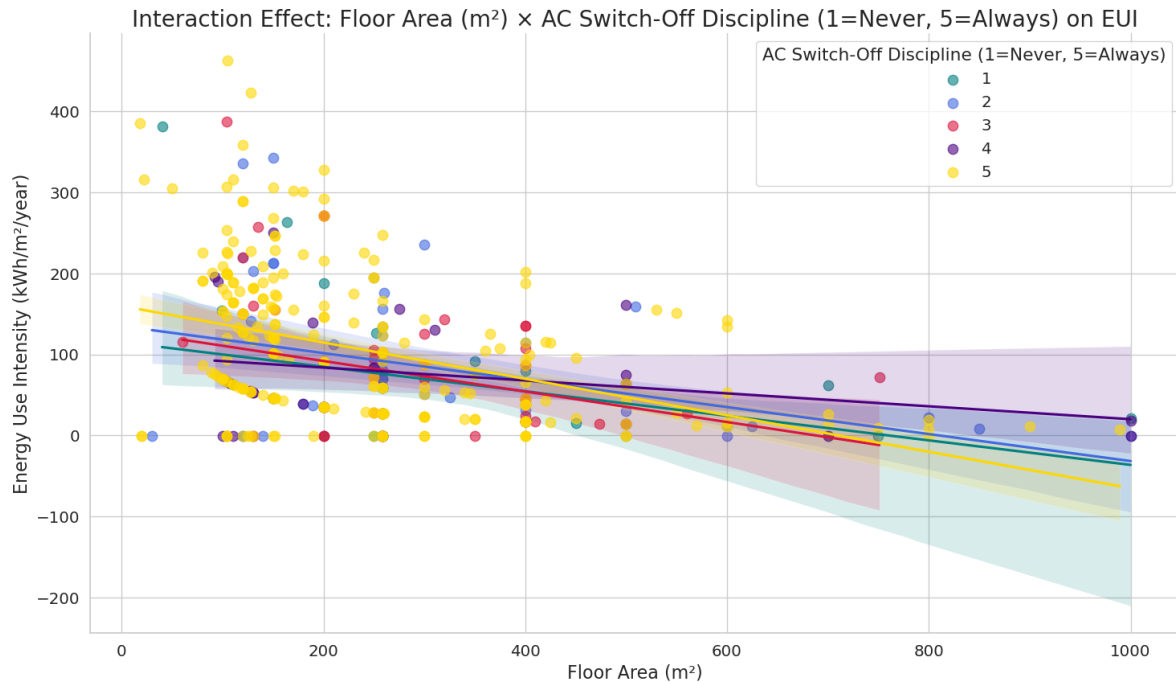


Figure 67: The interaction between building size and AC switch-off discipline on EUI

4.2.4 Key Findings & Interpretation

The analysis provided insights into energy consumption patterns, behavioral influences, and energy efficiency adoption. The most critical findings are summarized in Table 21.

Table 21: Summary Of Key Findings for Statistical Analysis.

Section	Analysis Type	Technique Used	Key findings
Correlation Analysis	Key Correlations with EUI	Pearson, Spearman	Building characteristics (size, type, ownership) are major drivers of EUI.
			Socioeconomic and behavioral factors also play a role, but awareness does not always lead to action.
			Financial pressure alone does not reduce energy use; targeted interventions are needed.

			Cooling system efficiency (central vs. split/window AC) significantly affects EUI.
			Rented properties and apartments have higher EUI, highlighting the split-incentive problem.
	Correlation of Behavioral Variables with Other Factors	Pearson, Spearman	Attitudes strongly influence energy-saving actions—households that believe behavior is important for efficiency are more likely to turn off lights, use daylight, and switch off AC.
			Awareness drives technology adoption—greater awareness of energy efficiency is linked to increased use of LED lighting and reliance on natural ventilation.
			Financial incentives matter—households that perceive low energy prices as a barrier are less likely to switch off AC, suggesting that subsidized electricity discourages conservation.
			Income influences cooling habits—higher-income households use AC for longer hours and set thermostats at higher temperatures, indicating affordability shapes cooling preferences.
			Demographic factors play a role—older individuals use AC for fewer months, while higher education levels correlate with increased adoption of energy-efficient technologies.
Interaction Analysis: Understanding Combined Effects	Building Size × LED Usage Frequency	Pearson Correlation	Smaller homes have higher EUI, and LED usage shows a stronger relative impact on reducing their energy consumption compared to larger homes.
			In larger homes, the effect of LED usage on EUI diminishes, as total energy use is driven by other factors (e.g., cooling, appliances).

			All LED usage groups show a negative correlation with floor area, confirming that EUI generally decreases as home size increases.
			Energy efficiency policies should prioritize LED adoption campaigns for smaller homes, while larger homes may benefit more from holistic efficiency measures (e.g., insulation, smart cooling).
	Education Level × Energy Efficiency Adoption	Spearman Correlation.	Education level does not significantly influence EUI.
			Adopting efficiency measures does not guarantee lower energy consumption.
			Higher education does not amplify energy-saving benefits—practical implementation matters more.
			Behavioral habits and home characteristics may play a stronger role than education level.
	Income Level × AC Usage Discipline	Spearman Correlation.	Energy efficiency programs should focus on behavioral reinforcement, not just awareness.
			Income alone is not a strong determinant of energy efficiency; other factors like insulation and cooling systems matter more.
			AC switch-off discipline does not consistently lead to lower EUI, challenging assumptions about behavioral interventions.
			Financial incentives alone may not be enough to encourage energy-saving behaviors in lower-income groups.
			Variability in EUI across all income levels suggests that structural upgrades (insulation, smart cooling) should be prioritized.

			Policy focus should shift from behavioral interventions to improving building efficiency and access to energy-saving technologies
	Building Ownership × Energy Efficiency Adoption	Spearman Correlation.	Efficiency adoption does not automatically reduce EUI for either owners or renters.
			Renters show higher variability in EUI, suggesting external factors like landlord policies and building conditions may play a role.
			Owners experience a more consistent EUI reduction with efficiency adoption, indicating that long-term investments in energy-saving measures may be more effective in owned properties.
			Policy efforts should target landlords and renters to promote the proper implementation of energy efficiency measures in rental housing.
	Building Size × AC Usage Discipline	Pearson Correlation.	Larger homes tend to have lower EUI per square meter.
			AC switch-off discipline is most effective in larger homes.
			Smaller homes do not show consistent EUI reductions with AC discipline.
			Energy policies should prioritize AC discipline awareness for large homes.
			Smaller homes require broader efficiency measures.

The statistical analysis provided a data-driven understanding of energy consumption patterns, behavioral influences, and socio-economic factors affecting energy efficiency. The findings highlight that building characteristics, including floor area, ownership,

insulation, and AC type, play a significant role in shaping Energy Use Intensity (EUI). Additionally, behavioral factors such as AC switch-off discipline and thermostat adjustments contribute to energy savings, though their impact varies across households and building types. These insights establish a strong foundation for the next phase of the study: predictive modelling using machine learning (ML) to further refine and enhance energy efficiency strategies.

4.3 Thematic Analysis of Qualitative Insights

In this section, a thematic analysis of the qualitative data collected from interviews is presented, aimed at uncovering the underlying personal, societal, institutional, and policy-driven factors that influence energy usage behaviors. This analysis is divided into three main sub-sections, as shown in Figure 68 , each addressing distinct but interconnected themes. Initially, personal and societal energy dynamics are explored, highlighting how economic considerations, household roles, and societal attitudes towards energy management shape individual and collective energy decisions. The discussion then shifts to the impact of institutional frameworks and policies on energy practices, illustrating how these structures are navigated by individuals and communities to optimize energy use. Finally, reflections on the economic and environmental implications of energy behaviors are presented, emphasizing the participants' perspectives on economic impacts and environmental concerns. Through this comprehensive analysis, deeper insights into the multifaceted nature of energy use and its implications for policy and practice are provided.

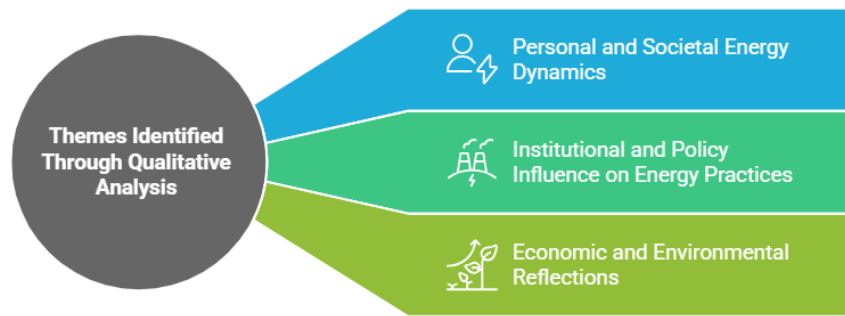


Figure 68: Themes Identified in Qualitative Data

4.3.1 Personal and Societal Energy Dynamics

4.3.1.1 Economic Pragmatism in Energy Use

Responses from Participant 01 indicate a pragmatic approach to personal energy use governed by economic rather than environmental considerations. Infrequent switching off of lights and routine use of air conditioners reflect a societal perception of abundant and inexpensive energy. It is acknowledged that although economic benefits of energy-efficient appliances are recognized, their full utilization is not achieved, indicating a selective adoption driven by cost savings rather than a comprehensive commitment to energy conservation. It is admitted, "No, lights are generally not turned off, and appliances are often used without much consideration for energy consumption." Additionally, it is noted that "Most homes around exhibit little concern for saving energy, partly because energy is still cheaper compared to other amenities of life."

A shift towards more energy-efficient choices is mentioned, though motivated by financial benefits rather than environmental ones: "Recently, consideration has been given to

energy-efficient gadgets when purchasing new, heavy appliances like air conditioners or heaters." However, barriers such as high costs are highlighted, with the mention, "An attempt has been made to purchase a timer for the exhaust fans in washrooms, which would automatically turn off after 15 minutes, but those timers have been found to be excessively costly." Moreover, the pragmatic view is encapsulated by stating, "Although the air conditioners run almost all the time, the bills are cheaper than before," underscoring economic rather than ecological drivers of energy use behaviors.

Broader societal attitudes are reflected as it is pointed out, "Energy conservation largely depends on ethnicity. For natives, saving energy is less important, whereas for expatriate communities, conserving energy is crucial to reduce their bills." This observation suggests that targeted approaches might be necessary. Furthermore, suggestions for broader societal changes include "Increasing the cost of electricity may reduce energy wastage," and promoting community initiatives that "Feel fun, not restrictive," which could enhance engagement with energy-saving practices.

4.3.1.2 Household Dynamics and Roles in Energy Decisions

The narrative from Participant 02 illustrates how energy management practices within the household are shaped by familial roles and internal household dynamics. While the efficiency of modern appliances and lighting systems is acknowledged, decision-making regarding broader energy-saving measures tends to be concentrated among specific members of the household, thereby limiting others' influence. These dynamics present notable challenges to optimizing household energy efficiency, particularly in contexts where cultural norms determine who holds primary responsibility for domestic decisions.

Direct quotes from the interview illuminate this dynamic: "In winter, yes, the air conditioner is turned off, but in summer, it remains on to keep the house cool. As for lighting, it is turned off when leaving the house; however, the television and other appliances are never unplugged." These statements reflect a passive approach influenced by household routines and established family decision patterns. Moreover, it is noted, "Low-efficiency appliances and machines are used; high-efficiency ones are not available." When asked about the reasons, the participant explained that such decisions typically lie outside their control and are handled by other household members.

Acknowledgment of the economic impacts of energy decisions within the household is evident, as mentioned: "All lights have been changed to LEDs; the air conditioner is always set to a specific temperature around 23–24 degrees Celsius." Despite having a background in architectural engineering and an awareness of energy-efficient strategies, the participant described how household roles constrained their ability to implement preferred practices, reflecting the influence of entrenched family structures on domestic energy behavior.

Regarding societal attitudes and economic pressures, it is stated, "Concern about energy conservation has grown, especially given the rising electricity bills. Discussions about increased tariffs are common, and concerns about them would certainly influence behavior towards energy usage." This reflects a broader societal response to economic pressures that could motivate shifts in energy consumption practices.

Ultimately, the narrative of Participant 02 points to the need for educational and financial incentives to address cultural and economic barriers. As suggested, "Education and awareness should be enhanced, and messages should be simplified to maximize their reach

and impact." This highlights the complex interplay between family dynamics, social norms, economic pressures, and energy consumption behaviors, underscoring the value of targeted interventions that consider the unique household contexts present in Saudi Arabia.

4.3.1.3 Disciplined Energy Management Amidst Societal Neglect

In stark contrast to the broader societal norms, Participant 06 exhibits a disciplined approach to energy management. This meticulous behavior in managing energy consumption, such as switching to LEDs and minimizing air conditioner usage, underscores a personal commitment diverging from the general trend of energy neglect observed in their community. This scenario suggests that personal conviction can indeed drive energy conservation, albeit being challenged by a lack of similar commitment at the societal level.

Direct statements from the interview highlight this disciplined approach, including: "A conscious effort is made to turn off appliances when not in use," and "All bulbs have been replaced with low-wattage LEDs, and appliances with minimal energy consumption are utilized." These actions contrast sharply with the general neglect, as noted: "It is mostly observed that people around me are quite negligent about energy consumption."

Further detailing their energy-saving measures, it is added: "Air conditioners are used for the minimum possible time, with the temperature set at 20 degrees. During winter, for about three to four months, air conditioners are not used and only utilized when necessary." This demonstrates a methodical and intentional approach to reducing energy use. Moreover, it is mentioned, "Energy-efficient appliances have contributed to reducing electricity bills,

providing quality service, reducing energy wastage, and operating quietly. Most importantly, they offer long-term cost savings."

On societal attitudes and incentives, Participant 06 expresses frustration with the prevalent lack of initiative: "The society in KSA is described as the most generous in the world, yet it is equally generous in wasting resources, whether time, energy, money, or food." The need for systemic change is emphasized, suggesting, "Efficient use of energy and energy conservation awareness should be promoted at all levels, from schools to local community levels."

To conclude their perspective on the necessary societal shift, strong measures are advocated to foster responsibility: "Households with low consumption levels should be encouraged through rebates or concessions on their bills, while fines should be imposed on those wasting energy at any level."

These insights reveal not only the individual commitment of Participant 06 to energy conservation but also highlight the broader societal challenges that hinder widespread adoption of such practices. The testimony underscores the potential for individual agency to influence greater community awareness and action toward energy conservation in Saudi Arabia.

4.3.2 Institutional Constraints and Individual Energy Management

Practices

4.3.2.1 Navigating Institutional Constraints

The experience of Participant 03 within university-provided housing exemplifies the impact of institutional constraints on personal energy conservation efforts. Despite awareness of energy-efficient practices, they are bound by housing policies that restrict modifications to the provided appliances and systems. This scenario underscores the need for institutional policies that support rather than hinder individual agency in sustainable energy practices.

Direct quotes from the interview illustrate these constraints and insights:

- "Mostly, the light is turned off when exiting; and sometimes during the day, the light is either turned off or dimmed slightly to utilize the daylight from the large window in the living room. Appliances are never unplugged. The AC is mostly always active during summer—thermostat settings are adjusted; for example, the temperature is decreased for sleeping and increased upon waking."
- "No energy-saving practices such as using LEDs have been implemented because residence in a university-provided apartment on campus does not permit any alterations. Thus, whatever appliances are provided are used, and the bills are managed by the university, remaining unknown to the occupants."
- "The appliances provided by the university campus in the apartment, such as the refrigerator, are not highly efficient. The coffee machine that was purchased

independently is also not efficient. When new items are purchased, their efficiency is neither considered nor deemed important."

These comments from Participant 03 highlight the limitations placed by institutional settings that often prevent individuals from implementing personal energy conservation measures, even when they have the knowledge and willingness to do so. They also touch upon the broader implications of such policies on personal behavior and the potential for improved energy management practices if institutional policies were more accommodating.

4.3.2.2 Understanding Energy Management Practices

Adaptive energy consumption behaviors from Participant 04 demonstrate a reliance on personal strategies and market-available options rather than specific governmental policies or incentives. This aligns with the broader trend where individuals use energy-efficient appliances and explore alternative energy sources such as solar energy based on market offerings rather than through direct governmental support. The discussion on the absence of specific policy-driven incentives offers insights into how individuals navigate energy conservation independently.

Quotes from the interview illustrate these personal initiatives:

- "The respondent indicated that appliances such as the washing machine, refrigerator, and TV are used as needed but are not disconnected from the electrical socket. Additionally, a gas oven is utilized instead of an electric one, and only necessary lights are turned on. Air conditioners are also used as required."

- "When asked whether the energy efficiency of a device is a consideration during purchase, the respondent affirmed that it is, noting a focus on the air conditioner's quality and energy-saving capabilities, irrespective of cost. The decision is influenced by three main factors: quality, efficiency, and energy conservation."
- "The respondent was queried about the types of initiatives available to assist users in saving electricity. The response emphasized practical methods like purchasing energy-saving air conditioners, which include market-driven discounts, and installing solar systems, which are influenced by cost factors such as size and capacity."

These comments from Participant 04 highlight a pattern where personal and market-driven decisions play a critical role in energy management practices, underscoring a gap in direct governmental interventions in promoting energy conservation among the populace.

4.3.3 Economic and Environmental Reflections

4.3.3.1 Economic Reflections Across Participants

Participants highlight economic factors as both a barrier and a motivator for energy conservation. The cost of energy-efficient technologies and the economic benefits of reduced energy bills are recurrent themes that influence energy consumption behaviors. This economic lens suggests that enhancing the affordability and accessibility of energy-saving options could catalyze broader adoption.

For instance, as highlighted by participant 01 that the economic drivers behind energy practices include considerations for energy-efficient gadgets when purchasing new heavy appliances like air conditioners or heating appliances."

"Recently, I have started to consider energy-efficient gadgets while purchasing new heavy appliances like air conditioners or heating appliances. I try to select appliances that are at least B level, if not A level, on the efficiency scale. The motivation for this technology is to reduce bills."(Participant 01). This highlights a selective adoption of energy-efficient technologies driven primarily by the desire for reduced costs.

4.3.3.2 Environmental Concerns and Policy Recommendations

While actions are shaped by immediate economic benefits, there is a palpable concern for environmental sustainability that is not being effectively addressed by current policies. Participants advocate for stronger regulatory frameworks, enhanced incentives for low-energy appliances, and greater public education on energy conservation. These measures are seen as essential to transforming personal energy behaviors into a collective societal shift towards sustainability.

Participant 06 expresses concerns about the general neglect towards energy conservation, "The society in KSA is the most generous in the world. However, at the same time, it is also most generous in wasting resources, be it time, energy, money, or food. Regrettably, there is a general lack of awareness and commitment to energy conservation." (Participant 06). This statement underscores the need for enhanced public education and regulatory measures to foster a more responsible approach to resource usage.

Moreover, the call for incentives resonates across discussions, as Participant 03 notes the lack of awareness and incentives: "In recent years, the increase in tariffs has somewhat affected people's behavior. An increase in tariffs will influence my energy use behavior, but since I reside on a University campus, the bills are managed by the institution." (Participant 03). This suggests that while economic pressures influence behavior, the presence of direct financial incentives or disincentives could further steer public behavior towards more sustainable practices.

The interviews reveal a complex interplay between personal behaviors, societal norms, institutional policies, and economic considerations in shaping energy consumption practices in Saudi Arabia. While individual efforts reflect a spectrum of energy consciousness, the broader societal and policy environments play pivotal roles in either supporting or hindering these efforts. Enhanced policy interventions, targeted educational programs, and economic incentives are critical to fostering a more sustainable energy paradigm across diverse Saudi communities.

4.4 Machine Learning Techniques and Performance

The integration of machine learning (ML) techniques in energy consumption analysis offers a powerful approach to understanding and predicting the impact of occupant behavior on energy use in residential buildings. This study applies ML models to estimate Energy Use Intensity (EUI) and classify households based on their energy consumption patterns, using data from 424 Saudi residential buildings. Various regression and classification algorithms, such as Random Forest, Gradient Boosting, and Support Vector Machines, are employed to identify key behavioral and structural factors influencing

energy use. In addition to predictive modeling, clustering and behavioral segmentation techniques are utilized to classify households into distinct energy consumption archetypes. This segmentation provides deeper insights into the varying patterns of energy use and allows for targeted interventions aimed at specific consumer groups. The following section outlines the steps taken to prepare the data, develop the models, evaluate feature importance, perform segmentation, and optimize the models for enhanced accuracy and interpretability. These analyses aim to inform more effective energy conservation strategies tailored to the diverse behavioral profiles of residential occupants in Saudi Arabia.

4.4.1 Data Preparation for Machine Learning

This section outlines the comprehensive data preparation process for developing predictive machine learning models aimed at quantifying the impact of occupant behavior on energy consumption (Energy Use Intensity, EUI) in Saudi residential buildings. The dataset comprises 424 survey responses encompassing demographic information, building characteristics, AC system details, energy usage behaviors, and awareness and attitudes towards energy efficiency. Initial preprocessing involved cleaning and standardizing data, handling missing values, encoding categorical responses, and deriving critical variables like Energy Use Intensity (EUI). From 57 original survey variables, 96 engineered features were created through rigorous preprocessing and encoding strategies:

- Categorical variables such as professional industry (Q1), region (Q7), and bill payer (Q9) were one-hot encoded due to their nominal nature, expanding these variables into multiple binary features.

- Ordinal variables such as education (Q3), age (Q5), and household size (Q6) were preserved through ordinal encoding and normalized using min-max scaling to maintain their ordered nature.
- Special cases such as monthly income (Q8) included handling a "Not Applicable" category as a separate binary flag .
- Variables like building type (Q10) and ownership (Q11) were converted into binary features using one-hot encoding .
- Floor area (Q12) underwent log transformation to address skewness and improve distribution symmetry, followed by min-max normalization .
- Building age (Q14) and window type (Q15) included separate binary flags for unknown categories to preserve data integrity .
- Quantities of different AC systems (Q17) were numerically encoded and scaled between 0 and 1.
- Variables representing AC usage patterns (months used, daily hours, thermostat settings) were also normalized numerically, capturing seasonal and daily operational characteristics.
- Energy habits (Q23.1–Q23.8), measured on Likert scales, were individually normalized using min-max scaling .
- Attitudinal variables (Q24–Q25) maintained separate normalized features, reflecting the varied psychological influences on energy consumption .

- Energy efficiency measures adoption (Q26) and reasons for not adopting measures (Q27) were transformed into multiple binary indicators, complemented by count features to represent the complexity of barriers faced by respondents.

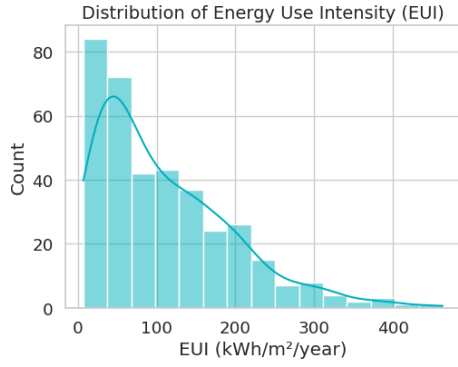
Post encoding, features underwent normalization:

- Continuous and ordinal features were scaled using min-max normalization to ensure all variables were on a comparable scale for modeling.
- Binary features, resulting from one-hot encoding, were kept unchanged to maintain their interpretability.

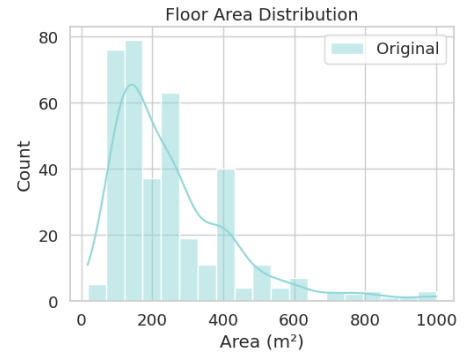
This preparation resulted in a model-ready dataset comprising 96 carefully engineered features. The dataset preserved essential distinctions across demographic, behavioral, and building characteristics, facilitating the accurate quantification of behavioral impacts on energy consumption. Visualization of the data preparation steps confirmed effective normalization and distribution correction:

- The distribution of Energy Use Intensity (EUI) showed moderate right skewness, typical in residential energy studies (Figure 69 (a)).
- Log transformation significantly improved the symmetry and normality of the floor area distribution, essential for accurate predictive modeling (Figures 69 (b) , (c) and (d)).

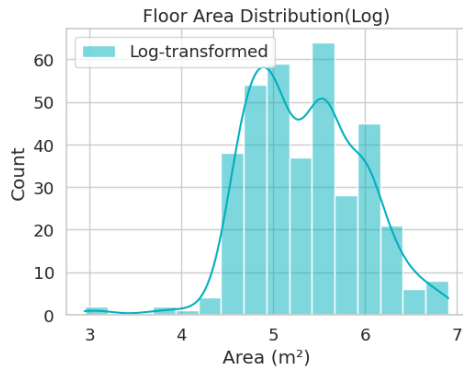
These transformations ensured a dataset suitable for developing accurate and interpretable predictive models to quantify the influence of occupant behavior on residential energy use in Saudi Arabia.



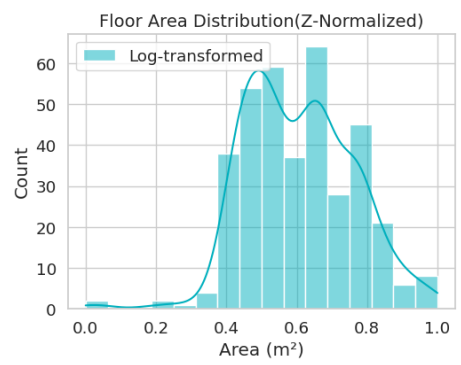
(a)



(b)



(c)



(d)

Figure 69: General Data Distribution including: (a) Distribution of (EUI); (b) Original Floor Area Distribution; (c) Log-transformed Floor Area Distribution; (d) Z-Normalized Floor Area Distribution.

4.4.2 Model Selection and Training

This section describes the methodology and results of predictive modeling applied to the prepared dataset, aimed at quantifying the impact of occupant behavior on residential energy consumption (Energy Use Intensity, EUI) in Saudi Arabia. Predictive modeling involved both regression and classification analyses due to the dataset characteristics

(n=424 observations, 96 features) and the research objective of assessing behavioral influences on energy use.

4.4.2.1 Regression Analysis

The regression analysis evaluated models capable of capturing linear and non-linear relationships between features and energy consumption:

- **Regularized Regression Models:** Ridge and Lasso regression were implemented to mitigate multicollinearity within the high-dimensional dataset.
- **Tree-based Models:** Random Forest and Gradient Boosting models were applied to model complex, non-linear interactions.
- **Support Vector Regression (SVR):** Utilized the radial basis function (RBF) kernel for modeling potential complex relationships.

4.4.2.2 Classification Analysis

The classification task involved categorizing households into high or low energy consumption groups, determined by the median EUI:

- **Baseline Model:** Logistic regression provided an interpretable baseline.
- **Tree-based Classifiers:** Random Forest and Gradient Boosting classifiers effectively managed diverse feature types and non-linear relationships.
- **Support Vector Classification (SVC):** Explored complex decision boundaries using an RBF kernel.

Given the dataset's relatively modest size, Leave-One-Out Cross-Validation (LOOCV) was selected. LOOCV maximizes the use of available data for training and provides robust error estimates.

4.4.2.3 Evaluation Metrics

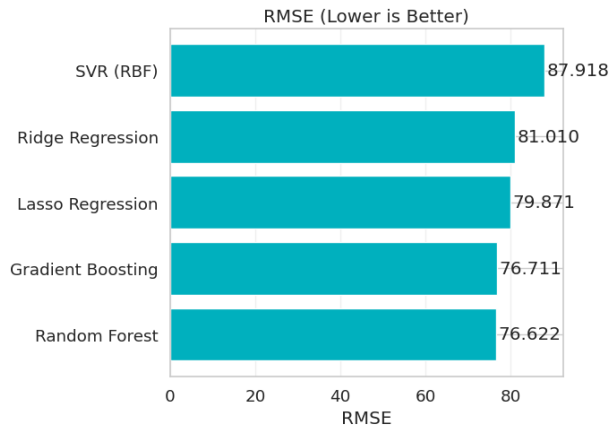
Regression models were assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

Classification models utilized accuracy, precision, recall, F1-score, and ROC-AUC as performance metrics.

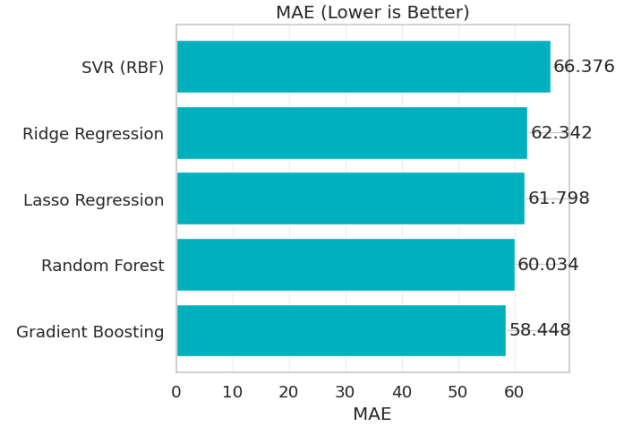
4.4.2.4 Model Training and Results

4.4.2.4.1 Regression Model Results

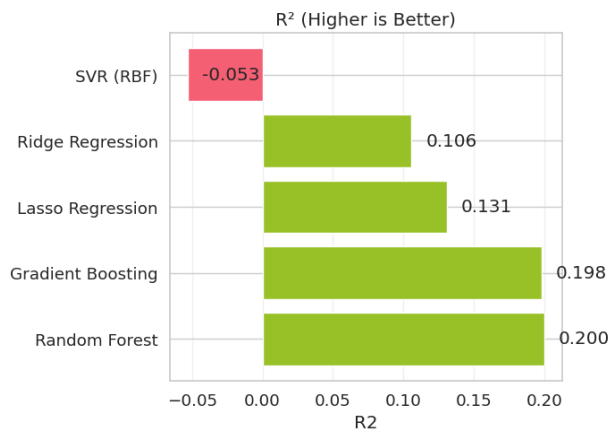
The regression analysis results highlighted the superior performance of tree-based methods (Figure 70 (a) , (b) & (c)). Random Forest regression exhibited the highest performance (RMSE = 76.62 kWh/m²/year; MAE = 60.03 kWh/m²/year; R^2 = 0.20), closely followed by Gradient Boosting regression. Linear models (Ridge and Lasso) showed moderate predictive capability, whereas SVR exhibited the weakest performance, underscoring limitations in handling complex data relationships. Figure 70 (d) further illustrates the predicted versus actual EUI, demonstrating model performance and highlighting areas of uncertainty at higher energy use levels.



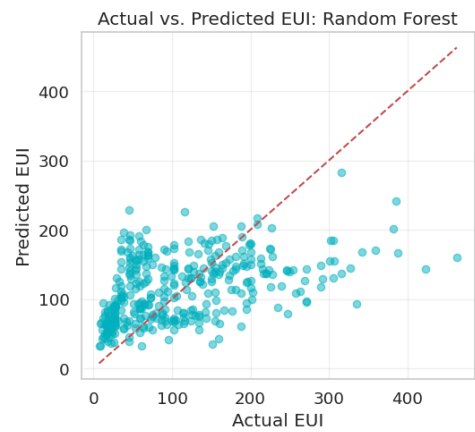
(a)



(b)



(c)



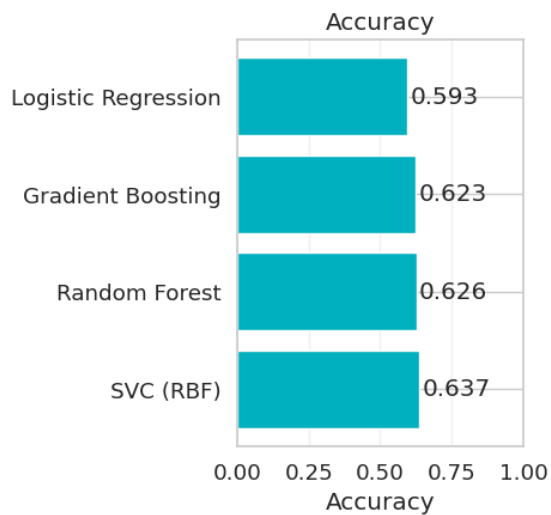
(d)

Figure 70: Regression Model Results for EUI Prediction : (a) RMSE values, (b) MAE values, (c) R^2 value, (d) Actual vs Predicted performance.

4.4.2.4.2 Classification Model Results

Classification analyses demonstrated that Support Vector Classification (SVC) yielded the best overall performance, achieving an accuracy of 63.7%, precision of 63.5%, and ROC-

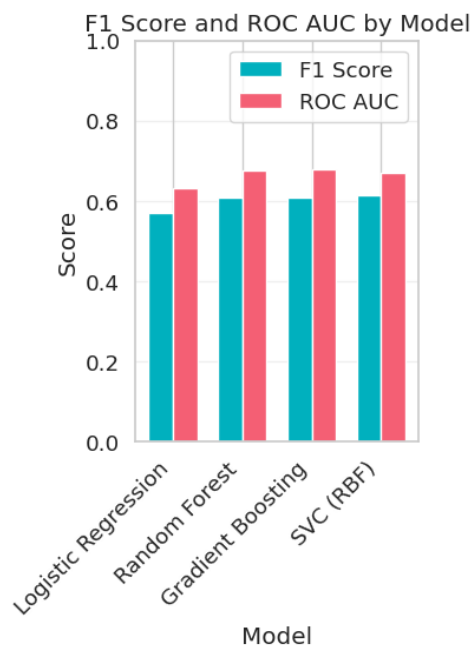
AUC of 0.669 (Figure 71). Tree-based classifiers showed similarly robust performances, with Random Forest and Gradient Boosting achieving comparable accuracy and F1 scores. The confusion matrix in Figure 71 (e) shows the relative strengths and weaknesses of the classification predictions, while the ROC curve indicates moderate model capability in distinguishing between high and low energy-consuming households.



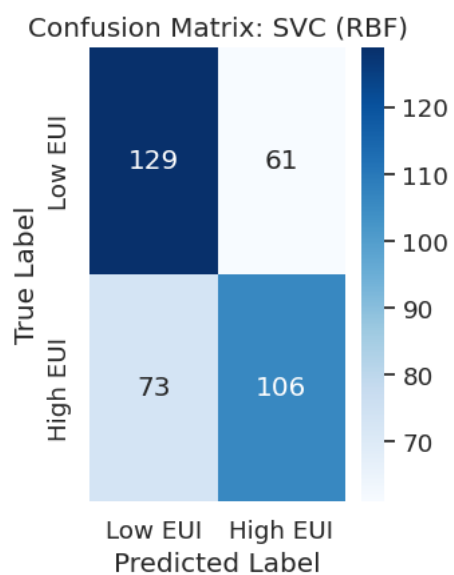
(a)



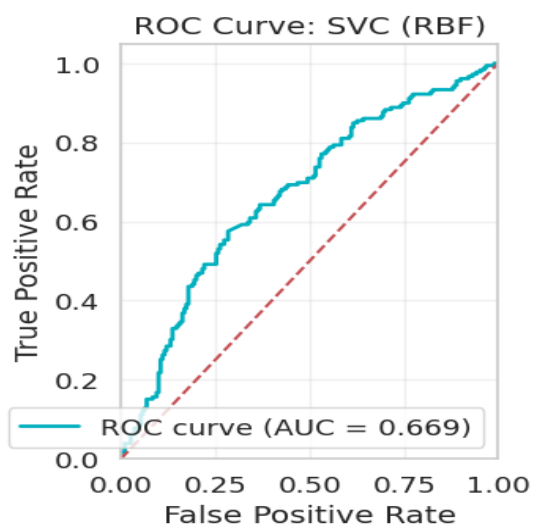
(b)



(c)



(d)



(e)

Figure 71: Classification Model Results: (a) Accuracy, (b) Precision, (c) F1 Score & AUC by model, (d) Confusion Matrix, (e) ROC curve

Best Regression Model: Random Forest (RMSE: 76.62 kWh/m²/year, MAE: 60.03 kWh/m²/year, R²: 0.20). Best Classification Model: Support Vector Classification (Accuracy: 63.7%, F1 Score: 0.61, ROC-AUC: 0.669)

4.4.3 Feature Importance Analysis Approach

Following the identification of tree-based models as most effective, this section quantifies the influence of individual features—particularly occupant behaviors—on residential energy consumption using two analytical methods: Permutation Importance and SHAP Analysis.

4.4.3.1 Permutation Importance

Permutation importance evaluates feature influence based on the increase in prediction error when a feature's values are shuffled randomly. This model-agnostic technique effectively captures both interactions and non-linear relationships between features. It was applied to the Random Forest model with multiple repetitions to ensure robust results. The top 20 features by permutation importance are illustrated in Figure 72, highlighting significant behavioral variables, particularly AC usage hours and daylight utilization habits.

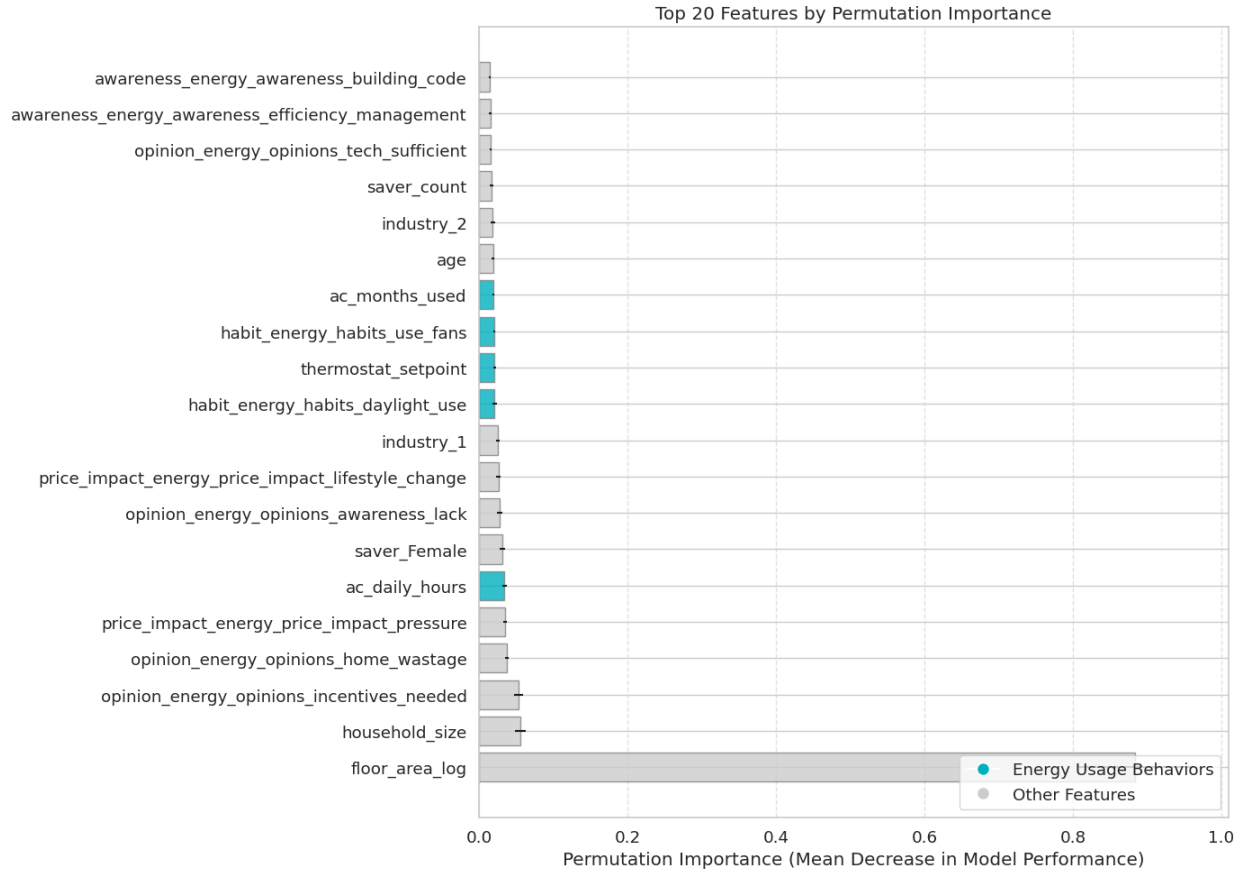


Figure 72: Top 20 Features By Permutation Importance

4.4.3.2 SHAP (SHapley Additive exPlanations) Analysis

SHAP analysis, grounded in cooperative game theory, provides consistent feature attribution values reflecting both magnitude and direction of feature influence. Figures 73 and 74 present the SHAP feature importance and summary plots, respectively. Floor area, household size, and daily AC usage hours emerged prominently, with daylight utilization and thermostat adjustment behaviors among top behavioral determinants (Figure 9).

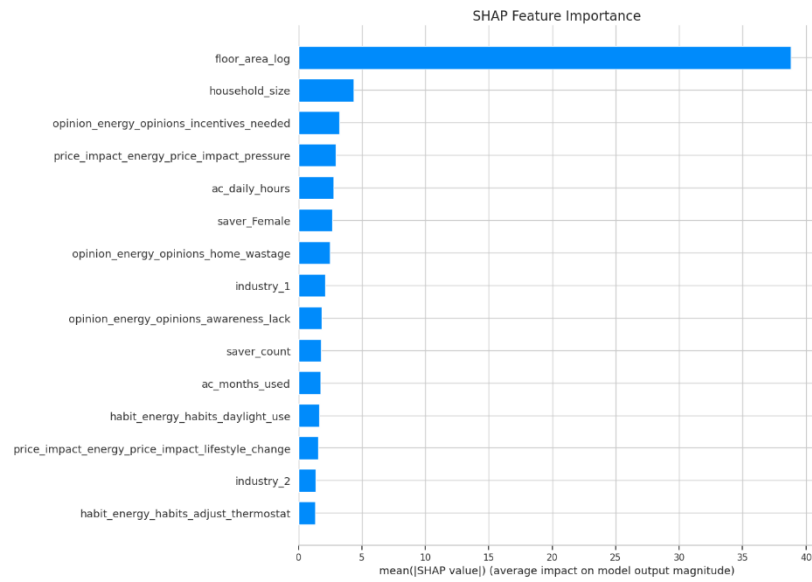


Figure 73: SHAP Feature Importance.

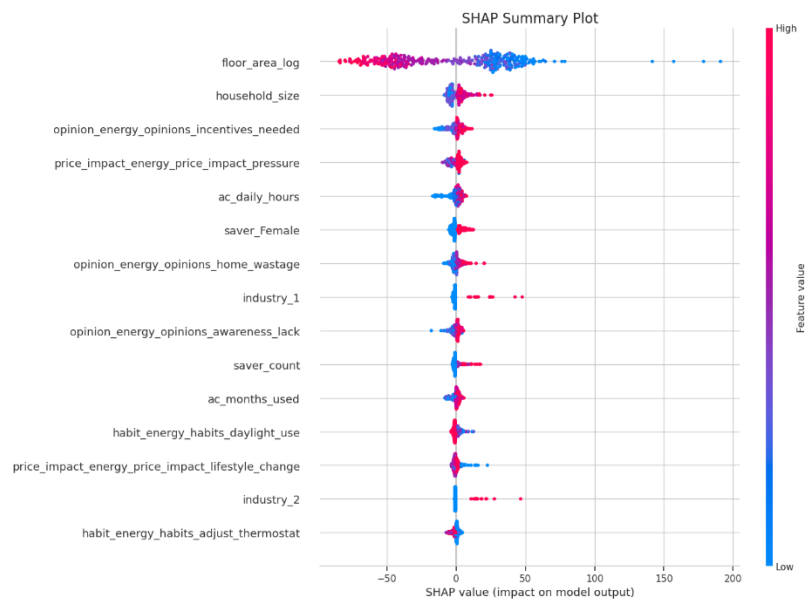


Figure 74: SHAP Summary Plot.

4.4.4 Feature Selection for Optimized Energy Consumption Modeling

The initial modeling and feature importance analysis indicated significant redundancy among the features, alongside clear patterns of predictive importance. A strategic, multi-stage feature selection approach is thus adopted to optimize model performance and enhance interpretability. This strategy combines statistical metrics and domain-specific knowledge to address the characteristics inherent to residential energy consumption data. The approach integrates:

- Importance-based filtering: Leveraging permutation importance and SHAP values to retain significant predictors and discard low-impact variables.
- Correlation-based pruning: Eliminating redundant variables that provide overlapping information.
- Domain-knowledge preservation: Ensuring minimum representation from key behavioral categories even when individual importance metrics are modest.
- Structural variables retention: Maintaining essential building characteristic variables to control their foundational influence.

4.4.4.1 Selection Criteria Justification

The implementation of feature selection is guided by empirical criteria:

- Importance threshold (≥ 0.01): Features below this threshold were considered negligible.
- Correlation threshold (≤ 0.75): Reducing redundancy by removing features highly correlated beyond this threshold.

- Domain category representation: Ensuring minimum feature counts from behaviorally relevant categories.

This structured selection maintains statistically and behaviorally significant predictors essential for accurate energy modeling in Saudi residential contexts. Figure 75 illustrates the permutation importance of the selected features, highlighting the retention of critical behavioral and structural variables.

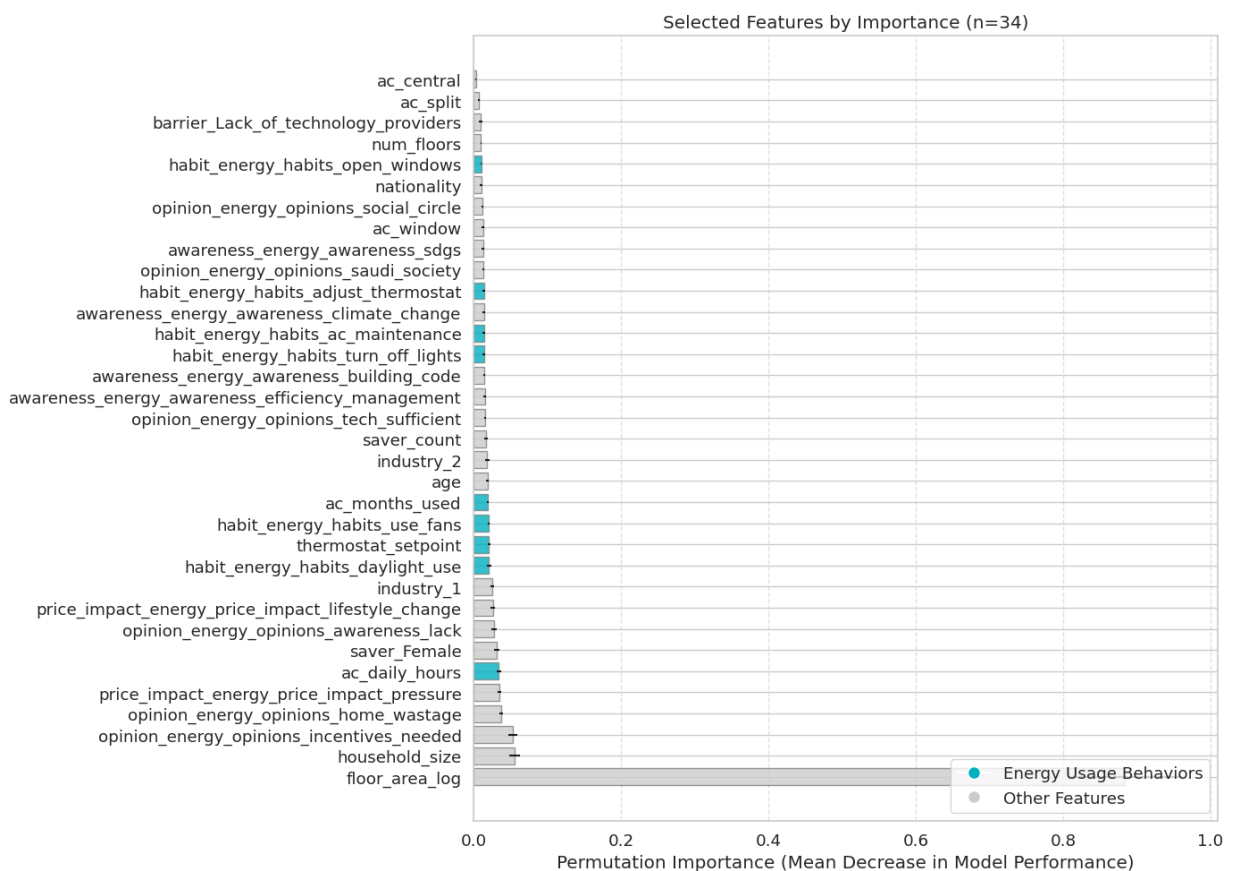
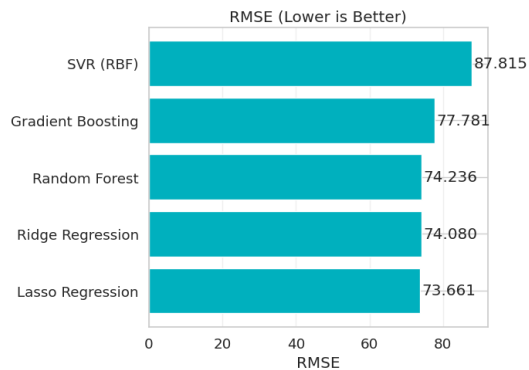


Figure 75: Selected Feature's Permutation Importance.

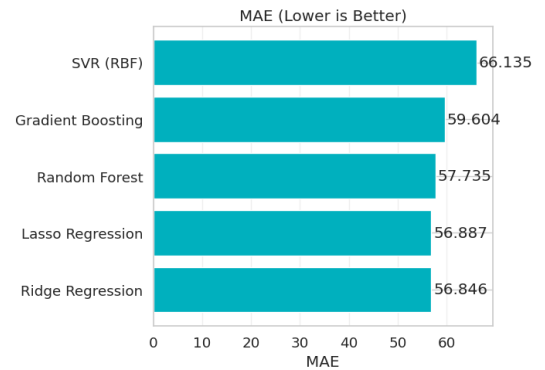
4.4.4.2 Optimized Model Performance

The streamlined model achieved through feature selection (34 features) improved predictive accuracy compared to the initial broader model. Performance enhancements are illustrated in Figure 76 (Regression Models) and Figure 77 (Classification Models):

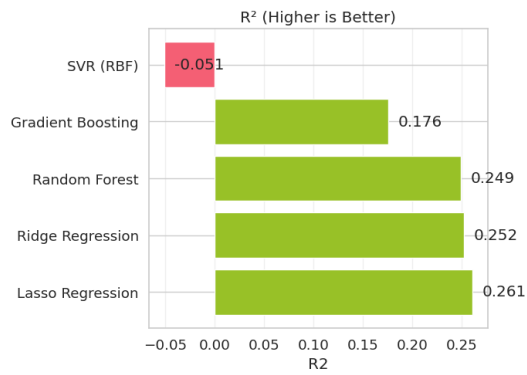
- Regression: Lasso Regression emerged as optimal, achieving the highest R^2 (0.261), lowest RMSE (73.66), and lowest MAE (56.89). This shift towards a linear model suggests clearer linear relationships between behavioral predictors and energy consumption after removing redundant features.
- Classification: Gradient Boosting achieved superior performance with improved accuracy (66.9%), F1 score (0.651), and ROC-AUC (0.713). The confusion matrix (Figure 77) shows improved predictive accuracy in distinguishing high versus low energy consumption, beneficial for targeted interventions.



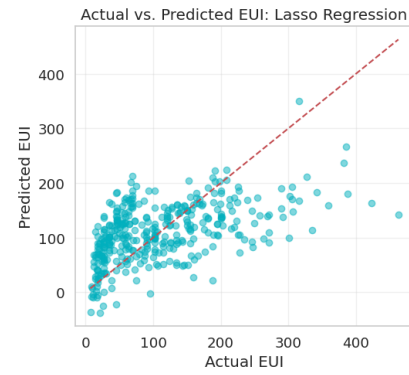
(a)



(b)

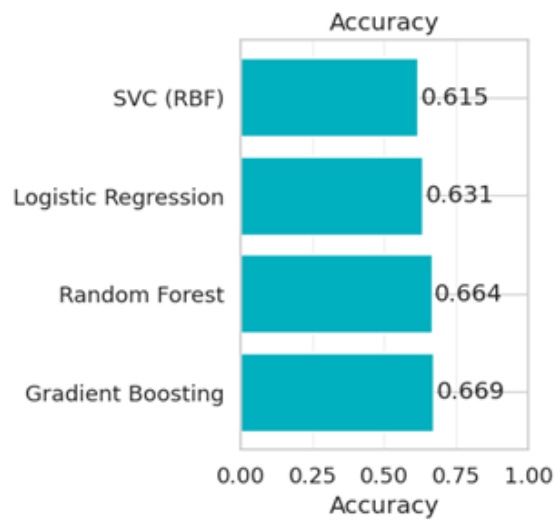


(c)



(d)

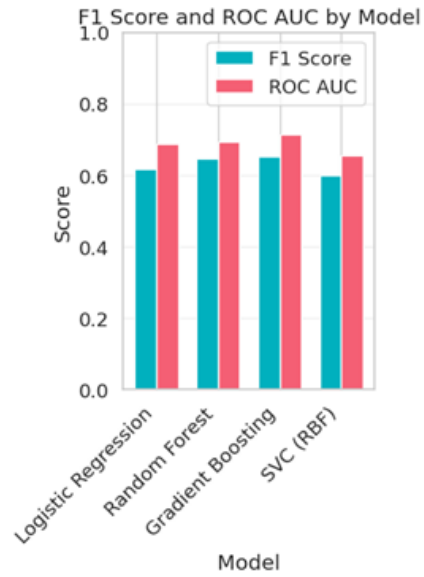
Figure 76: Optimized Regression Model Results for EUI Prediction : (a) RMSE values, (b) MAE values, (c) R2 value, (d) Actual vs Predicted performance.



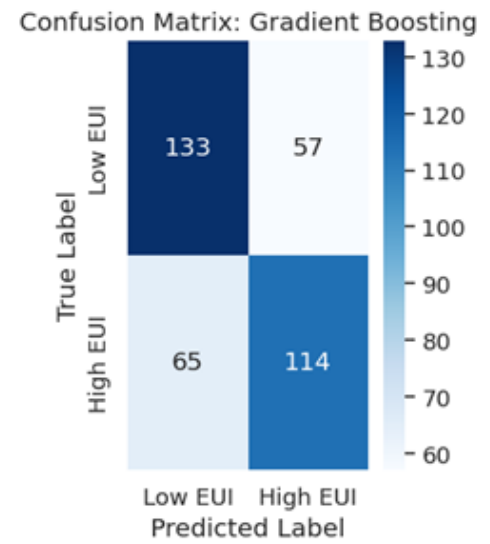
(a)



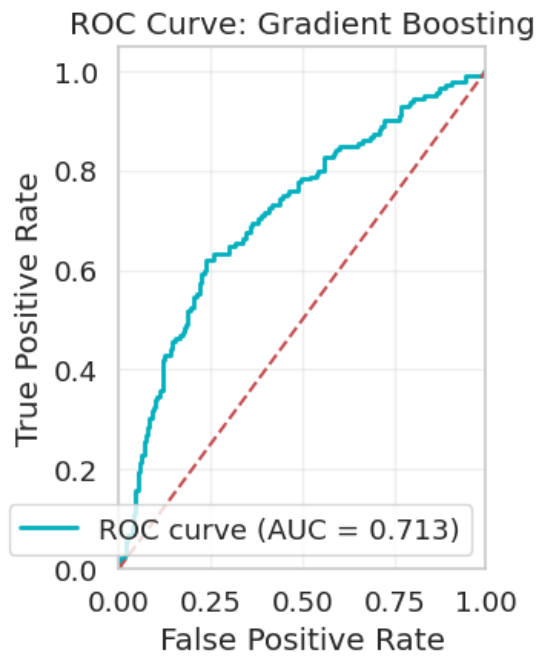
(b)



(c)



(d)



(e)

Figure 77: Optimized Classification Model Results: (a) Accuracy, (b) Precision, (c) F1 Score & AUC by model, (d) Confusion Matrix, (e) ROC curve.

4.4.4.3 Feature Selection Impact

The feature selection effectively distilled the predictors, preserving representation across essential domains:

- **Structural Variables:** Floor area remains the most critical predictor, with household size also significant.
- **AC-Related Behaviors:** Variables such as daily AC operational hours and thermostat settings maintained high predictive relevance.
- **Energy-Saving Behaviors:** Daylight utilization and other specific habits demonstrated meaningful impacts on reducing energy use.
- **Demographic and Attitudinal Variables:** These provided contextual differentiation, especially helpful in distinguishing consumption segments.

4.4.4.4 Analytical and Methodological Implications

The improved model highlights the utility of integrated feature selection, demonstrating that reducing dimensionality through principled approaches reveals clearer behavioral patterns in energy consumption. The improved performance of linear models post-selection implies more interpretable relationships exist than previously suggested by broader models. This optimized approach establishes a methodological template for future energy consumption research in similar residential contexts, ensuring the balance of comprehensive measurement and analytical simplicity.

4.4.4.5 Category-Level Analysis of Selected Features

Figure 75 provides detailed permutation importance scores for the final selected features.

Key insights per category include:

- **Building Characteristics:** Floor area and household size remain the foundational predictors.
- **AC Systems:** Window AC units significantly influence energy consumption, consistent with regional cooling demands.
- **Behavioral Factors:** Daily AC usage and thermostat preferences critically affect consumption levels.
- **Demographics and Attitudes:** Variables like household size, income, and energy-related attitudes support effective consumption segmentation.
- **Energy Efficiency Barriers:** Perceptions of barriers remain modestly predictive, indicating their relevance in identifying consumption patterns.

4.4.5 Category Contribution Analysis

4.4.5.1 Categorical Ablation Study

To methodically assess the relative importance of each variable category in predicting residential energy consumption, a categorical ablation study was conducted. This experimental framework systematically removed entire categories of predictors to measure resultant degradation in model performance, providing direct quantification of each category's unique predictive contribution.

This ablation approach employed a sequential category exclusion procedure. Specifically, multiple model variants were generated, each excluding one complete category from the optimized feature set, with all other categories retained. Each variant's performance was evaluated using Leave-One-Out Cross-Validation (LOOCV), ensuring consistent and rigorous comparisons against the baseline full-feature model. Performance degradation was assessed using regression metrics: coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

The categorical exclusion was guided by the original survey design, encompassing:

- Building characteristics (Q10-Q16)
- Air conditioning systems (Q17)
- Behavioral factors (Q18-Q20, Q23)
- Demographics (Q1-Q9)
- Attitudes and awareness factors (Q24-Q25, Q29)
- Energy efficiency barriers (Q26-Q27)

The implemented ablation methodology proceeded through several structured steps:

- **Variable Removal:** For each iteration, all variables within a selected category were removed from the optimized feature set.
- **Model Training:** A Lasso regression model (with $\alpha = 0.1$), previously identified as the best performing regression algorithm, was trained with the reduced feature set.

- **Performance Evaluation:** Each model variant's predictive capability was assessed using the defined LOOCV protocol, calculating performance metrics (R^2 , RMSE, MAE).
- **Comparative Metrics Calculation:** The difference in R^2 values (ΔR^2) between the baseline and each reduced model provided the quantitative basis for interpreting each category's unique predictive contribution.

The categorical ablation analysis yielded insightful results regarding the relative significance of each variable category (Figures 78 and 79):

- **Building Characteristics:** Removal of building characteristics produced the most substantial degradation in predictive accuracy ($\Delta R^2 = 0.2947$, 113% reduction relative to baseline), confirming their foundational importance in residential energy consumption modeling in Saudi Arabia.
- **Demographic Variables:** Demographic features showed the second-largest impact on model performance ($\Delta R^2 = 0.0189$, 7.25% reduction). Although modest compared to building characteristics, their absence led to meaningful accuracy deterioration, underscoring their relevance in explaining residential energy patterns.
- **Energy Efficiency Measures:** Exclusion of variables related to energy efficiency measures resulted in minor but notable accuracy reduction ($\Delta R^2 = 0.0091$, 3.48% reduction), highlighting their moderate yet measurable predictive value.

- **Attitudes/Opinions:** Attitudinal and opinion-related features displayed minimal performance impact upon removal ($\Delta R^2 = 0.0031$, 1.20% reduction), suggesting partial redundancy with other behavioral or demographic factors.
- **Energy Bills:** The category associated with energy bills demonstrated negligible predictive contribution ($\Delta R^2 \approx 0.0$, 0% reduction), indicating redundancy or limited incremental explanatory value in the model.
- **AC Systems, Awareness, and Energy Usage Behaviors:** Interestingly, removing these categories resulted in slight negative impacts on model accuracy (e.g., $\Delta R^2 = -0.0137$, -5.24% for energy usage behaviors). This counterintuitive result indicates potential redundancy or collinearity with other categories, reflecting overlapping explanatory capacities rather than genuinely detrimental impacts.

The detailed comparative visualization (Figure 7.1a) shows the absolute importance (percentage reduction in R^2) of each category upon removal, clearly demonstrating building characteristics' dominant influence. Figure 7.1b further illustrates R^2 performance across different categorical exclusions relative to the baseline, visually confirming these interpretations.

Analytical and Policy Implications

The categorical ablation findings carry substantial implications for data collection prioritization and energy conservation policy formulation in Saudi Arabia. Primarily, the outsized importance of building characteristics validates their foundational role, suggesting policies must continue prioritizing building envelope improvements and structural energy efficiency measures.

Demographic factors' significant impact advocates incorporating household composition and socioeconomic contexts into targeted interventions, while moderate effects of attitudes and efficiency measures reinforce the utility of integrating behavioral campaigns alongside technical improvements.

Conversely, categories such as AC systems and specific awareness behaviors, while individually important, exhibit overlapping informational content with other factors, indicating opportunities for future survey simplification or enhanced feature engineering to eliminate redundancy and improve data collection efficiency.

In summary, this structured categorical ablation study successfully quantified each variable category's unique contribution, providing robust empirical evidence to inform methodological refinement and energy efficiency policy in the Saudi residential sector.

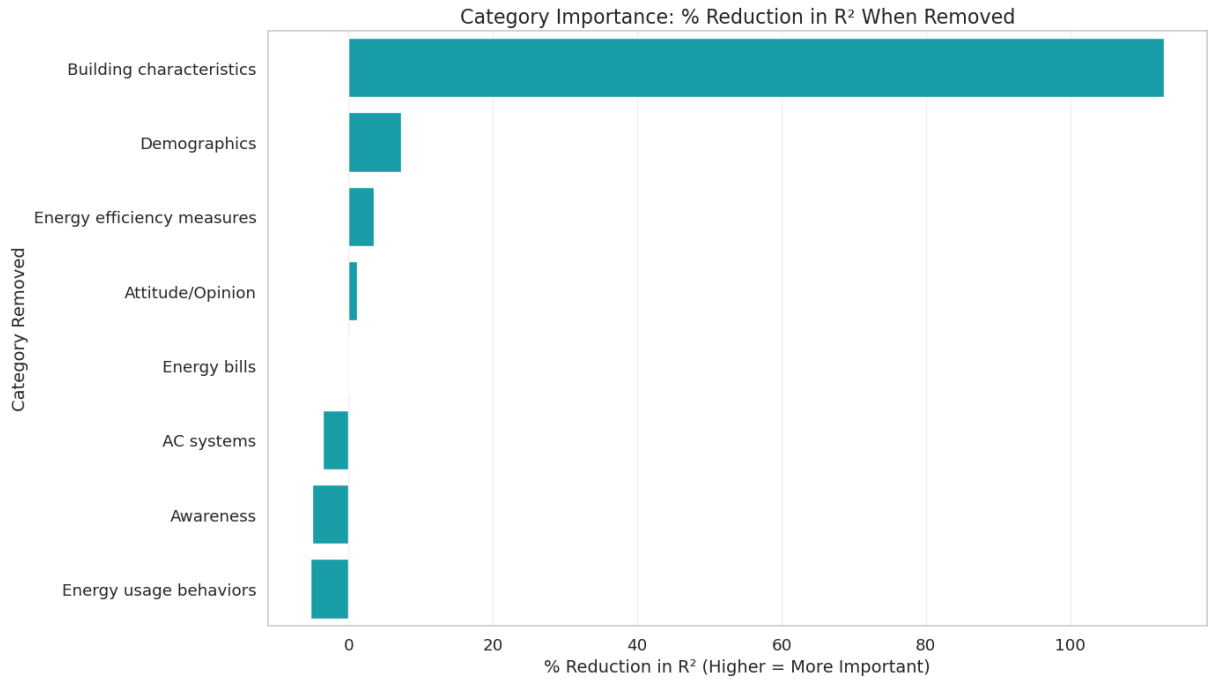


Figure 78: Categorical Ablation Analysis: Category Importance (% Reduction In R^2)

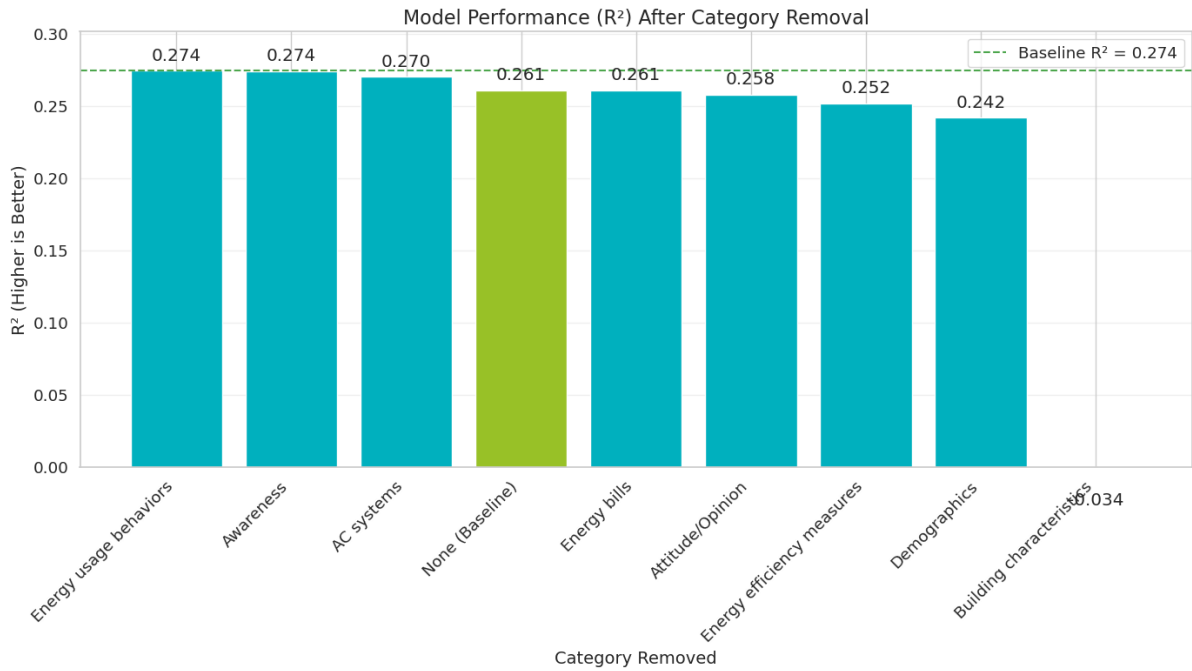


Figure 79: Categorical Ablation Analysis : Reduction In Model Performance.

4.4.6 Behavioral Segmentation: Identifying Energy Consumption

Archetypes

The initial analysis using both the elbow method and silhouette scores (Figure 80 & Figure 81) indicated an optimal segmentation into four clusters. Specifically, the elbow curve exhibited a noticeable inflection point at four clusters, beyond which inertia reductions became marginal. Concurrently, silhouette scores supported this determination by suggesting a balanced cluster cohesion and separation at this number. Thus, a four-cluster model was established to optimally capture distinct behavioral patterns in energy use.

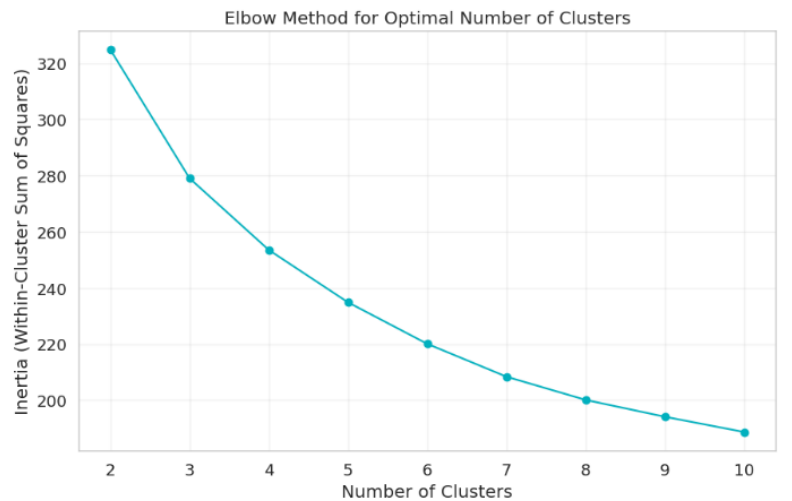


Figure 80: Elbow Method For Optimal Number Of Clusters.

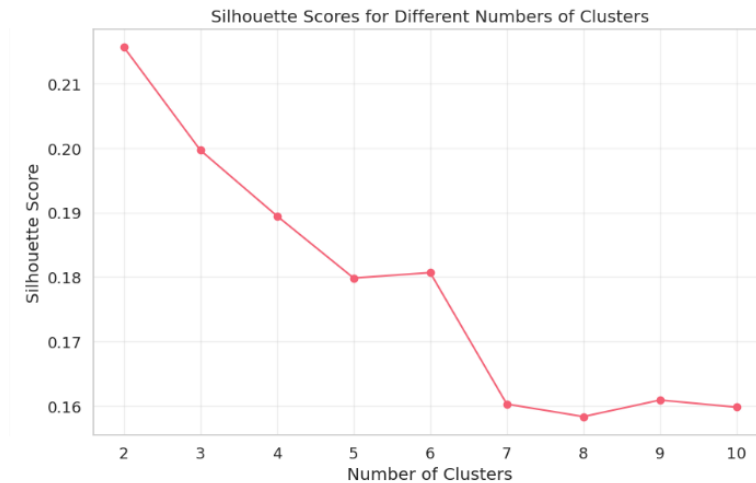


Figure 81: Silhouette Scores For Different Number Of Clusters.

The resulting segmentation identified four distinct consumer archetypes. Figure 82 illustrates the cluster size distribution, highlighting the distribution of households across clusters:

Cluster 0: 126 households (34.1%)

Cluster 1: 116 households (31.4%)

Cluster 2: 66 households (17.9%)

Cluster 3: 61 households (16.5%)

This distribution underscores significant segmentation diversity, indicating substantial representation across multiple behavioral archetypes rather than dominance by a single archetype.

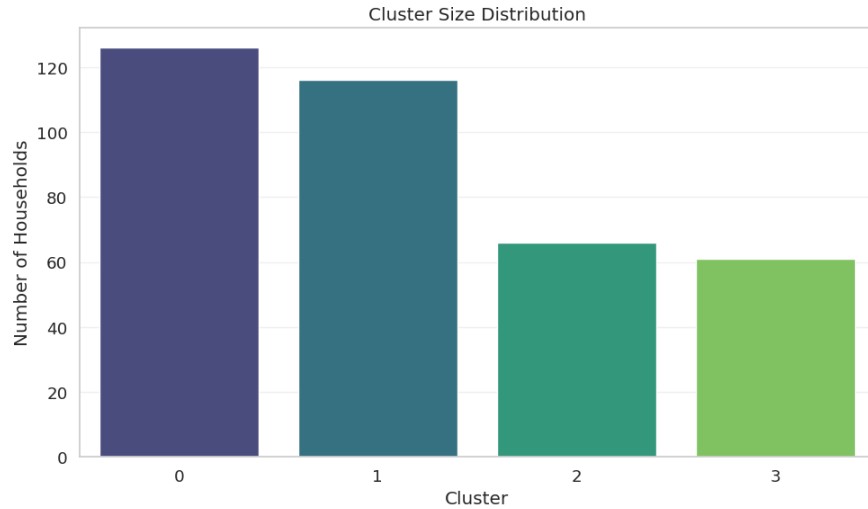


Figure 82: Cluster Size Distribution

4.4.6.1 Behavioral Characteristics of Clusters

Figure 83 provides detailed behavioral characteristics of each identified cluster relative to the overall population mean, clarifying distinct behavioral tendencies. Key behavioral differentiators included AC usage patterns, thermostat adjustments, lighting habits, and daylight utilization:

- Cluster 0 households demonstrated high use of energy-efficient lighting (LED usage), proactive daylight utilization, and responsible practices such as turning off unused lights. However, they showed limited thermostat adjustments and fan usage.
- Cluster 1 reflected lower-than-average energy conservation behaviors in daylight usage, LED lighting, and habitual switching off of lights, marking them as comparatively less engaged in proactive energy-saving behaviors.

- Cluster 2 notably used fans extensively, adopted proactive thermostat adjustments, and maintained diligent air conditioning (AC) maintenance. Their overall behavioral profile suggested active involvement in managing energy consumption but reduced reliance on prolonged AC usage.
- Cluster 3 exemplified significantly active thermostat adjustments combined with above-average daylight utilization and conscientious switching off of unused lights. Their practices indicated a highly proactive, energy-conscious archetype.



Figure 83: Behavioral Characteristics Of Each Identified Cluster.

4.4.6.2 Energy Consumption Profiles by Behavioral Cluster

Figure 84 visually examines how Energy Use Intensity (EUI) varies across the four clusters, providing deeper insights into how behavioral differences manifest in actual energy consumption patterns:

- Cluster 0 displayed higher-than-average EUI, suggesting that despite certain positive behaviors, overall consumption remained elevated, possibly due to limited thermostat adjustments and fan usage.
- Cluster 1 and Cluster 2 demonstrated near-average EUI profiles, suggesting mixed results from their respective behavioral patterns, wherein positive behaviors partially offset less efficient habits.
- Cluster 3 consistently exhibited notably lower EUI, classifying it as an "Energy Efficient" cluster, significantly outperforming other clusters regarding reduced energy consumption.

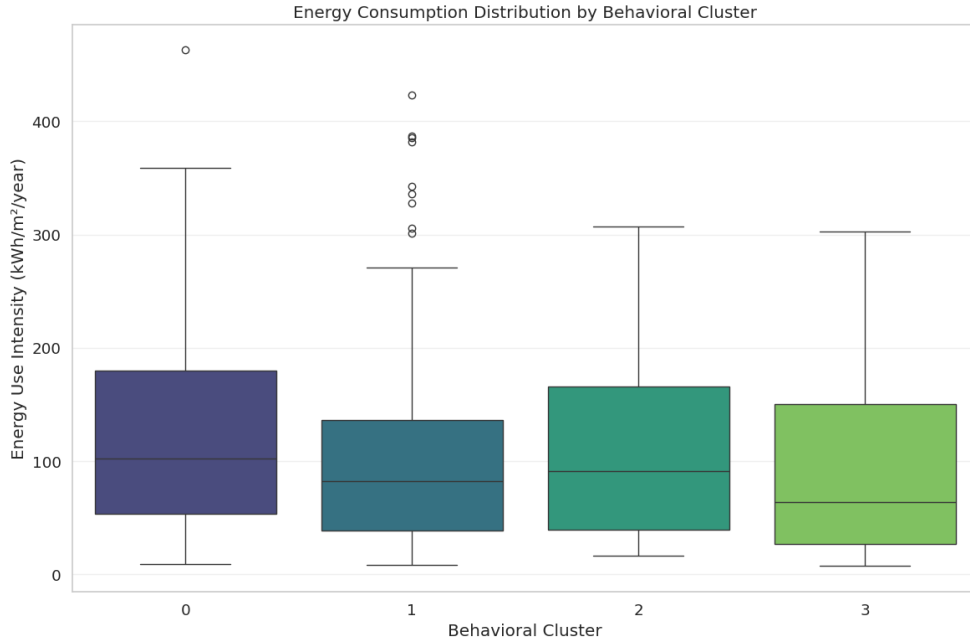


Figure 84: Energy Use Intensity (EUI) Variation Across The Identified Clusters.

4.4.6.3 Behavioral Profiles

The radar plot in Figure 85 offers a comparative visualization of normalized behavioral attributes for each cluster, clearly distinguishing patterns and providing intuitive insights into archetype-specific strengths and areas for improvement. This visualization succinctly encapsulates complex multidimensional behavioral data into an accessible comparative framework:

- Cluster 0 excels in lighting efficiency but lacks effective thermostat and fan-related energy-saving behaviors.
- Cluster 1 shows relatively lower scores across almost all behavioral dimensions, revealing substantial potential for targeted behavioral intervention improvements.
- Cluster 2 showcases superior fan usage and thermostat adjustments, indicating effective management practices despite moderate AC-related behaviors.

- Cluster 3 emerges prominently with balanced high scores across nearly all significant energy-saving behaviors, clearly illustrating their proactive and conscientious approach toward residential energy efficiency.

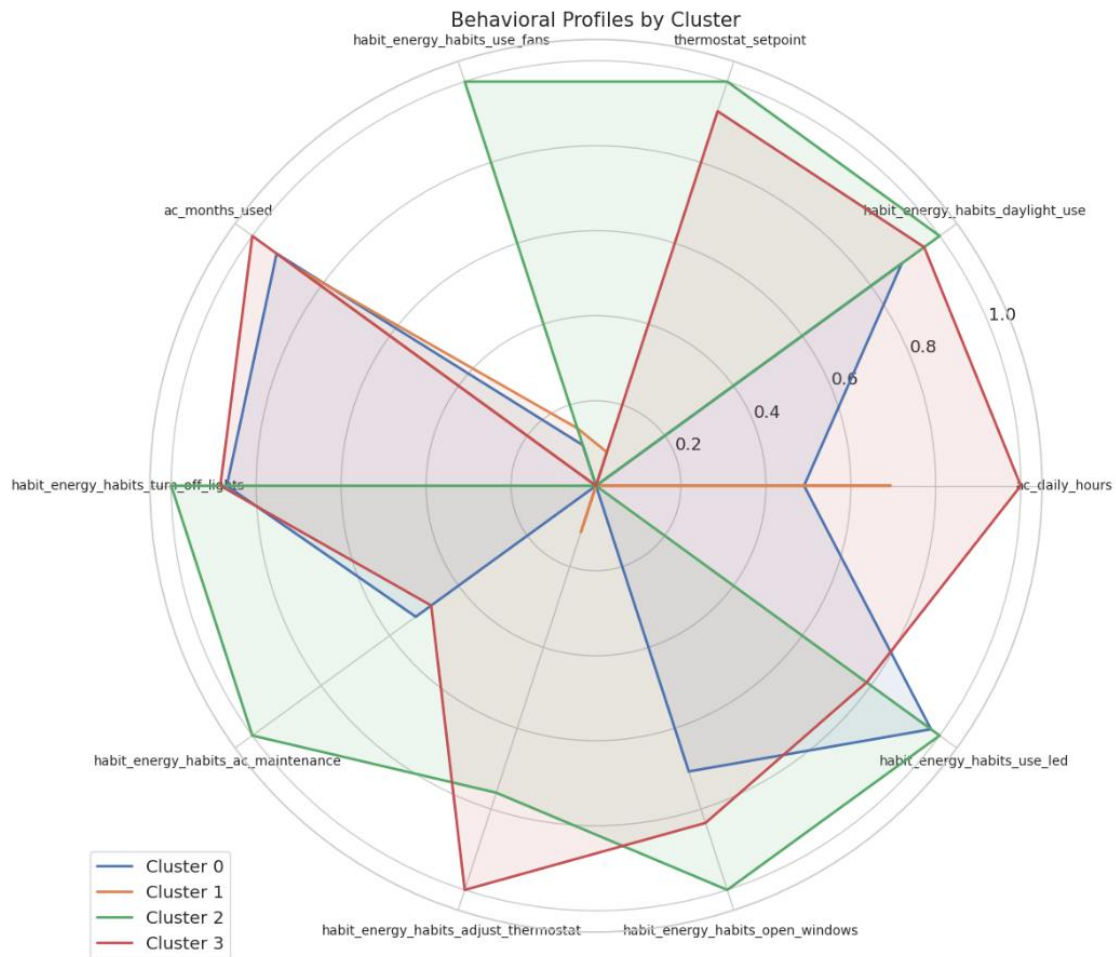


Figure 85: Behavioural Profiles By Cluster.

4.4.6.4 Synthesis and Strategic Implications

The behavioral segmentation analysis provided meaningful insights, revealing the heterogeneity of residential consumer practices in Saudi Arabia. By identifying distinct

archetypes and understanding their unique energy usage behaviors, policymakers and stakeholders can more effectively target interventions, optimize resource allocation, and foster behavior-specific conservation strategies. For instance, Cluster 3 can serve as a benchmark for educational and incentive-based programs, while targeted intervention strategies for Cluster 1 could considerably improve overall energy savings.

These results demonstrate the efficacy and practical value of behavior-focused segmentation analysis in developing nuanced, empirically-grounded energy conservation strategies tailored specifically to different consumer archetypes. Such targeted interventions hold significant potential for enhancing residential energy efficiency outcomes in Saudi Arabia.

4.5 Integration of Findings

The integration of multiple analytical methods in this study offers a comprehensive approach to understanding how user behavior impacts energy consumption in residential buildings in Saudi Arabia (KSA). By combining statistical analysis, machine learning models, and qualitative insights, the research highlights the complexity of energy usage behaviors and provides a holistic view of the factors that influence energy consumption. As shown in Table 22, each research objective is addressed through a combination of distinct methods and analysis techniques, ensuring a comprehensive approach to understanding the factors influencing energy consumption in residential buildings. The methods, including literature reviews, statistical analysis, machine learning, and qualitative interviews, were strategically employed to achieve the study's objectives.

Table 22: Integration of Research Objectives with Analytical Techniques.

Research Objectives	Research Methods	Analysis Techniques	Purpose
1. Identify and analyse critical aspects of user behavior	Literature Review	Bibliometric and Systematic Analysis	To identify key user behaviors impacting energy consumption globally.
	Survey Design & Data Collection	Quantitative Survey, Behavioral Questions	To capture behaviors, habits, attitudes, and factors influencing energy use.
	Qualitative Interviews	Thematic Analysis.	To explore deeper personal and societal dynamics that affect energy behavior.
	Statistical Analysis	Correlation, Regression, Feature Importance	To quantify the relationships between behaviors and energy use patterns.
	Machine Learning	Ridge, Lasso, Random Forest, Gradient Boosting, SVC	To identify and model the behavioral factors most predictive of energy consumption.

2. Develop an AI-driven predictive model for energy consumption	Machine Learning	Cross-validation, Feature Engineering, Model Tuning	To create a predictive model based on key features.
	Feature Importance Analysis	SHAP, Permutation Importance	To identify the most influential behaviors and factors for energy predictions.
	Behavioral Segmentation	K-Means Clustering	To classify households into segments for targeted energy-saving interventions.
3. Craft actionable strategies for optimizing user behavior	Qualitative Interviews	Theme Identification, Insights Extraction	To gather insights on barriers and motivators for energy conservation in households.
	Statistical Analysis	Regression, Interaction Effects	To identify critical behaviors to target in policy or intervention strategies.
	Machine Learning	Model Optimization, Behavioral Clusters	To develop data-driven strategies for energy

			consumption reduction based on behaviors.
	Formulation of Policy Recommendations	Derived from Statistical, Machine Learning, and Qualitative Insights	To create actionable strategies for optimizing user behavior and energy use.

Each of the methods employed in this study served a distinct purpose and contributed to the overall understanding of energy consumption behaviors. The statistical analysis provided a solid foundation for identifying correlations between key variables such as energy use intensity (EUI) and behavioral factors, revealing significant relationships and trends. This quantitative approach enabled a robust understanding of the direct impacts of user behaviors like thermostat settings, air conditioning usage, and lighting habits.

The machine learning (ML) models built upon this statistical foundation by offering predictive insights. Techniques such as Ridge, Lasso, and Random Forest provided deeper insights into which behaviors are the most predictive of energy consumption, while feature importance analysis (SHAP and permutation importance) allowed for the identification of key factors that drive energy use. The behavioral segmentation also provided a unique contribution, clustering households based on their energy use profiles and further enabling the design of tailored interventions.

Qualitative insights, collected through interviews, added another layer of depth to the analysis. These insights helped contextualize the statistical and machine learning findings

by exploring the socio-cultural, economic, and institutional factors that influence individual energy behaviors. Thematic analysis of interview responses revealed key barriers, such as economic constraints and societal attitudes, that might not have been evident through quantitative methods alone. This qualitative data provided critical understanding of how people's perceptions, household dynamics, and institutional constraints shape their energy consumption habits.

Together, these methods offered a comprehensive picture of the factors influencing energy behavior, while also enabling the development of data-driven recommendations for interventions.

Several challenges emerged during the data analysis process. The first major hurdle was the initial model performance in machine learning. Early models yielded modest predictive results ($R^2 \sim 0.20$) due to complexities inherent in human behavior and the limitations of the data, particularly the reliance on self-reported behaviors in surveys. Addressing these challenges required several rounds of data cleaning, feature engineering, and model optimization to improve accuracy. Even with these improvements, achieving high predictive accuracy remained difficult. However, such performance levels are not unexpected in behavioral studies, where human actions are influenced by numerous unobserved and contextual factors. The use of self-reported data introduces additional variability that inherently limits model precision. Therefore, the focus of the machine learning component was not solely on maximizing predictive metrics, but rather on interpretability, generalizability, and the extraction of actionable insights through feature importance analysis and segmentation techniques.

Another challenge was the complexity of combining qualitative and quantitative data. Thematic analysis required careful interpretation of interview responses, which was time-consuming and subjective. Ensuring that the qualitative insights aligned with the statistical and machine learning results required a deep, iterative process of cross-checking findings, but it ultimately resulted in a richer and more comprehensive understanding of user behaviors.

The methods used in this research were highly relevant to addressing the research questions and provided critical insights into the role of user behavior in energy consumption. Statistical analysis was crucial for identifying broad patterns and understanding how different variables interacted to influence energy use. The machine learning models took this further by quantifying the predictive power of specific behaviors and factors, providing actionable insights for energy management and policy development.

Qualitative interviews, meanwhile, allowed for a deeper exploration of the underlying socioeconomic, cultural, and institutional factors that influence energy decisions in residential buildings. These factors often cannot be captured fully through quantitative data alone but are vital for understanding the broader context in which energy-saving behaviors are adopted (or not adopted).

By integrating these methods, the study was able to triangulate data from different sources, ensuring more reliable and comprehensive findings. The synergy between statistical analysis, machine learning, and qualitative insights allowed for a multi-faceted approach that not only identified key behavioral drivers but also provided contextual understanding

of the challenges and barriers that households face when trying to adopt energy-efficient behaviors.

CHAPTER 5

DISCUSSION

5.1 Interpretation of Results

This study sought to understand how user behavior impacts energy consumption in residential buildings in Saudi Arabia (KSA) and how AI and machine learning techniques can predict and optimize these behaviors. By integrating statistical analysis, machine learning models, and qualitative insights, a comprehensive view of the factors influencing energy consumption was captured.

Objective 1: Identify and analyze critical aspects of user behavior was addressed through various methods. The literature review (including bibliometric and systematic reviews) helped gain insights into the domain of energy conservation, especially the user behavior domain and the factors that impact energy consumption. The survey design and data collection phase, which included behavioral questions, allowed for capturing specific habits, attitudes, and factors influencing energy consumption in KSA. Statistical analysis quantified the relationships between key variables like AC usage, thermostat settings, and lighting behaviors. Through machine learning models (Ridge, Lasso, Random Forest, and Gradient Boosting), the most predictive behaviors of energy consumption were identified. This comprehensive approach enabled the identification of key user behaviors affecting energy consumption in Saudi residential buildings.

Objective 2: Develop an AI-driven predictive model for energy consumption was achieved through the use of several machine learning techniques. The cross-validation process, alongside feature engineering and model tuning, helped create a predictive model based on various socio-demographic, building characteristics, and behavioral factors, including awareness and attitude factors. Although the predictive power of the models was modest ($R^2 \sim 0.27$ for regression and $AUC \sim 0.73$ for classification), such outcomes are not uncommon in behavioral modeling studies. Human behavior—especially related to energy use—is influenced by a multitude of contextual, unobserved variables, and the reliance on self-reported survey data introduces additional variability. Therefore, while high predictive precision was limited, the model’s performance is reasonable given the nature of the data.

Importantly, the models successfully identified relatively influential predictors within the behavioral category, such as AC daily usage and thermostat settings. Additionally, feature importance analysis (using SHAP and permutation importance) provided further clarity on the most influential factors for energy predictions. The behavioral segmentation conducted via K-Means clustering revealed distinct energy consumption patterns across different household archetypes, which can guide targeted energy-saving interventions. The overall emphasis of this component was on deriving interpretable and generalizable insights rather than solely maximizing accuracy, aligning with the study’s goal to support practical, behavior-focused energy strategies.

Objective 3: Craft actionable strategies for optimizing user behavior was addressed by integrating statistical, machine learning, and qualitative interview insights. By analyzing behavioral patterns and barriers to energy conservation, key behaviors—such as AC usage, lighting habits, and thermostat settings—were identified for targeting in energy-saving

interventions. Statistical analysis identified critical behavioral drivers that should be prioritized for policy or intervention strategies. The machine learning models provided actionable insights through model optimization and behavioral clusters, which can help design data-driven strategies for reducing energy consumption based on user behavior. The insights derived from the qualitative interviews emphasized the need for addressing economic constraints, cultural attitudes, and institutional barriers to optimize energy behaviors.

5.2 Comparison with Existing Literature

This study's findings align with existing literature on the importance of cooling systems (AC usage) in shaping residential energy consumption. Previous studies [148], [149] have consistently shown that AC usage is one of the most significant contributors to high energy consumption in hot climates, which is consistent with the findings of this study.

Additionally, the study found that education level was not a strong predictor of energy-saving behaviors, contrary to much of the existing literature that suggests higher education correlates with more sustainable behaviors [150]. This finding underscores the importance of considering economic incentives and institutional policies in addition to education when designing energy conservation interventions. Qualitative insights from participants highlighted that even well-educated individuals often fail to adopt energy-saving practices due to institutional barriers.

5.3 Significance of Findings

The results of this study have significant implications for both theory and practice. Theoretically, this research contributes to the understanding of how user behavior and building characteristics interact to influence energy consumption. It demonstrates the value of integrating quantitative models with qualitative insights to provide a more nuanced understanding of energy use.

Practically, the study provides actionable recommendations for energy-saving interventions in KSA. These recommendations include focusing on cooling system optimization, energy-efficient appliances, and behavioral interventions that encourage better thermostat management, reduced AC usage, and more sustainable lighting habits. Furthermore, the behavioral segmentation results suggest that targeted policies should be tailored to specific household archetypes. For example, high-consumption households (such as those in Cluster 0) should be prioritized for immediate interventions, while energy-efficient households (such as those in Cluster 3) can serve as models for promoting positive energy-saving behaviors.

5.4 Unexpected Results and Their Implications

One of the most unexpected findings of this study was the limited role of education level in driving energy-saving behaviors. While existing research often suggests a strong link between higher education and pro-environmental behaviors, this study found that economic constraints and institutional policies were more influential in shaping energy behaviors in KSA. This highlights the need for energy policies that focus on economic

incentives (e.g., subsidies for energy-efficient appliances) and institutional support (e.g., incentives for landlords to implement energy-saving measures in rental properties), rather than relying solely on educational campaigns.

These findings suggest that simplistic behavioral interventions may not be sufficient to optimize energy use. Future interventions will need to consider these non-linear relationships and develop context-specific strategies that account for the complexity of human behaviors.

5.5 Limitations of the Study

While this study provides valuable insights, it has several limitations that must be considered:

1. **Data Quality and Biases:** The reliance on self-reported data from surveys introduces the possibility of response biases. Participants may not accurately report their energy behaviors, which could affect the accuracy of the predictive models. Future studies could benefit from incorporating real-time data from smart meters to improve model accuracy.
2. **Sample Size for Qualitative Interviews:** The qualitative interviews conducted in this study were based on a relatively small sample, which limits the generalizability of the findings. A larger sample size would strengthen the insights drawn from the interviews and provide a more representative view of the broader population.
3. **Cultural Context:** The findings are specific to Saudi Arabia, and their applicability to other countries with different cultural, economic, and institutional contexts may

be limited. Future research could explore how these findings apply to other regions with similar climates but differing socio-cultural and institutional environments.

5.6 Future Research Directions

1. **Incorporating Real-Time Data:** Future studies could integrate real-time energy consumption data from smart meters to validate and refine the predictive models developed in this study. This would provide more accurate and reliable predictions of energy consumption.
2. **Longitudinal Studies:** Longitudinal studies would help track how energy behaviors change over time and how interventions influence long-term energy consumption patterns. This could provide more insight into the sustainability of energy-saving behaviors.
3. **Exploring the Role of Institutional Policies:** Future research could further investigate the impact of institutional policies and financial incentives on energy-saving behaviors. This would help identify effective policy measures that can encourage energy-efficient practices.
4. **Cross-Cultural Comparisons:** Research could benefit from cross-cultural comparisons to examine how energy consumption behaviors differ across countries. This would help identify universal energy use and energy-saving behaviors, while also considering regional differences in energy consumption practices.

CHAPTER 6

CONCLUSION

This study aimed to explore how user behavior influences energy consumption in residential buildings in Saudi Arabia (KSA) and how AI-driven techniques, such as machine learning, could predict and optimize these behaviors. By combining statistical analysis, machine learning models, and qualitative insights, the study provides a comprehensive understanding of the complex factors affecting energy use patterns in KSA.

The research successfully identified critical aspects of user behavior that impact energy consumption, including thermostat settings, air conditioning (AC) usage, and lighting habits. The use of machine learning models—such as Ridge, Lasso, Random Forest, and Gradient Boosting—enabled the development of a predictive model that identified key behavioral patterns influencing energy consumption. Although the predictive accuracy was modest ($R^2 \sim 0.27$ for regression and $AUC \sim 0.73$ for classification), this level of performance is understandable given the nature of the data. Human behavior, particularly in the domain of residential energy use, is shaped by complex and often unobserved contextual factors. Moreover, the reliance on self-reported survey responses introduces inherent variability that can limit model precision.

Nevertheless, the findings provided valuable insights into the behavioral factors that need to be prioritized in energy-saving interventions. Rather than focusing solely on optimizing predictive accuracy, the study emphasized the importance of interpretability and generalizability. Additionally, the behavioral segmentation results, derived from K-Means

clustering, revealed four distinct household archetypes—High-Consumption Light Savers, Moderate Users, Energy-Efficient Adjusters, and Fan-Heavy Moderates. These segments offer a more granular understanding of how different household types approach energy use, enabling more tailored and effective energy-saving strategies. Furthermore, the thematic analysis of qualitative interviews revealed that economic constraints, cultural attitudes, and institutional barriers significantly shape household energy behaviors, providing a deeper understanding of the socio-cultural context that quantitative data alone could not capture.

This research contributes to the field of energy consumption analysis by demonstrating the importance of integrating multiple research methods to gain a holistic view of energy use behaviors. The combination of statistical, machine learning, and qualitative methods allowed for the identification of not only the key behavioral drivers of energy consumption but also the complex socio-cultural and institutional factors influencing these behaviors. Furthermore, the study advances our understanding of energy consumption behaviors in Saudi Arabia, a region with a unique socio-economic and cultural context that has been underrepresented in energy research.

The practical implications of this study are substantial for designing targeted energy-saving interventions in residential buildings. Policymakers should focus on optimizing cooling systems, particularly AC usage, which was identified as a major behavioral contributor to high energy consumption. Energy efficiency programs should also emphasize the adoption of energy-efficient appliances, such as thermostats and lighting, while promoting behavioral changes like reducing AC usage and managing thermostat settings more efficiently. The behavioral segmentation results suggest that energy-saving policies should be tailored to specific household archetypes, with high-consumption households requiring

immediate interventions and energy-efficient households serving as models for promoting positive behaviors.

Despite its contributions, this study has several limitations. The reliance on self-reported data from surveys introduces the possibility of biases, and future studies could benefit from incorporating real-time data from smart meters for more accurate energy predictions. The qualitative sample size was also limited, and a larger, more diverse sample would provide a more representative view of energy consumption behaviors across KSA. Additionally, while this study focused on Saudi Arabia, the applicability of these findings to other regions with different socio-cultural and institutional contexts may be limited. Future research could explore how these findings apply to other countries with similar climates but differing cultural, economic, and policy environments.

Future studies could also consider longitudinal designs to track how energy behaviors change over time and how interventions affect long-term consumption patterns. Further exploration into the role of institutional policies, financial incentives, and cross-cultural comparisons would be beneficial for gaining a deeper understanding of the drivers of energy consumption and the most effective strategies for promoting energy-saving behaviors on a global scale.

This research highlights the complexity of user behavior in residential energy consumption and the potential of AI-driven methods to inform energy-saving interventions. While the study's findings provide useful insights for energy management in Saudi Arabia, they also underscore the need for a multi-faceted approach that combines technological, behavioral, and policy interventions to optimize energy use in residential buildings. By addressing both

the behavioral and structural factors influencing energy consumption, future interventions can be more effective in driving long-term, sustainable energy practices.

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Publications and Conferences

➤ Peer-Reviewed Journal Articles

Jan, B., & Asif, M. (2025). Energy conservation research trajectories: A systematic analysis of methods, technologies, and knowledge gaps. *Energy and Buildings*, 330, 115304. <https://doi.org/10.1016/j.enbuild.2025.115304>

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➤ Conference Presentations

Jan, B., & Asif, M. (2024). Energy conservation research trajectories: A systematic analysis of methods, technologies, and knowledge gaps.

Presented at the 3rd IAEE MENA Conference, Riyadh, Saudi Arabia.

The presentation focused on global energy conservation strategies and evaluated their effectiveness through the lens of policy interventions, technological advancements, and user behavior.