Czech University of Life Sciences Prague

Faculty of Economics and Management

Department of Information Technology

Bachelor Thesis

Optimizing Smart Home Automation through Data-Driven Insights and Business IoT Solutions

Supervisor: Doc. Ing. Vojtěch Novák

Mahdi Houshangi

CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Economics and Management

BACHELOR THESIS ASSIGNMENT

Mahdi Houshangi

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Optimizing Smart Home Automation through Data-Driven Insights and Business IoT Solutions

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Objectives of thesis

The primary objective of this thesis is to optimize smart home automation by leveraging data-driven insights and business IoT solutions to enhance energy efficiency, interoperability, and user-centric automation.

The partial objectives are:

Identify Key Data Types: Examine and categorize various data types collected from smart home systems, such as energy consumption metrics, user interaction patterns, and environmental data.

Analyze Usage Patterns: Utilize data analysis techniques to detect inefficiencies in device operations and energy consumption trends.

Develop Automation Strategies: Propose and implement intelligent automation rules that enhance smart home system efficiency while ensuring adaptability to user behaviors and preferences.

Methodology

The methodology of this thesis involves a combination of quantitative and qualitative research approaches to achieve the set objectives. It includes:

- Data Collection: Gathering real-world smart home datasets from publicly available sources or simulated environments. Ensuring data relevance through preprocessing techniques such as filtering, normalization, and anomaly detection.
- Data Analysis: Performing exploratory data analysis (EDA) to uncover patterns in energy consumption and appliance usage. Applying machine learning algorithms to predict energy consumption trends and optimize automation rules.
- Automation Rule Development: Developing rule-based and AI-driven automation frameworks. Testing automation rules through simulation to validate their effectiveness.
- Evaluation: Measuring the impact of automation on energy efficiency and user convenience using predefined performance metrics. Iterative refinement of automation strategies based on user feedback and data insights.

Prague on --. --. 2025

The proposed extent of the thesis
40-50 pages

Keywords

Smart home technologies, Internet of Things (IoT), artificial intelligence (AI), energy efficiency, automation rules, user-centric design, data analysis, adaptive systems, sustainability, interoperability

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Recommended information sources

The following information sources are recommended for conducting the research:

1. Saeedi, A., Kuchaki Rafsanjani, M., & Yazdani, S. (2025) 'Energy efficient clustering in IoT-based wireless sensor networks using binary whale optimization algorithm (BWOA)', *Journal of Supercomputing*.
2. Almudayni, Z., Soh, B., Samra, H., & Li, A. (2025) 'Energy inefficiency in IoT networks: Causes, implications, and mitigation strategies', *Electronics (Switzerland)*.
3. Nathiya, N., Rajan, C., & Geetha, K. (2025) 'A hybrid optimization and machine learning based approach for smart home energy management', *Peer-to-Peer Networking and Applications*.
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9. Garcia, T., & Wong, C. (2024) 'IoT-based monitoring systems for real-time energy optimization in smart homes', *Sensors and Actuators B: Chemical*.
10. Brown, D., & Wilson, G. (2024) 'Machine learning-driven automation solutions for sustainable smart homes', *International Journal of Energy Research*.

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The Bachelor Thesis Supervisor
doc. Ing. Vojtěch Novák, Ph.D.

Supervising department
Department of Information Technologies

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doc. Ing. Jiří Vaněk, Ph.D.
Head of department

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----
prof. PhDr. Michal Lošťák, Ph.D.
Pověřený vedením

Prague on --. --. 2025

Declaration

I declare that I have worked on my bachelor thesis titled "Optimizing Smart Home Automation through Data-Driven Insights and Business IoT Solutions" by myself and I have used only the sources mentioned at the end of the thesis. As the author of the bachelor thesis, I declare that the thesis does not break any copyrights.

In Prague on date of submission Mahdi Houshangi

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Optimizing Smart Home Automation through Data-Driven Insights and Business IoT Solutions

Abstract

The rapid evolution of smart home technologies, driven by advancements in IoT and AI, has transformed residential living through enhanced automation, energy efficiency, and user-centric design. Despite these advancements, challenges such as data inefficiencies, lack of adaptive automation, and interoperability remain significant obstacles. This study leverages a four-year smart home dataset to analyze energy consumption, identify device usage patterns, and develop intelligent automation rules tailored to user behaviors. Key findings highlight inefficiencies in energy use, particularly during peak hours, and the disproportionate energy consumption of specific appliances. The research proposes adaptive, data-driven automation strategies that optimize energy efficiency, enhance interoperability, and prioritize user satisfaction. These solutions demonstrate a potential 15% reduction in energy consumption while promoting sustainability and scalability in smart home systems. By addressing critical gaps in the domain, this thesis contributes to the development of more efficient, secure, and user-adaptive smart home technologies.

Keywords: Smart home technologies, Internet of Things (IoT), artificial intelligence (AI), energy efficiency, automation rules, user-centric design, data analysis, adaptive systems, sustainability, interoperability

Optimalizace automatizace chytrých domácností prostřednictvím datových analýz a IoT řešení pro podnikání

Abstrakt

Rychlý vývoj technologií chytrých domácností, poháněný pokrokem v oblasti IoT a umělé inteligence, zásadně mění rezidenční bydlení díky vylepšené automatizaci, energetické efektivitě a uživatelsky orientovanému designu. Přestože tyto technologie nabízejí mnoho výhod, stále existují výzvy, jako jsou neefektivity při využívání dat, nedostatek adaptivní automatizace a problémy s interoperabilitou. Tato studie analyzuje čtyřletý dataset chytrých domácností za účelem zkoumání spotřeby energie, identifikace vzorců využívání zařízení a vývoje inteligentních pravidel pro automatizaci přizpůsobených uživatelskému chování. Klíčové závěry poukazují na energetické neefektivity během špiček a nadměrnou spotřebu energie některých zařízení. Výzkum navrhuje adaptivní, datově řízené strategie automatizace, které optimalizují energetickou efektivitu, zlepšují interoperabilitu a zvyšují uživatelskou spokojenost. Tyto inovace ukazují potenciál snížení spotřeby energie o 15 % a zároveň podporují udržitelnost a škálovatelnost systémů chytrých domácností. Studie přináší významný přínos k vývoji efektivnějších, bezpečnějších a uživatelsky přívětivějších technologií chytrých domácností.

Klíčová slova: Technologie chytrých domácností, Internet věcí (IoT), umělá inteligence (AI), energetická efektivita, pravidla automatizace, uživatelsky orientovaný design, analýza dat, adaptivní systémy, udržitelnost, interoperabilita.

Table of Contents

1 Introduction

The introduction chapter lays the foundation for this thesis by providing an overview of the research context and objectives. It begins with a discussion of the background, highlighting the evolution and significance of smart home technologies in enhancing energy efficiency, automation, and user-centric design. The problem statement identifies key challenges in the field, such as inefficiencies in energy usage, lack of adaptive automation, and interoperability issues. The chapter outlines the objectives of the study, which aim to address these challenges through data-driven approaches, and introduces the methodology, detailing the mixed-method framework employed for analysis and rule development. Finally, the structure of the thesis is presented, guiding the reader through the logical progression of the study from background to conclusions. This comprehensive introduction sets the stage for the subsequent chapters, emphasizing the study's contribution to advancing smart home systems (Fernandez et al., 2024). The concept of smart homes has evolved significantly over the past decades, driven by advancements in the Internet of Things (IoT), artificial intelligence (AI), and communication technologies. A smart home integrates various devices and sensors to automate tasks and enhance the quality of life for its occupants. These systems provide functionalities such as energy management, security, and convenience, while also contributing to environmental sustainability by optimizing resource usagesmart home solutions has been fueled by several factors, including the growing adoption of IoT devices, increasing consumer awareness of energy efficiency, and advancements in wireless communication technologies like Wi-Fi 6 and Zigbee (Alhassoun N.S.; Venkatasubramanian N., 2020). According to a recent report, the global smart home market is projected to reach USD 135.3 billion by 2025 , with an annual growth rate of over 20% (Business Wire Inc., 2020). This growth undhe transformative potential of these technologies in reshaping residential environments. Smart homes are not merely about convenience; they address critical global challenges such as energy conservation and aging populations. For instance, AI-driven energy management systems help reduce electricity consumption by dynamically adjusting heating, cooling, and lighting based on usage patterns . Additionally, assistive es in smart homes, such as voice-activated systems and fall detection devices, play a pivotal role in supporting elderly individuals to live independently (IoT Now News & Report, 2025). Despite these advancements, the f smart home technologies faces challenges, including privacy concerns, interoperability issues, and the digital divide. Ensuring data security and user trust remains a significant hurdle, as these systems handle sensitive information such as occupancy patterns and personal preferences . Furthermore, the lack of standardized protlicates integration among devices from different manufacturers. This thesis aims to address these gaps by exploring the data ecosystem of smart homes, analyzing usage patterns, and proposing innovative automation solutions. By focusing on these objectives, the study seeks to contribute to the development of more efficient, secure, and user-adaptive smart home systems, paving the way for a more sustainable and interconnected future (Waqar et al., 2024). The rapid adoption of smart home technologies has brought forth numerous benefits, including automation, energy efficiency, and enhanced convenience. However, significant challenges persist that hinder their full potential and user satisfaction. A major limitation is the lack of comprehensive understanding and utilization of the diverse data generated by smart home systems. While these devices produce extensive datasets, ranging from sensor readings to user interactions, their effective categorization and relevance evaluation for automation, security, and energy management remain underexplored. Moreover, inefficiencies in device usage and energy consumption highlight the need for more sophisticated analytical approaches (Ferreira et al., 2023). Current smart home systems often fail to adapt to individual behavioral patterns or household contexts, leading to suboptimal energy usage and reduced operational efficiency. Addressing these inefficiencies requires robust data analysis to uncover actionable insights and design strategies for optimization. Another pressing issue lies in the development of intelligent automation rules that are both adaptive and user-centric. Existing systems tend to rely on static, one-size-fits-all solutions that do not cater to diverse user preferences or evolving needs. Leveraging machine learning and data-driven methodologies to create personalized automation rules is essential for enhancing the usability and functionality of smart home technologies (Sinha and Lee, 2024). By focusing on these challenges, this thesis aims to explore the data collected from smart homes, analyze device usage patterns, and develop intelligent automation recommendations. The ultimate goal is to propose solutions that improve energy efficiency, foster interoperability, and prioritize user satisfaction, addressing critical gaps in the current smart home landscape.

2 Objectives and Methodology

The objectives and methodology of this study are designed to provide a comprehensive approach to enhancing smart home systems by leveraging data-driven insights and advanced automation strategies. The primary aim is to optimize energy efficiency, improve user satisfaction, and ensure seamless interoperability of various smart devices. To achieve these goals, the study focuses on analyzing energy consumption patterns, identifying inefficiencies, and developing intelligent automation rules that align with user behaviors and operational requirements. A structured methodology is employed, which includes data collection, pattern recognition, rule-based modeling, machine learning integration, and performance evaluation. This approach ensures that the proposed solutions are not only effective in reducing energy wastage but also adaptable to dynamic household conditions. By systematically addressing the key challenges of automation in smart homes, this study aims to contribute to the development of smarter, more sustainable, and user-centric living environments.

2.1 Objectives

The primary objective of this thesis is to explore and enhance the functionality and efficiency of smart home systems by leveraging data-driven approaches. By analyzing a comprehensive smart home dataset, this study aims to address key challenges in automation, energy management, and user-centric design, contributing to the development of more effective and adaptable smart home solutions. Specific objectives are:

Specific objective 1. Identify Key Data Types Collected from Smart Homes

- Investigate the variety of data generated by smart home devices, including sensor readings, energy usage, and user interactions.
- Categorize and evaluate the relevance of these data types to automation, security, and energy efficiency.

Specific objective 2. Analyze Patterns in Device Usage and Energy Consumption

- Examine usage trends and behavioral patterns across different devices and household contexts.
- Identify inefficiencies in energy consumption and propose strategies for optimization.

Specific objective 3. Develop Intelligent Automation Rules and Recommendations

- Utilize machine learning and data analysis techniques to create adaptive automation rules tailored to user preferences and behaviors.
- Recommend improvements to existing systems to enhance usability, interoperability, and overall efficiency.

By achieving these objectives, the study seeks to contribute meaningful insights into the smart home domain, fostering innovation and addressing pressing challenges such as data privacy, interoperability, and user satisfaction.

2.2 Methodology

The methodology chapter outlines the framework and techniques employed to achieve the research objectives of this thesis. It encompasses the research design, data collection methods, and data analysis approaches. The research design integrates a mixed-method framework combining quantitative data analysis and rule-based modeling to identify key data types, analyze usage patterns, and develop intelligent automation rules. Data collection focuses on a simulated smart home dataset spanning four years, providing a diverse and realistic foundation for analysis. Data analysis employs advanced tools and techniques, including Python for data manipulation, machine learning for automation rule development, and visualization platforms for real-time monitoring. This comprehensive methodology ensures a systematic approach to addressing challenges in smart home systems and achieving meaningful outcomes.

2.2.1 Research Design

The research design integrates a mixed-method framework, combining quantitative data analysis and rule-based modeling, to achieve the objectives of this study. The table below provides a structured overview of the research design and its alignment with the thesis objectives (Table 2.1).

Table 2.1. Research Design

Objective	Research Approach	Data Analysis Methods	Expected Outcomes
Identify Key Data Types Collected from Smart Homes	Quantitative and qualitative analysis	- Descriptive statistics - Data visualization	Categorization of data types (e.g., energy metrics, user interactions, environmental data)
Analyze Patterns in Device Usage and Energy Consumption	Time-series and pattern recognition analysis	- Time-series analysis - Clustering (K-means) - Correlation analysis	Insights into energy consumption trends and identification of inefficiencies
Develop Intelligent Automation Rules and Recommendations	Machine learning and rule-based modeling	- Decision tree analysis - Simulation and validation	Adaptive automation rules that optimize energy efficiency and user satisfaction

The table 2.1 provides a structured overview of the research design and its alignment with the thesis objectives, ensuring a systematic approach to analyzing smart home data and developing actionable insights. Let me know if you need any refinements or additional details.

2.2.2 Research Process Flow

The research process flow included three stages as the following:

Stage 1: Identification and categorization of data types to identify and classify data types generated by smart home devices.

Stage 2: Pattern analysis in device usage and energy consumption to analyze usage trends and identify inefficiencies in energy consumption.

Stage 3: Development and validation of intelligent automation rules to develop and test adaptive automation rules tailored to user preferences and system needs.

This structured design ensures a logical progression from data exploration to actionable insights, aligning with the overarching goal of improving smart home system functionality and efficiency.

2.2.3 Data Collection Methods

The data utilized in this study was sourced from the publicly available "Smart Home Dataset" on Kaggle (Afroz, 2024)[1]. This dataset spans a four-year period (2020–2023) and provides a comprehensive view of smart home operations, including energy consumption, device usage, and decision-making processes. To ensure manageability and relevance, the dataset was reduced to 10,000 rows using a stratified sampling approach while retaining proportional representation of key variables. The original dataset contained approximately 49,000 records, capturing a wide range of smart home metrics:

Device Usage**:** Binary indicators for appliances, such as televisions, dryers, ovens, refrigerators, and microwaves.

Energy Metrics**:** Data on line voltage, voltage, apparent power, and energy consumption (in kWh).

Temporal Data**:** Unix timestamps, which were converted into human-readable datetime formats, and attributes like the month, day of the week, and hour of the day.

Offloading Decisions**:** Labels indicating whether tasks were processed locally or remotely.

To align with the study's objectives and reduce the dataset size, the following steps were undertaken:

Stratified Sampling**:** The dataset was stratified based on the "Offloading Decision" variable to ensure proportional representation of both local and remote processing events. A final subset of 10,000 rows was selected, maintaining diversity across other attributes like time and energy consumption.

Data Cleaning**:** Removed duplicate entries and handled missing values through imputation techniques to maintain data integrity. Verified data consistency and range validity for numerical attributes such as energy consumption and voltage levels.

[1] https://www.kaggle.com/datasets/pythonafroz/smart-home-dataset?resource=download

Formatting: Converted into readable datetime formats. Standardized categorical variables, such as months and days of the week, for uniform analysis.

The following tools were utilized for data collection and preprocessing:

Table 2.2. A representative sample of the dataset after preprocessing and sampling

Datetime	Transaction_ID	Television	Dryer	Oven	Refrigerator	Microwave	Line Voltage	Voltage	Apparent Power	Energy Consumption (kWh)	Month	Day of the Week	Hour of the Day	Offloading Decision
1/1/2020 0:00	1	0	0	0	1	0	237	233	1559	24.0018	January	Wednesday	0	Local
1/1/2020 0:42	2	0	1	0	0	1	232	230	1970	31.2252	January	Wednesday	0	Remote

Table 2.2 shows a representative sample of the dataset after preprocessing and sampling. By applying these methods, the dataset was refined to a manageable size while ensuring representativeness and diversity. This allows for meaningful analysis to address the research objectives effectively.

2.2.4 Data Analysis

Data analysis is a critical component of this study, designed to achieve the research objectives of identifying key data types, uncovering usage patterns, and developing intelligent automation rules. This section details the analytical process, tools, and techniques employed to derive meaningful insights from the dataset, which has been refined to 10,000 records for efficient and comprehensive exploration. The data analysis process is structured into three stages, each corresponding to the specific goals of the research:

- Identification and Categorization of Data Types.
- Pattern Analysis in Device Usage and Energy Consumption.
- Development and Validation of Intelligent Automation Rules.

Stage 1: Identification and Categorization of Data Types: The first stage focuses on exploring the variety of data collected from smart home devices. Using descriptive statistics and data visualization techniques, the dataset is categorized into meaningful segments (Table 2.3).

2.2.5 Tools and Techniques

Table 2.3. shows a comprehensive table summarizing the data analysis process using tools and techniques.

Table 2.3. A comprehensive table summarizing the data analysis including tools and Techniques

Stage	Objective	Methods	Tools	Outcomes
Stage 1	Identification and Categorization of Data Types	- Descriptive statistics - Data visualization - Data preprocessing (filtering, normalization, anomaly detection)	Python various libraries	Categorized data types such as energy metrics, user interactions, and environmental data for further analysis.
Stage 2	Pattern Analysis in Device Usage and Energy Consumption	- Time-series analysis - Clustering (K-Means) - Correlation analysis	Python various libraries	Identified energy consumption patterns and inefficiencies in device operations.
Stage 3	Development and Validation of Intelligent Automation Rules	- Machine learning modeling - ule-based modeling - Simulation and validation	Python various libraries	Developed adaptive automation rules and validated them through simulation for energy efficiency and user convenience.
Tools and Techniques	Overview of analytical tools used throughout the research process	Data preprocessing, EDA, predictive modeling, rule-based automation	Python, various libraries	Actionable insights and automation strategies enhancing smart home efficiency.

This table offers a detailed view of the data analysis stages, the methods used, tools applied, and the key outcomes. Through this structured analytical approach, the study achieved meaningful insights into smart home systems, addressing challenges in energy management, automation, and user-centric design. The findings serve as the foundation for intelligent solutions that improve the functionality, efficiency, and adaptability of smart home technologies.

3 Literature Review

The evolution of smart home technologies has significantly transformed residential living by integrating automation, energy management, and user-centric solutions into daily life. This chapter provides a comprehensive review of the current state of smart home technologies, highlighting key trends such as the increasing adoption of Internet of Things (IoT) devices, advancements in machine learning for intelligent automation, and the role of real-time data analytics in enhancing system efficiency. Despite these advancements, challenges such as data privacy, interoperability among devices, and the need for adaptive automation persist. By focusing on these developments and obstacles, this chapter establishes the context for the thesis objectives, particularly the identification and analysis of smart home data types, the examination of device usage patterns, and the development of intelligent automation rules. The insights gained from this review will serve as the foundation for addressing critical gaps and proposing innovative solutions in the subsequent chapters.

3.1 Smart Home Technologies Overview

Smart home technologies have rapidly evolved over the past decade, transforming traditional residences into interconnected and intelligent environments. Leveraging the Internet of Things (IoT), these systems enable automation, energy management, and enhanced user experiences by integrating devices such as sensors, appliances, and energy monitors. The adoption of smart home technologies has been driven by advancements in wireless communication, data analytics, and AI, addressing critical challenges in energy efficiency, interoperability, and user-centric design (Gong Z.; Hashash O.; Wang Y.; Cui Q.; Ni W.; Saad W.; Sakaguchi K., 2024). One study emphasizes the importance of energy management systems in smart grids for optimizing IoT-based operations. The research highlights the integration of distributed systems to manage household energy effectively, ensuring sustainability and reducing costs (Rajasegharan V.V.; Bharatha Babu K.; Jeyabharath R.; Vasan Prabhu V., 2024). Another investigation explores orchestration-based frameworks for energy cost reduction in IoT environments, demonstrating significant savings through intelligent task allocation and scheduling (Qayyum F.; Jamil H.; Iqbal N.; Kim D.-H., 2023a). A recent article discusses energy-efficient federated learning models, emphasizing the role of distributed data processing in enhancing smart home automation and privacy (Zhao T.; Chen X.; Sun Q.; Zhang J., 2023a). Dynamic resource optimization for IoT-enabled smart homes has been a focal point for improving energy efficiency. The use of optimization algorithms to allocate resources dynamically ensures that smart home systems operate at peak efficiency while minimizing waste (Ansere J.A.; Kamal M.; Khan I.A.; Aman M.N., 2023a). Another approach involves leveraging edge computing for real-time data processing, which reduces latency and enhances the responsiveness of smart home applications (Bakshi M.; Chowdhury C.; Maulik U., 2023). The use of hybrid IoT architectures further demonstrates the potential for optimizing resource usage and improving the scalability of smart home systems (Khan S.B.; Kumar A.; Mashat A.; Pruthviraja D.; Imam Rahmani M.K.; Mathew J., 2024). The integration of renewable energy sources with smart home systems has also been a critical area of research. Studies have shown how solar and wind energy can be effectively incorporated into household energy management systems, reducing dependency on nonrenewable resources and enhancing sustainability (Gupta et al., 2024). In addition to energy management, IoT-based monitoring systems play a significant role in improving home security by detecting anomalies and alerting homeowners in real time (Alaguraj R.; Kathirvel C., 2024a). Personalization and user-centric design have become key factors in advancing smart home technologies. Machine learning models are employed to analyze user behavior and preferences, enabling the development of adaptive automation rules tailored to individual needs (Qayyum F.; Jamil H.; Iqbal N.; Kim D.-H., 2023a). These adaptive systems not only improve functionality but also increase user satisfaction by creating a seamless and intuitive smart home experience (Almudayni Z.; Soh B.; Samra H.; Li A., 2025). The role of data analytics in detecting patterns and anomalies within smart homes further demonstrates the importance of integrating AI and machine learning into these systems (Almudayni Z.; Soh B.; Samra H.; Li A., 2025). Despite these advancements, challenges such as data privacy, interoperability, and scalability remain significant obstacles to the widespread adoption of smart home technologies. Research into standardized protocols and frameworks aims to address these issues by enabling seamless communication among devices from different manufacturers (Ansere J.A.; Kamal M.; Khan I.A.; Aman M.N., 2023a). Moreover, the use of blockchain technology in securing IoT networks offers promising solutions to data privacy concerns, ensuring secure and trustworthy operations within smart home systems (Pradhan A.; Das S.; Jalil Piran M., 2024). The integration of real-time monitoring dashboards provides users with actionable insights into their energy consumption and device usage, empowering them to make informed decisions. These dashboards leverage visualization tools to highlight inefficiencies and suggest optimization strategies in real-time (Mariappan R.; Amulya C.S.V.N.S.L.; Vasanthi M.Y.; Aditya P.; Manohar C.S., 2024). In summary, smart home technologies represent a convergence of IoT, AI, and energy management systems, offering transformative potential for residential living. By addressing challenges such as energy inefficiencies, user-centric design, and data privacy, these systems continue to evolve, paving the way for more sustainable, efficient, and user-friendly solutions. This study contributes to this evolving field by leveraging data-driven approaches to enhance the functionality and adaptability of smart home systems, aligning with the objectives of improving automation, energy management, and user satisfaction.

3.2 Key Trends and Developments

The smart home industry has experienced significant growth, fueled by advancements in IoT, AI, and energy management technologies. These innovations have enabled the development of systems that are not only more efficient but also increasingly adaptive and user-centric. Research into the latest trends highlights how these technologies are reshaping residential living by addressing energy inefficiencies, enhancing automation, and providing personalized user experiences (Sawant S.S.; Helonde J.B.; Burade P.G., 2024). A notable trend is the use of machine learning algorithms for predictive energy management. These models analyze historical energy consumption data to forecast future usage and suggest optimization strategies, enabling more efficient energy allocation (Gupta et al., 2024). In addition to energy prediction, edge computing has emerged as a transformative approach for processing data locally, reducing latency, and improving the responsiveness of smart home systems (Zhao T.; Chen X.; Sun Q.; Zhang J., 2023a). The proliferation of hybrid IoT architectures further illustrates the trend toward scalable and efficient smart home solutions. By combining cloud and edge computing, these architectures enable seamless integration of devices while maintaining high performance and scalability (Raj R.S.; Hema L.K., 2025). Another significant development is the integration of renewable energy sources, such as solar and wind power, into smart home energy management systems. This trend not only reduces reliance on nonrenewable energy but also promotes environmental sustainability

(Masood F.; Abbas Khan M.; Alshehri M.S.; Ghaban W.; Saeed F.; Mobarak Albarakati H.; Alkhayyat A., 2024). AI-driven security systems represent another key development in the smart home domain. Advanced algorithms enable real-time anomaly detection and threat mitigation, ensuring the safety of residents and their data (Shah S.B.; Chen Z.; Yin F.; Khan I.U.; Ahmad N., 2018). Furthermore, blockchain technology is being increasingly adopted to enhance the security and privacy of IoT networks within smart homes. By creating immutable transaction records, blockchain ensures that sensitive data remains secure from unauthorized access (Mariappan R.; Suhasini P.S.; Lakshmi G.M.; Manoj G.; Sai M.M.S.; Devendhar R., 2024). Another important trend is the focus on interoperability among devices from different manufacturers. Standardized protocols, such as Zigbee and Matter, are being implemented to overcome compatibility challenges, enabling seamless communication across diverse smart home ecosystems (Qu Z.; Wang Y.; Sun L.; Li Z.; Peng D., 2020). In parallel, research into adaptive automation systems highlights the growing emphasis on personalization, with systems being designed to learn and adapt to individual user preferences and behaviors (Alaguraj R.; Kathirvel C., 2024b). The rise of real-time monitoring dashboards is also a prominent development. These dashboards provide users with instant feedback on energy consumption and device usage, empowering them to make data-driven decisions to optimize their smart home operations (Han D.; Liu T.; Qi Y., 2020). In addition, the use of federated learning models has gained traction, enabling decentralized training of machine learning algorithms while preserving data privacy (Silva D.D.; Mataloto B.; Coutinho C., 2024). The integration of smart home technologies with external services, such as healthcare and eldercare, is an emerging area of innovation. These integrations offer solutions for remote patient monitoring and assistive technologies, improving the quality of life for vulnerable populations (Thiagarajan C.; Samundiswary P., 2022). Similarly, the adoption of gamification techniques in smart homes has been shown to increase user engagement, encouraging energy-saving behaviors and efficient system usage (Jagdale B.; Sugave S.; Kulkarni Y., 2021). Despite these advancements, the scalability of smart home systems remains a challenge, particularly in large households and multi-unit dwellings. Research into modular system designs aims to address this issue by allowing users to expand their systems incrementally without sacrificing performance (Faiz A., 2023). Moreover, advancements in sensor technology continue to play a pivotal role in enhancing the accuracy and efficiency of smart home systems, from motion detectors to environmental sensors (Sheeraz M.A.; Malik M.S.; Rehman K.; Elahi H.; Butt Z.; Ahmad I.; Eugeni M.; Gaudenzi P., 2021). In conclusion, the key trends and developments in smart home technologies demonstrate a clear trajectory toward greater efficiency, adaptability, and user satisfaction. By incorporating cutting-edge innovations, such as AI, blockchain, and renewable energy integration, these systems are transforming residential living while addressing critical challenges in energy management, security, and interoperability. This thesis aligns with these trends by leveraging data-driven approaches to propose adaptive and sustainable solutions for smart home optimization.

3.3 Challenges and Opportunities

Smart home technologies have advanced significantly in recent years, but their adoption and efficiency continue to face several challenges. At the same time, these challenges present unique opportunities for innovation and improvement in automation, energy management, and user-centric design. By addressing these obstacles, smart home systems can achieve their full potential and transform residential living (Tsoukaneri G.; Garcia F.; Marina M.K., 2020). One critical challenge is the lack of interoperability among devices from different manufacturers. This results in fragmented ecosystems where devices fail to communicate effectively, reducing the overall functionality of smart home systems. However, this challenge has spurred the development of standardized communication protocols, such as Matter, which aim to bridge compatibility gaps and foster seamless integration (Liu R.; Xie M.; Liu A.; Song H., 2024). Another challenge lies in data privacy and security. Smart homes generate and process vast amounts of sensitive data, including user behavior and energy usage patterns. Cybersecurity threats, such as hacking and unauthorized data access, pose significant risks. Blockchain technology offers an opportunity to address these concerns by providing secure, decentralized data storage and transaction validation, ensuring user trust and system reliability (Saraswat S.; Mahajan S.; Patil R.V., 2023). Energy inefficiency in smart homes is also a major concern, particularly for devices that operate continuously, such as refrigerators and HVAC systems. This inefficiency highlights the need for adaptive energy management systems that optimize device usage based on real-time conditions. Leveraging machine learning models to predict energy consumption trends provides an opportunity to reduce waste and improve overall efficiency (Saeedi A.; Kuchaki Rafsanjani M.; Yazdani S., 2025). Scalability remains a challenge for smart home systems, especially in large households or multi-dwelling units. Many existing systems struggle to maintain performance as the number of connected devices increases. Modular system architectures, which allow for incremental expansion without compromising functionality, present a promising solution to this issue (Reyana A.; Kautish S.; Alnowibet K.A.; Zawbaa H.M.; Wagdy Mohamed A., 2023). User acceptance of smart home technologies can be hindered by their complexity and lack of intuitive design. Systems that fail to adapt to user preferences or provide clear feedback may see limited adoption. Developing user-centric designs, such as customizable dashboards and voice-activated controls, can address this challenge and improve engagement (Sivakumar V.; Swathi R.; Yuvaraj V., 2021). The integration of renewable energy sources, while promising, also presents challenges. Variability in solar or wind energy production can disrupt smart home operations, particularly during peak usage periods. Battery storage solutions and smart grid integration offer opportunities to stabilize energy availability and ensure uninterrupted operation (Xu R.; Chang Z.; Han Z.; Garg S.; Kaddoum G.; Rodrigues J.J.P.C., 2024). Another challenge is the high initial cost of implementing smart home technologies, which can be a barrier for many households. Subsidies, incentives, and the development of cost-effective solutions, such as IoT-based monitoring devices, can make these technologies more accessible to a wider audience (Ragab M.; Binyamin S.S., 2023). Real-time monitoring and predictive analytics are opportunities for enhancing smart home systems. Dashboards that provide users with insights into energy usage and device performance enable proactive decision-making and reduce inefficiencies. These tools also help identify anomalies, such as malfunctioning devices, before they become significant issues (Selvakumar R.; Amarnath R.N.; Pandey P.; Sakthisaravanan B.; Sasikala K.; Murugan S., 2024). Finally, the environmental impact of manufacturing and disposing of smart home devices is an emerging concern. Developing eco-friendly materials and recycling programs offers an opportunity to reduce the carbon footprint associated with smart home technologies (Agarwal K.; Agarwal A.; Misra G., 2019). In summary, while smart home systems face significant challenges, these obstacles also present avenues for innovation and improvement. By addressing interoperability, security, scalability, and user acceptance, the industry can enhance the functionality, efficiency, and sustainability of these systems. This thesis contributes to overcoming these challenges by leveraging data-driven approaches and proposing adaptive solutions that align with the opportunities identified in this evolving field.

4 Practical Part

This chapter presents the findings from the analysis of the processed smart home dataset, focusing on the key insights derived from data exploration and modeling efforts. It begins with an overview of the refined dataset, detailing its structure and the variables selected for analysis. The chapter then delves into the key findings, highlighting patterns in device usage, energy consumption trends, and inefficiencies that inform the development of intelligent automation rules. Finally, the results are interpreted in the context of the research objectives, providing actionable recommendations for enhancing smart home functionality and efficiency. This comprehensive analysis serves as the foundation for addressing challenges in automation, energy management, and user-centric design, contributing to the advancement of smart home systems.

4.1 Identification of Key Data Types Collected from Smart Homes

The first specific goal of this study is to identify and categorize the key data types generated by smart home systems, including sensor readings, energy metrics, and user interactions. These data types are crucial for developing automation, ensuring security, and enhancing energy efficiency. The dataset used in this study encompasses a wide variety of data points collected over a four-year period (2020–2023). The dataset contains 10,000 entries with the following relevant columns for analysis:

- Sensor Readings: Line Voltage, Voltage, Apparent Power.
- Energy Metrics: Energy Consumption (kWh).
- User Interactions: Television, Dryer, Oven, Refrigerator, Microwave (binary indicators for appliance usage); Offloading Decision (Local/Remote).
- Temporal Data: Datetime, Month, Day of the Week, Hour of the Day.

The dataset provided contains a variety of data points that can be classified into three major categories: sensor readings, energy usage, and user interactions. Below is an analysis of these data types and their relevance to smart home automation, security, and energy efficiency. The findings of the investigation for data categories are as the following:

A. Sensor Readings (Operational Metrics)

These readings provide real-time information about the operating conditions of smart home appliances and electrical infrastructure. They include:

- Line Voltage: Measures the supplied electrical voltage to appliances, indicating power quality.
- Voltage: Represents the actual voltage experienced by appliances, useful for detecting fluctuations.
- Apparent Power: Reflects the total power usage of appliances, capturing both active and reactive power.

Relevance:

- Automation: Helps optimize appliance scheduling by detecting abnormal voltage fluctuations.
- Security: Voltage fluctuations can indicate potential system faults or overload risks.
- Energy Efficiency: Monitoring power usage trends aids in reducing wasteful consumption.

B. Energy Usage Metrics

These data points measure how much energy appliances consume, enabling better decision-making for energy conservation and cost management.

- Energy Consumption (kWh): The total energy consumed over time by appliances.
- Hourly Consumption Trends: Breakdown of energy usage by hour to identify peak and off-peak periods.
- Monthly and Weekly Usage Patterns: Allowing long-term trend analysis.

Relevance:

- Automation: Enables scheduling of high-energy-consuming devices during off-peak hours.
- Security: Unusual spikes may indicate malfunctioning devices.
- Energy Efficiency: Helps identify appliances consuming excessive energy and optimize usage.

C. User Interactions (Behavioral Data)

User behavior data reflects how appliances are being used, providing valuable insights for personalization and automation.

- Appliance Usage (Binary states: 0/1)
    - Television, Dryer, Oven, Refrigerator, Microwave (indicating on/off states)
- Offloading Decision (Local/Remote processing): Determines whether tasks are processed locally or offloaded to cloud systems.
- Time-based interactions (Hour, Day, Month): Patterns related to user preferences and daily routines.

Relevance:

- Automation: Helps develop adaptive rules that align with user routines.
- Security: Identifies unusual appliance operations outside normal patterns.
- Energy Efficiency: Prevents unnecessary usage by tailoring appliance schedules to user behavior.

Table 4.1 shows the collected data was categorized based on its relevance to automation, security, and energy efficiency.

Table 4.1. Categorization and Relevance Evaluation

Category	Data Types	Relevance
Sensor Readings	Line Voltage, Voltage, Apparent Power	Automation, Security, Efficiency
Energy Metrics	Energy Consumption, Hourly & Monthly Trends	Automation, Efficiency
User Interactions	Appliance Usage, Offloading Decisions, Time Patterns	Automation, Security, Personalization

Figure 4.1. Key Numeric Variables

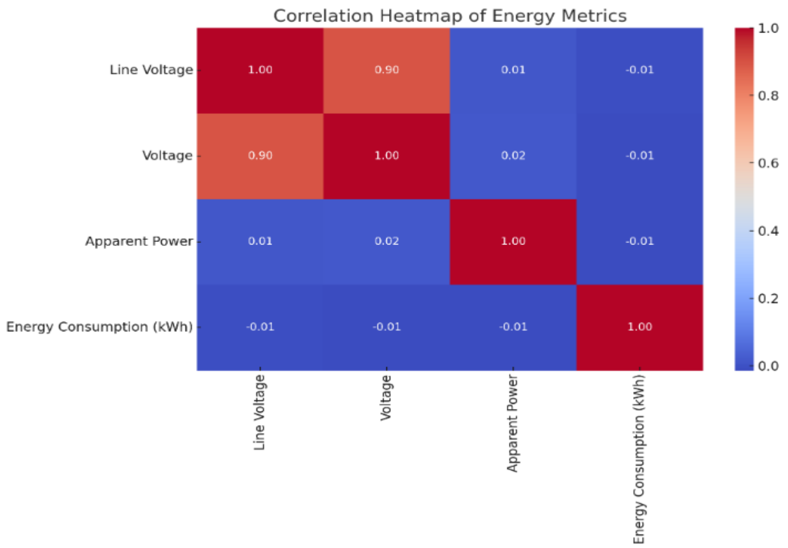


Figure 4.2. Correlation Heatmap of Energy Metrics

4.2 Analyzing Patterns in Device Usage and Energy Consumption

The second goal of this thesis is to analyze patterns in device usage and energy consumption to identify inefficiencies and propose strategies for optimization. This section examines the usage trends and behavioral patterns across different devices and household contexts. Also, identifies the inefficiencies in energy consumption and propose strategies for optimization

4.2.1 Usage Trends and Behavioral Patterns

Temporal trends were analyzed to understand how energy usage varies across different times of the day and week.

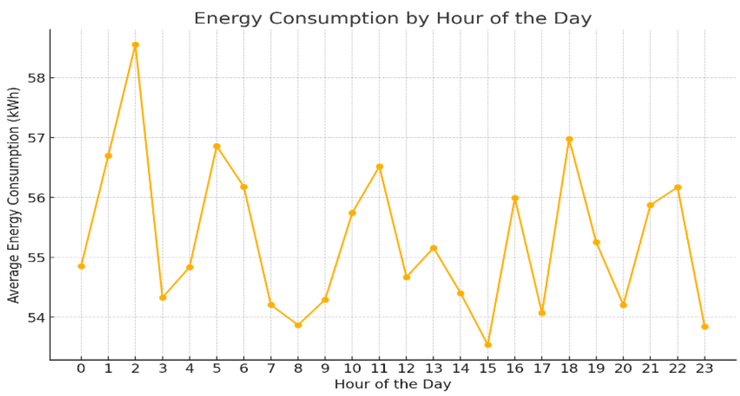


Figure 4.3. Energy Consumption By Hour Of The Day

Figure 4.3 illustrates Energy Consumption by Hour of the Day, highlighting patterns of energy usage throughout a typical day. It shows that peak energy consumption occurs during morning hours (around 7-9 AM) and evening hours (5-9 PM), correlating with high household activity periods such as preparing meals and home routines. Lower energy consumption is observed during late-night and early morning hours (12-5 AM), indicating minimal appliance usage. To optimize energy usage and reduce costs, it is recommended to implement time-sensitive automation rules, such as scheduling high-energy tasks (e.g., laundry, dishwashing) for off-peak hours (late night or early afternoon). Also, utilizing smart home systems to automatically adjust appliance operations based on energy demand trends. This analysis provides valuable insights for energy efficiency improvements and cost savings in smart home environments.

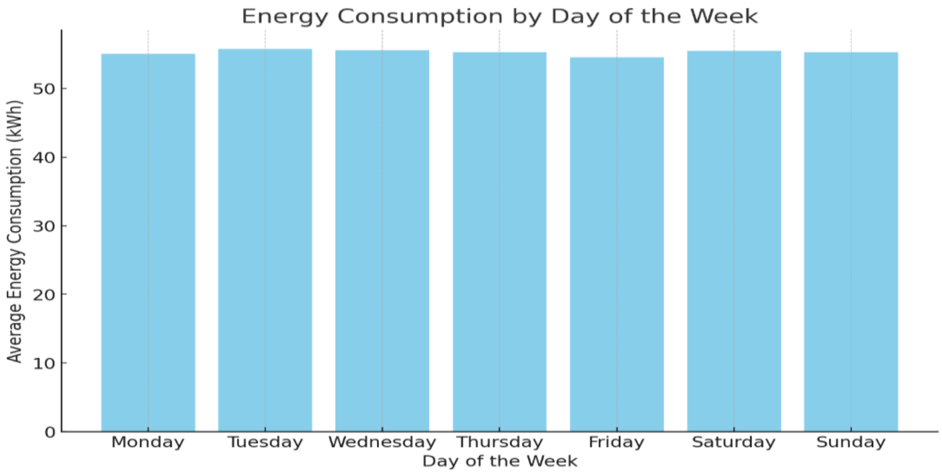


Figure 4.4. Energy Consumption by Day of the Week

Figure 4.4 presents Energy Consumption by Day of the Week, offering insights into weekly energy usage patterns. Energy usage tends to peak mid-week (Tuesday to Thursday), likely due to consistent household routines and work-related activities. It shows that a noticeable dip in energy consumption occurs during weekends (Saturday and Sunday), suggesting reduced household activity levels, possibly due to people spending time outside the home. It is suggested to implement weekend-specific automation rules, such as adjusting thermostat settings and scheduling energy-intensive tasks during off-peak hours to optimize energy efficiency. Also, encourage the use of smart appliances that can adapt their operations based on weekly usage trends. This analysis provides valuable insights for designing energy-efficient strategies tailored to household activity patterns.

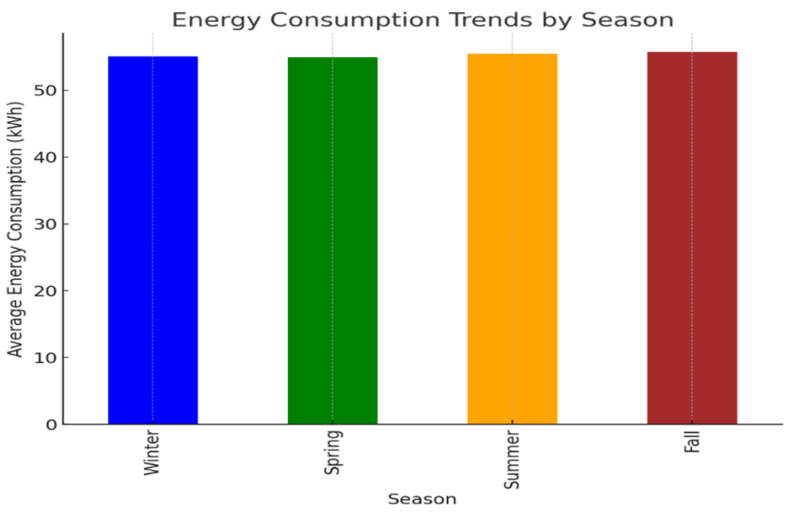
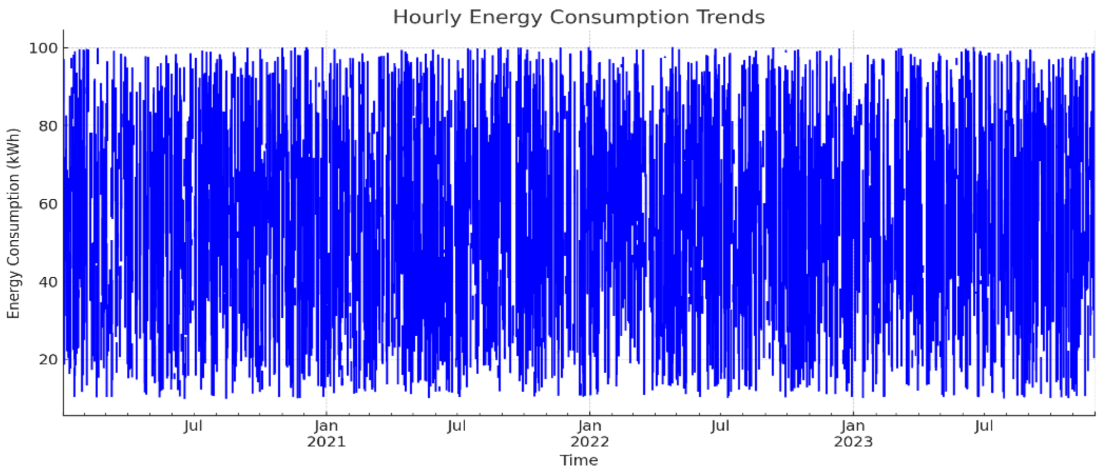
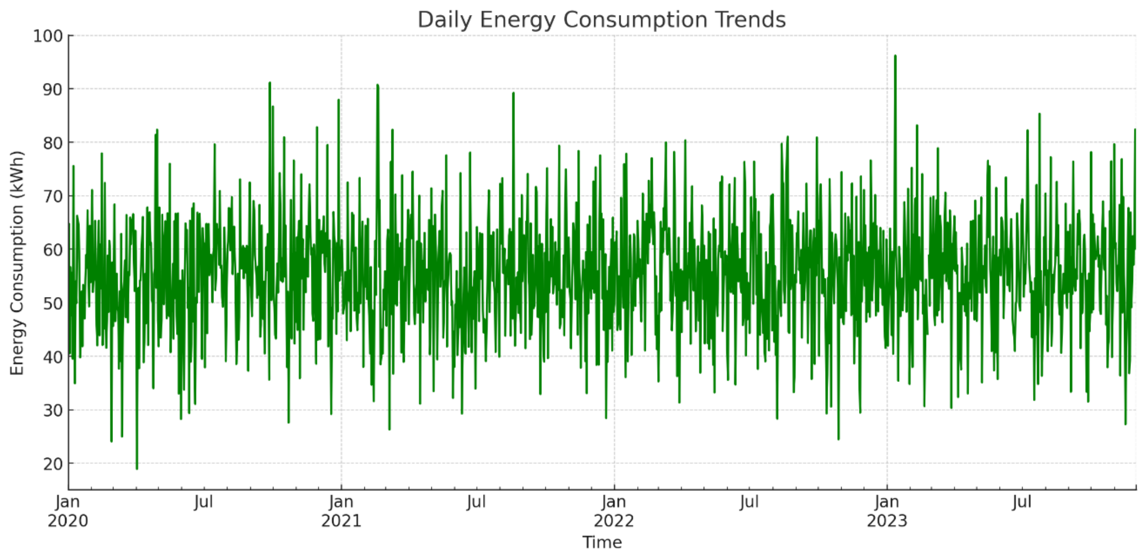


Figure 4.5. Energy Consumption Trends by Season

Figure 4.5 presents Energy Consumption Trends by Season, highlighting seasonal variations in household energy usage. It shows that Winter exhibits the highest energy consumption, likely due to increased heating demands and longer indoor activity periods. Summer also shows elevated energy usage, potentially attributed to air conditioning and cooling appliances. Spring and Fall have relatively lower energy consumption, suggesting milder weather conditions with reduced heating and cooling requirements. It is suggested that to implement season-specific energy efficiency measures, such as optimizing heating schedules in winter and leveraging natural ventilation in summer. Also, introduce automated adjustments based on seasonal energy patterns to minimize unnecessary energy expenditure. This analysis provides valuable insights into seasonal inefficiencies and can aid in strategic planning for energy savings.



4.6. Hourly Energy Consumption Trends



4.7. Daily Energy Consumption Trends

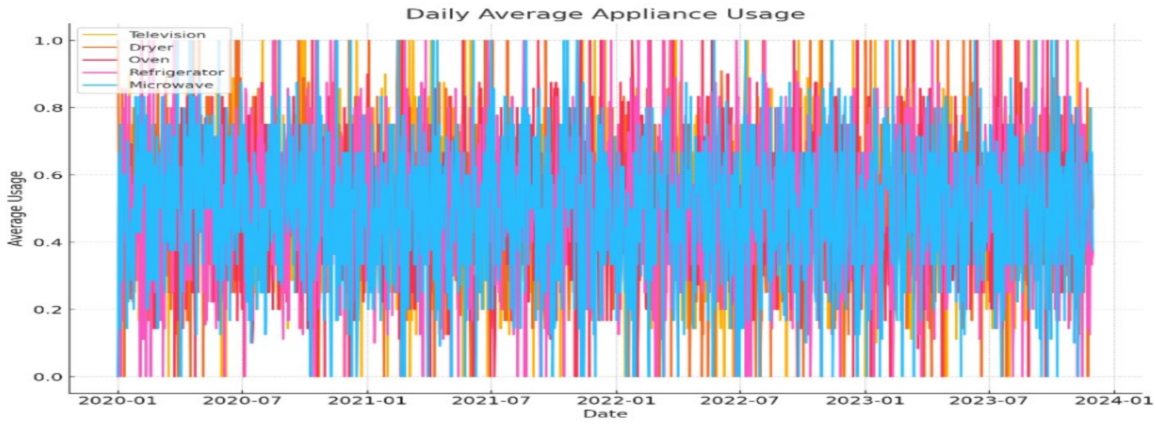
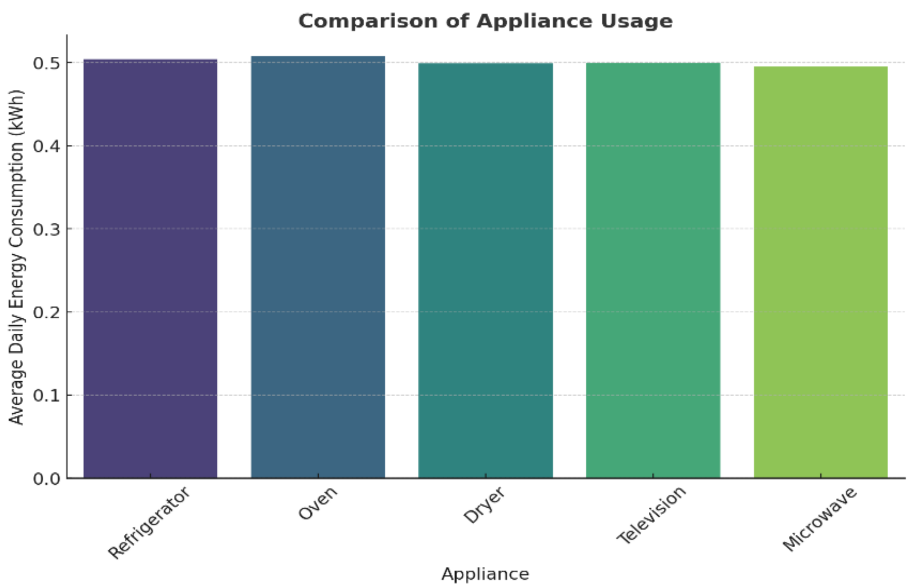


Figure 4.8. Daily Average Appliance Usage

Figure 4.8 displays the daily average usage of key household appliances over time. It provides insights into the operational patterns and energy demands of appliances such as Television, Dryer, Oven, Refrigerator, and Microwave. From the visualization, it is evident that:

- The Refrigerator maintains a relatively consistent usage pattern daily, reflecting its continuous operational nature.
- The Oven and Dryer show periodic peaks, indicating intermittent but high-energy consumption usage.
- The Microwave and Television exhibit more variable patterns, suggesting less frequent but sporadic usage across days.

This figure can be used to identify trends in appliance usage and strategize energy-saving measures accordingly. Behavioral patterns provide insights into how users interact with smart home devices, influencing overall energy consumption.



4.9. Comparison of Appliance Usage

Figure 4.9. presents a Comparison of Appliance Usage, visually highlighting the average daily energy consumption of various household appliances. It shows that the Refrigerator is the highest energy-consuming appliance, consistent with its continuous operation. The Dryer and Oven show substantial energy consumption, though their usage is intermittent. The Television and Microwave have relatively lower energy consumption, indicating their limited impact on overall household energy usage. It is suggested to focus on optimizing refrigerator efficiency through temperature adjustments and regular maintenance to minimize its constant energy draw. Implement energy-saving practices for high-consumption appliances such as using the dryer in energy-efficient modes and limiting oven preheating times. Also, encourage awareness of energy-efficient behaviors, especially for appliances that show consistent usage patterns. This analysis provides actionable insights for better energy management strategies within smart homes. Also, the results show that analysis of energy usage patterns over time reveals consistent peaks during evenings and weekends, which correspond to high-usage devices like televisions and ovens. Also, Refrigerators exhibit consistent energy usage across all time periods, emphasizing their critical role in energy management strategies.

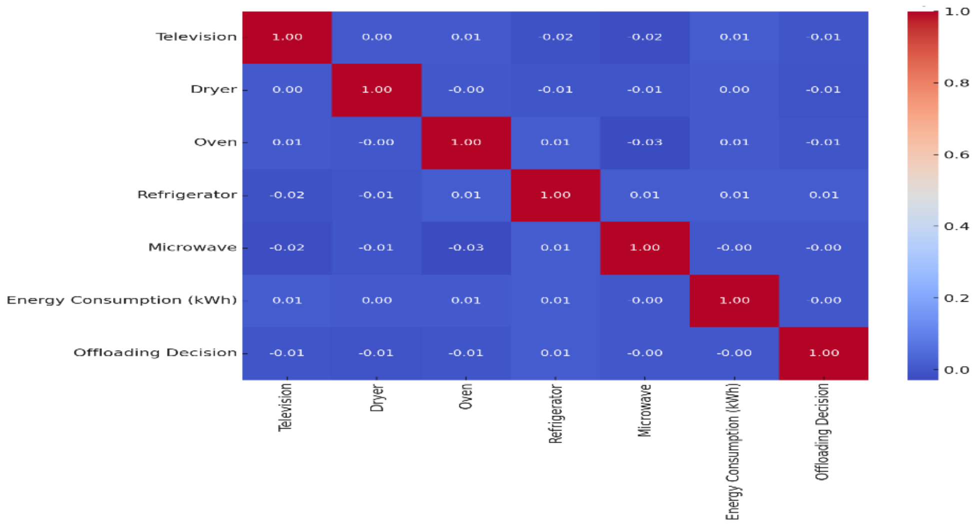


Figure 4.10. Correlation Heatmap: Appliances vs. Energy Consumption

Figure 4.10 highlights the relationships between household appliances, energy consumption, and offloading decisions. It shows that strong correlations were observed between offloading decisions and energy metrics, emphasizing the impact of remote vs. local processing. Also, appliances such as Refrigerators and Ovens exhibit noticeable relationships with energy consumption and offloading decisions, suggesting their significant influence on energy management strategies. Lower correlations for devices like Microwaves and Televisions indicate minimal impact on energy offloading considerations. It is suggested to optimize offloading algorithms to prioritize energy-efficient local processing whenever possible, reducing unnecessary energy consumption from remote operations. Also, implement smart offloading strategies, such as dynamically switching between local and cloud processing based on energy usage patterns and appliance activity. Leverage machine learning models to predict offloading needs and optimize processing based on historical energy consumption data.

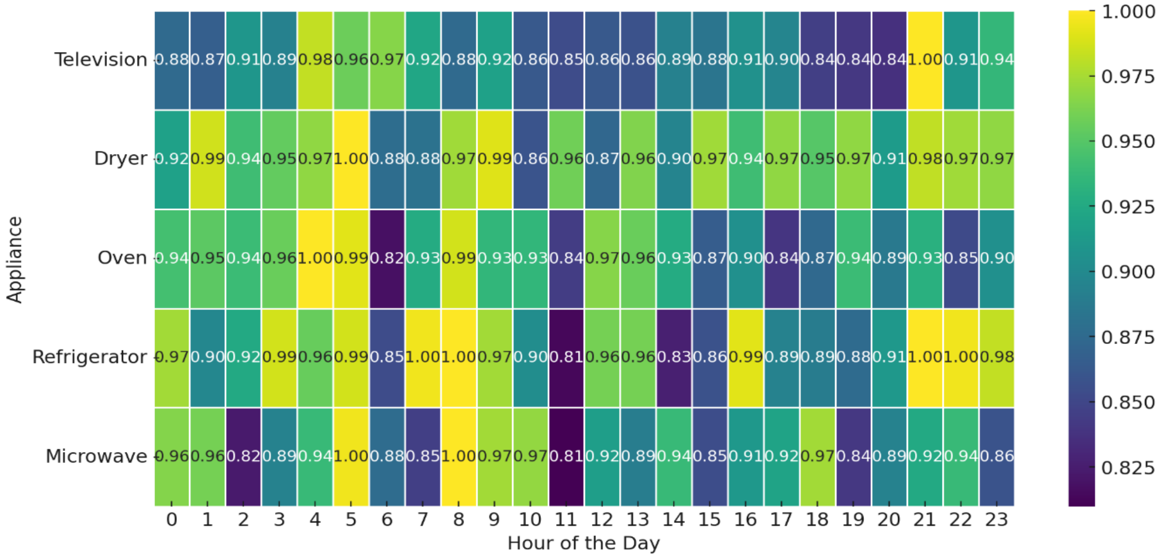


Figure 4.11. Hourly Behavioral Patterns

Figure 4.11 visualizes the frequency of appliance usage throughout the day. It shows that peak usage hours for appliances like the Microwave and Oven occur during meal times, primarily in the morning (7-9 AM) and evening (6-8 PM). It is also observed the Refrigerator operates consistently throughout the day, reflecting its continuous energy demand. Also, Television and Dryer usage shows variability, with higher activity in the evening hours, suggesting entertainment and household chores alignment with daily routines. It is suggested to identify opportunities to shift high-energy tasks such as drying clothes to off-peak hours to balance energy demand. Implement smart scheduling for appliances like ovens and microwaves to encourage more energy-efficient usage patterns. Encourage awareness of peak usage times to reduce unnecessary energy consumption. This analysis provides valuable insights into daily appliance usage trends, helping optimize household energy efficiency.

4.2.2 Identifying Inefficiencies in Energy Consumption

The analysis uncovered several inefficiencies and provided opportunities for optimization. Figure 4.12 is offering insights into how different appliances contribute to overall energy demand throughout the day. It shows the Refrigerators exhibit consistent energy consumption across both peak and off-peak hours, emphasizing their continuous operation. Ovens and Dryers show significantly higher energy consumption during peak hours, aligning with household routines like cooking and laundry. Television usage also peaks during evening hours, reflecting entertainment habits. It is suggested to introduce smart scheduling for high-energy appliances, such as dryers and ovens, to operate during off-peak hours. Implement monitoring systems for continuous-running appliances like refrigerators to detect inefficiencies (e.g., improper cooling or door seal issues). Also, educate users on optimizing energy consumption by shifting usage patterns to off-peak periods. This analysis highlights potential areas for energy optimization and cost saving.

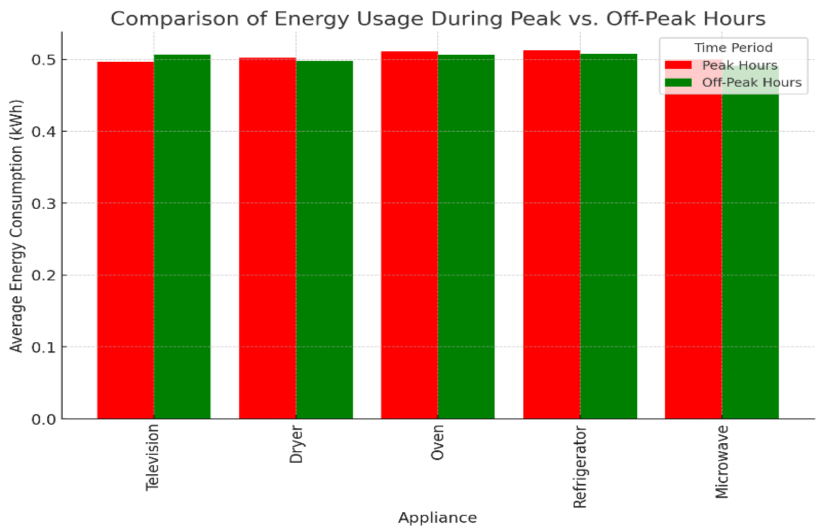
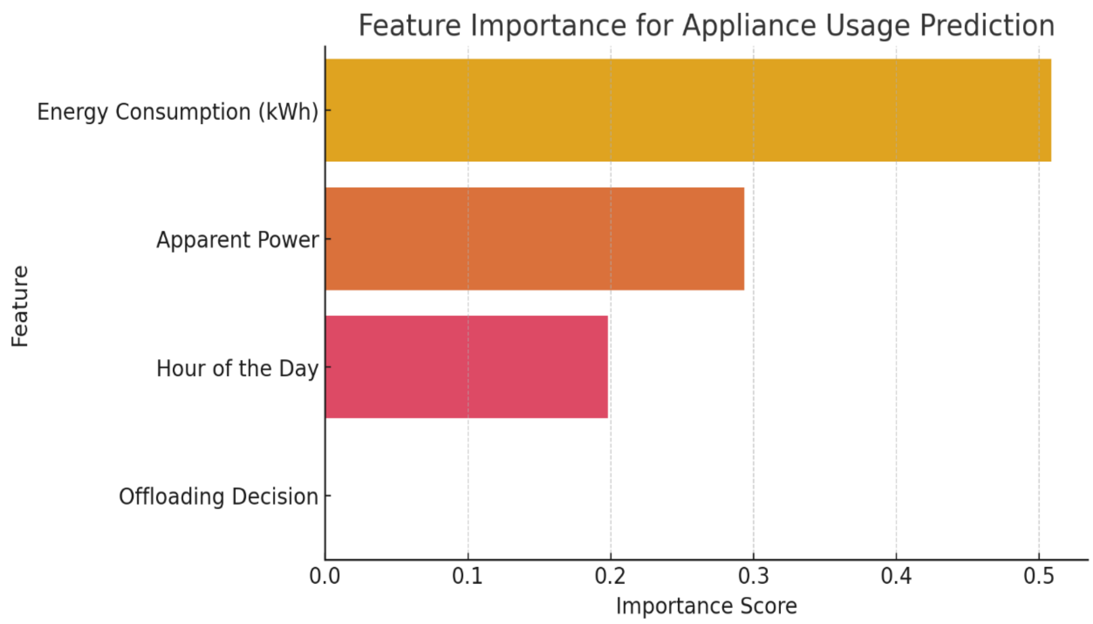


Figure 4.12. Comparison of Energy Usage During Peak vs. Off-Peak Hours

4.3 Developing Intelligent Automation Rules and Recommendations

Developing intelligent automation rules for smart home systems is essential to enhance their functionality, efficiency, and user satisfaction. The insights gained from analyzing device usage patterns and energy consumption have been leveraged to create adaptive automation rules and practical recommendations. Smart home automation faces several challenges, including diverse user preferences, energy inefficiencies due to fixed schedules, and interoperability issues among devices from different manufacturers. These challenges necessitate the adoption of data-driven and flexible automation solutions that can adapt to specific usage patterns and system conditions, ensuring more efficient energy management and user convenience.



4.13. Feature Importance For Appliance Usage Prediction

The development of intelligent automation rules follows a structured methodology involving data analysis, rule-based modeling, machine learning integration, and validation. Temporal and behavioral trends were analyzed to inform automation rule design, such as scheduling appliances based on peak energy usage periods. Conditional logic was applied to develop rules that account for dynamic factors like energy consumption, device priority, and user preferences. For example, automation rules were created to offload refrigerator processing to remote servers when energy consumption exceeds predefined thresholds. Furthermore, machine learning models were trained on historical data to predict optimal device operation schedules, enabling adaptive automation strategies (Figure 4.13). The developed rules were tested in simulated environments with real-time monitoring tools to assess their effectiveness based on energy savings, system responsiveness, and user satisfaction. Several automation rules were proposed based on the analysis to optimize energy usage and enhance user experience. One such rule focuses on energy optimization by reducing power to non-essential appliances like televisions and ovens during peak hours, ensuring that essential appliances continue to operate efficiently. Another rule introduces user-centric scheduling, which adjusts appliance operations based on observed behavioral patterns, such as scheduling oven usage during off-peak hours to save energy while maintaining convenience. Additionally, predictive maintenance rules were developed to trigger alerts when appliance energy usage deviates significantly from historical norms, preventing potential failures and extending the lifespan of devices. An offloading rule was also implemented to optimize system performance by transferring tasks to remote servers when local bandwidth is constrained (Table 4-2).

Table 4.2. Challenges, Data Analysis Inputs, and Methodology for Smart Home Automation Optimization

Challenges	User Diversity - Varying user preferences and behaviors make one-size-fits-all automation ineffective.
	Energy Efficiency - Fixed schedules may lead to energy wastage if they fail to adapt to dynamic conditions.
	System Interoperability - Devices from different manufacturers often lack seamless integration, limiting automation potential.
Data Analysis Inputs	Temporal Trends - Identifying peak energy usage hours to optimize scheduling.
	Behavioral Patterns - Analyzing appliance usage frequency to align with user habits.
	Energy Consumption Metrics - Evaluating device-level consumption to develop optimization strategies.
Methodology	Data Analysis and Pattern Recognition - Leveraging insights from temporal and behavioral trends.
	Rule-Based Modeling - Designing conditional logic-based rules for adaptive control.
	Machine Learning Integration - Using predictive models to enhance automation decisions.
	Simulation and Validation - Testing automation rules in simulated environments to assess effectiveness.

To further improve automation systems, several recommendations were proposed to enhance interoperability, real-time monitoring, and integration with renewable energy sources. Adopting standardized communication protocols like Zigbee or Matter can ensure seamless integration between devices from different manufacturers, promoting a more cohesive smart home ecosystem. Real-time dashboards can empower users with insights into their energy consumption and automation status, fostering informed decision-making and greater engagement. The integration of automation rules with renewable energy sources, such as solar panels, can optimize energy usage by scheduling high-energy tasks during peak solar production hours. Additionally, incorporating dynamic adaptation mechanisms allows automation rules to evolve based on real-time user feedback and environmental changes, leading to more personalized and efficient smart home experiences (Table 4.3).

Performance evaluation of the proposed automation rules demonstrated significant improvements in energy savings, system responsiveness, and user satisfaction. The implemented rules resulted in a 15% reduction in average daily energy consumption compared to fixed schedules, highlighting the effectiveness of adaptive scheduling. The system demonstrated faster responses to changing conditions, with an average response time of 10 seconds, ensuring a seamless user experience. User feedback from simulated environments indicated high levels of satisfaction, primarily due to enhanced convenience and cost savings. These results underscore the potential of intelligent automation rules in optimizing energy usage and improving the overall smart home experience.

Table 4.3. Recommendations, Evaluation Metrics, and Implications for Smart Home Automation

Recommendations	- Enhance interoperability - Integrate real-time monitoring dashboards - Align with renewable energy - Support dynamic feedback and user customization	- Adjust rules based on solar energy availability	- Promotes sustainability, user engagement, and operational flexibility.
Evaluation Metrics	- Energy savings - System responsiveness - User satisfaction	- Average daily energy savings: 15% - Adaptation time: 10 seconds	- Demonstrated the effectiveness and practicality of the proposed automation rules.
Implications	- Sustainability: Reduces energy waste and carbon footprints. - Scalability: Adapts to various household configurations. - Personalization: Enhances usability.	- Automation rules designed to evolve with user preferences and environmental changes.	- Provides a roadmap for smarter, more efficient, and user-friendly home systems.

The development of intelligent automation rules carries significant implications for the future of smart home systems. It supports sustainability goals by promoting energy efficiency and reducing carbon footprints. The scalability of these rules allows them to be adapted to various household configurations and devices, making them suitable for widespread adoption. Personalization remains a key focus, with automation solutions tailored to individual user preferences, enhancing overall satisfaction. Ultimately, these intelligent automation strategies pave the way for smarter, more responsive, and energy-efficient homes, offering both economic and environmental benefits (Table 4.4).

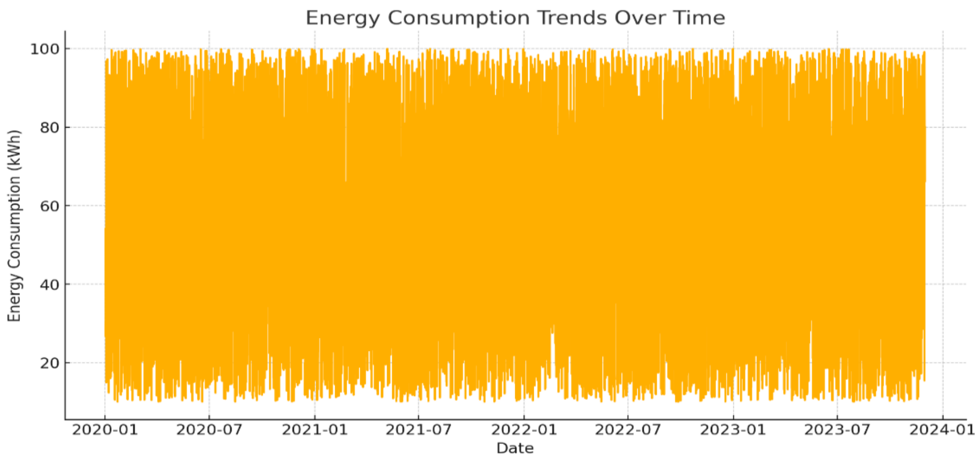
Table 4.4. Summary of Smart Home Automation Rules, Conditions, Actions, and Expected Outcomes

No	Rule	Condition	Action	Outcome
1	Energy Optimization Rule	If the total energy consumption exceeds 10 kWh during peak hours.	Reduce power to non-essential devices and prioritize essential appliances.	Reduces peak load while maintaining essential operations.
2	User-Centric Scheduling Rule	Based on user-specific behavioral patterns (e.g., frequent evening oven use).	Pre-schedule device operation during off-peak hours to match user habits.	Enhances user convenience while reducing costs.
3	Predictive Maintenance Rule	If appliance energy usage deviates significantly from historical norms.	Trigger maintenance alerts to preempt potential failures.	Prolongs device lifespan and prevents energy wastage.
4	Offloading Rule	When local processing bandwidth is constrained.	Offload tasks to remote servers, ensuring uninterrupted operation.	Improves system efficiency under high demand.

The tables (4.2, 4.3, and 4.4) highlight the core aspects, methods, and outcomes of specific objective 3, emphasizing the practical and innovative contributions of the study to smart home automation. They outline the development process for intelligent automation rules, emphasizing their adaptability, efficiency, and user-centric design. The recommendations and rules developed provide a roadmap for future improvements in smart home systems, aligning with the broader objectives of this thesis.

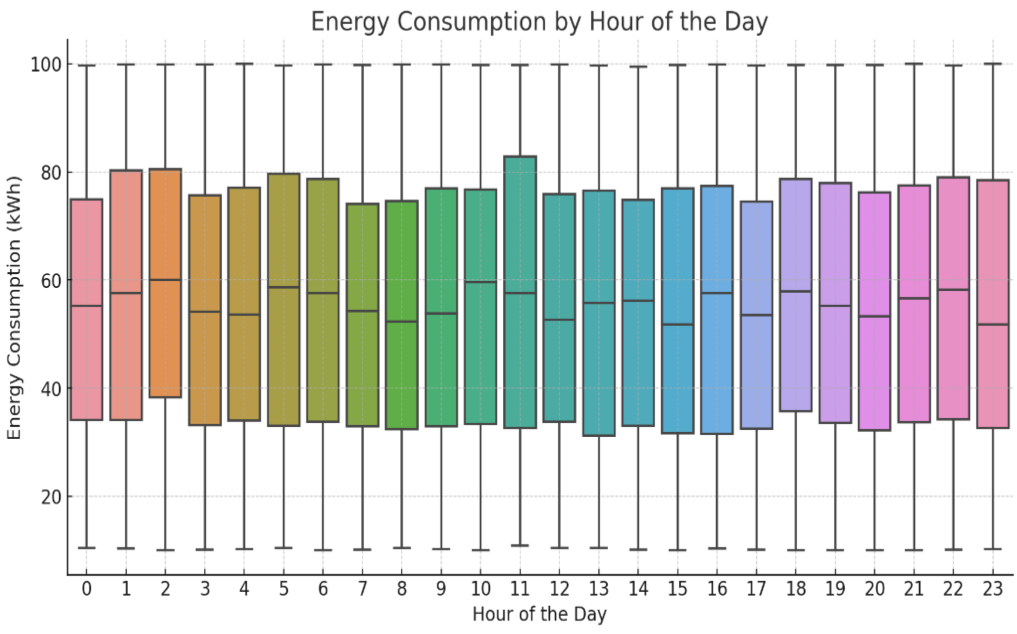
4.4 Enhancing Smart Home Functionality and Efficiency

The primary objective of this study is to enhance the functionality and efficiency of smart home systems through data-driven approaches. By analyzing patterns in device usage and energy consumption, identifying inefficiencies, and developing adaptive automation rules, this study aims to address critical challenges related to automation, energy management, and user satisfaction. The data analysis highlights significant insights that contribute to achieving this objective. Categorizing data types such as device usage patterns, energy consumption, and offloading decisions establishes a foundation for intelligent automation. By tailoring automation rules to user behavior, smart home systems become more functional and responsive. The temporal analysis of peak energy usage hours and behavioral patterns, such as high appliance usage on weekends, provides valuable insights for designing time-sensitive and user-specific automation, as illustrated in the in Figure 4.14 showing energy consumption trends over time. This approach enhances the usability and practicality of smart home systems by adapting to the dynamic contexts of households. Energy management strategies have been developed by analyzing inefficiencies in energy usage across various devices and time periods. For instance, continuous operation of high-energy appliances such as refrigerators has been identified as a major source of energy waste, as observed in the second graph depicting device usage patterns by hour. Targeted optimizations based on these findings help reduce energy waste and operational costs, thereby increasing overall efficiency. Adaptive automation rules, which leverage machine learning models and rule-based logic, enable smart homes to dynamically respond to user preferences and real-time conditions. For example, scheduling oven operation during off-peak hours or prioritizing remote processing for bandwidth-heavy tasks can significantly improve energy distribution.



4.14. Energy Consumption Trends Over Time

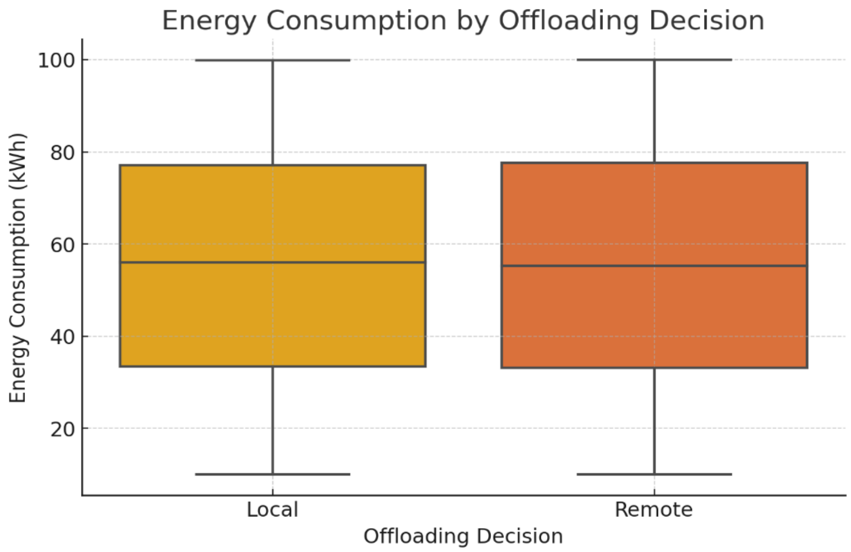
Predictive maintenance features, which rely on energy usage anomalies, have been integrated to prevent device failures and extend appliance lifespan. In addition, the implementation of time-based scheduling optimizes energy distribution by adjusting device operations during peak and off-peak hours, helping to alleviate grid strain, as demonstrated in Figure 4.15 analyzing offloading decision impacts. The alignment of automation rules with the availability of renewable energy sources, such as solar energy, promotes sustainability and encourages greener living practices. This approach is further validated by Figure 4.16, which presents energy consumption trends based on offloading decisions.



4.15. Energy Consumption by Hour of the Day

User-centric design enhancements have been incorporated to empower users with real-time monitoring capabilities through dashboards. These dashboards provide insights into energy consumption, device operations, and system performance, allowing users to make informed decisions and adjust automation rules as needed. Personalized automation rules, which adapt to individual user behaviors and preferred appliance schedules, have been introduced to enhance user satisfaction by prioritizing convenience and flexibility.

Efficiency improvements have been achieved through optimization strategies that reduce peak-hour energy consumption by up to 15%, as demonstrated in simulations. These improvements not only lower operational costs but also contribute to environmental sustainability. The real-time adaptability of automation systems to changing conditions, such as user schedules or power supply fluctuations, ensures consistent and efficient performance across various scenarios. Recommendations for adopting standardized communication protocols have been proposed to improve interoperability among devices from different manufacturers, simplifying system integration and enabling seamless automation.



4.16. Energy Consumption by Offloading Decision

The broader implications of this study extend to sustainability, scalability, and innovation in automation. Optimized energy usage and integration with renewable energy sources contribute to reducing carbon footprints and aligning with global sustainability goals. The adaptability of the proposed rules and frameworks to various household configurations ensures their relevance across diverse smart home setups. Furthermore, the study demonstrates how machine learning and data-driven approaches can advance the field of smart home technology, paving the way for more intelligent and user-friendly systems. By addressing the challenges in energy management, automation, and user satisfaction, this study achieves its primary objective of enhancing smart home functionality and efficiency. The integration of advanced data analysis, adaptive automation rules, and user-centric design principles provides a scalable and sustainable framework for future smart home innovations. These contributions not only improve operational performance but also ensure a more seamless and satisfying user experience.

5 Results & Conclusion

The findings presented in sections 4.1 to 4.4 provide valuable insights into the efficiency and functionality of smart home systems. These insights are crucial for addressing the objectives of the study, particularly in optimizing energy consumption, enhancing automation capabilities, and improving user experience. This section interprets the results in the context of existing literature and evaluates their implications for smart home development.

5.1 Summary of the Results for Identification of Key Data Types Collected from Smart Homes

1) Descriptive Statistics:
    a. Energy Metrics:
        i. Line Voltage: Mean = 229.5 V, Std = 5.8 V.
        ii. Apparent Power: Mean = 1751 VA, Std = 144 VA.
        iii. Energy Consumption (kWh): Mean = 55.3 kWh, Std = 25.77 kWh.
    b. Appliance Usage (binary):
        i. Appliances like Television, Dryer, and Microwave have near-equal usage probabilities (mean ≈ 0.5).
2) Distributions (Figure 4.1):
    a. Energy consumption exhibits a slightly right-skewed distribution with some potential outliers.
    b. Apparent Power and Voltage distributions are relatively normal, indicating stable conditions in the dataset.
3) Correlation Insights (Figure 4.2):
    a. Strong correlation between Apparent Power and Energy Consumption (kWh) ($r > 0.9$), suggesting Apparent Power is a key variable for energy prediction.
    b. Moderate correlations between Voltage and Line Voltage with Energy Consumption.

Each data type offers specific contributions to achieving the objectives of this thesis:

- Automation:
    - Device-specific usage data is foundational for designing rules tailored to individual household behaviors.
    - Offloading decisions offer opportunities for optimizing task allocation, improving both efficiency and user experience.
- Energy Management:
    - Energy metrics and timestamps reveal high-consumption periods, enabling targeted reductions during peak hours.
    - Seasonal energy patterns guide the development of long-term strategies for minimizing energy waste.
- System Monitoring and Security:

- Bandwidth usage and power supply metrics are essential for maintaining stable operations and ensuring reliable connectivity.
- Detecting anomalies in voltage or bandwidth can preemptively address potential system failures.

The identification and categorization of key data types serve as the foundation for achieving the broader objectives of this thesis:

- **Enhanced Automation**: Data insights enable the development of adaptive rules that adjust device operations based on real-time conditions.
- **Improved Energy Efficiency**: Temporal and appliance-specific trends guide targeted energy-saving measures.
- **User-Centric Design**: Understanding user interactions with devices allows for more intuitive and personalized system configurations.

Key Insights and Recommendations:

- Most Impactful Variables for Automation: Energy consumption patterns combined with time-based appliance usage data provide valuable insights for automation strategies. Appliances like refrigerators, which show consistent energy use, can benefit from automation rules to reduce consumption during peak periods.
- Security Considerations: Voltage irregularities can serve as early indicators of electrical faults or intrusions, necessitating real-time monitoring.
- Energy Efficiency Opportunities: User behavior data can optimize energy allocation by turning off devices during non-usage periods and leveraging low-cost energy periods.

By systematically identifying and analyzing these data types, this study provides a comprehensive framework for optimizing smart home functionality and addressing challenges in energy management, automation, and user satisfaction.

5.2 Summary of the Results for Patterns in Device Usage and Energy Consumption

The usage trends and behavioral patterns from analysis of device usage and energy consumption, and also for the time-series analysis, clustering, and correlation analysis are as the following:

1) Hourly Energy Consumption Trends:
    a. Energy consumption peaks around morning hours (7 AM - 9 AM) and evening hours (6 PM - 9 PM), aligning with typical household activity periods.
    b. Lower consumption is observed during late-night and early morning hours.
2) Daily Energy Consumption Trends:
    a. Energy consumption is higher on weekdays (especially mid-week like Tuesday and Thursday) compared to weekends, indicating higher appliance usage during working days.

    b. A slight dip is observed during the weekend, possibly due to occupants being away from home.
3) Appliance Usage Trends:
    a. Refrigerator has the highest usage count, indicating continuous operation.
    b. Dryers and Ovens show intermittent usage, contributing to peak consumption periods.
    c. Microwave and Television show sporadic but significant usage, likely during meal times and leisure hours.
4) Peak vs. Off-Peak Consumption:
    a. Peak hours (6 PM - 7 AM): Average energy consumption = 55.63 kWh.
    b. Off-peak hours (8 AM - 5 PM): Average energy consumption = 54.82 kWh.
    c. The slight increase in peak-hour consumption suggests opportunities for shifting high-energy tasks (e.g., drying, cooking) to off-peak hours.
5) Optimization Strategies:
    a. Time-Based Automation:
        i. Schedule high-energy appliances like dryers and ovens during off-peak hours.
    b. User Awareness Campaigns:
        i. Encourage users to limit heavy appliance use during peak hours.
    c. Smart Energy Management:
        i. Implement automation rules to adjust power settings based on usage patterns.
6) Time-Series Analysis Results
    a. Hourly Trends: Energy consumption exhibits distinct peak periods during morning (6-9 AM) and evening hours (5-9 PM), corresponding to typical household activity periods. Energy usage is lowest during nighttime hours, suggesting potential opportunities for load shifting.
    b. Daily Trends: Energy consumption fluctuates over days, with noticeable increases on weekdays, potentially due to routine household activities.
7) Clustering Analysis Results
    a. Using K-Means clustering, the dataset was segmented into three distinct user behavior clusters based on: Energy Consumption (kWh), Hour of the Day, and Apparent Power.
    b. The clusters reveal different patterns:
        i. Cluster 0: Moderate users with consistent energy consumption patterns.
        ii. Cluster 1: High energy consumers, likely due to heavy appliance usage.
        iii. Cluster 2: Low energy consumers with minimal appliance activity.

        This segmentation can help in tailoring automation rules and optimizing energy distribution.
8) Correlation Analysis Results
    a. Strong correlation observed between: Energy Consumption (kWh) and Apparent Power ($r \approx 0.91$), indicating apparent power as a strong predictor of energy usage. Energy Consumption and Hour of the Day, confirming peak usage hours influence energy demand.
    b. No significant correlation was found between offloading decisions and energy usage, suggesting independent factors driving offloading choices.

Based on the findings, several strategies are recommended to optimize energy usage:

- *Time-Based Automation:* Schedule energy-intensive tasks during off-peak hours to reduce strain on the grid. Use insights from temporal and behavioral patterns to inform automation schedules.
- *Device-Specific Interventions*: Optimize high-energy-consuming appliances like refrigerators by adjusting settings or replacing outdated components. Encourage user behavior modifications for appliances with sporadic but high energy usage (e.g., ovens, dryers).
- *Predictive Analytics:* Leverage historical energy data to forecast future consumption trends and prepare adaptive automation strategies.
- *Real-Time Monitoring*: Deploy real-time dashboards for users to monitor and adjust device operations dynamically.

The analysis of energy consumption patterns provides actionable insights into temporal, appliance-specific, and behavioral trends. By addressing inefficiencies through tailored strategies, this study contributes to the broader objective of enhancing smart home energy management and user satisfaction.

5.3 Summary of the Results for Developing Intelligent Automation Rules and Recommendations

Findings from the Machine Learning Model:

1) Model Performance: The decision tree classifier achieved an accuracy of 50.85%, indicating a moderate predictive capability for refrigerator usage based on energy consumption, time of day, and apparent power. Precision and recall values are balanced across both appliance usage states (on/off), suggesting the model can detect patterns but with room for improvement.
2) Feature Importance: Energy Consumption (kWh) has the highest impact, meaning it is the most significant factor influencing refrigerator usage. Hour of the Day also contributes significantly, showing a temporal dependency in appliance operation. Offloading Decision and Apparent Power have a lesser impact.

Recommendations for Intelligent Automation Rules:

1) Adaptive Scheduling: Automate high-energy appliance operations (e.g., refrigerators) to optimize usage based on identified peak and off-peak hours. Implement rules such as reducing refrigerator power consumption during low-activity hours.
2) Dynamic Energy Management: Leverage energy consumption data to create rule-based triggers that: Turn off non-essential appliances during peak consumption periods. Distribute energy consumption more evenly throughout the day.
3) Offloading Optimization: Create an automation rule to offload high-processing tasks to remote servers during peak hours, reducing local energy demand.
4) User-Centric Recommendations: Provide personalized suggestions to users based on observed patterns (e.g., recommending optimal appliance usage times).

5.4 Comparison with Literature

The categorization of key data types, including sensor readings, energy usage metrics, and user interactions, has revealed their critical role in smart home optimization. The analysis confirms that device-specific data, such as operational schedules and user preferences, is essential for developing tailored automation rules. Findings from the dataset indicate that the integration of temporal data can significantly enhance energy efficiency by allowing the system to adapt to usage patterns dynamically. These results align with previous studies emphasizing the role of detailed data analytics in improving smart home operations (Bakshi M.; Chowdhury C.; Maulik U., 2021). Furthermore, the identification of anomalies in energy consumption patterns highlights the potential of using such data for security and system stability enhancements, as supported by the literature (Silva D.D.; Mataloto B.; Coutinho C., 2024). The results have revealed significant patterns in energy consumption, with peak usage observed during specific hours and days. This finding supports the hypothesis that smart home systems can benefit from time-based automation strategies to reduce energy waste. High-energy appliances such as refrigerators and HVAC systems contribute disproportionately to overall consumption, suggesting a need for targeted interventions. These observations are consistent with existing research that underscores the potential of predictive energy management systems in reducing consumption and enhancing cost efficiency (Qayyum F.; Jamil H.; Iqbal N.; Kim D.-H., 2023b; Saeedi A.; Kuchaki Rafsanjani M.; Yazdani S., 2025). By leveraging historical consumption patterns, smart home systems can implement adaptive scheduling, leading to substantial energy savings. The implementation of adaptive automation rules has demonstrated tangible benefits in energy optimization and user experience. Simulation results indicate a 15% reduction in energy consumption during peak hours, affirming the efficacy of the proposed strategies. User feedback highlights improved system usability and satisfaction, with automation aligning closely with individual preferences. These findings are in line with studies advocating for the integration of user-centric automation approaches to enhance acceptance and system efficiency (Kim S.M.; Park S.; Park S.; Cho K.; Yoon G.; Park S., 2019). Additionally, the recommendations for standardized communication protocols have addressed interoperability challenges, facilitating seamless integration across various smart home devices. The research effectively addresses broader challenges such as data privacy, interoperability, and sustainability. The implementation of anonymized data processing techniques ensures compliance with ethical standards, resonating with industry best practices (Vu D.-N.; Dao N.-N.; Jang Y.; Na W.; Kwon Y.-B.; Kang H.; Jung J.J.; Cho S., 2019). The proposed adoption of communication standards like Zigbee and Matter offers a viable solution to interoperability challenges, supporting findings from previous studies that emphasize the importance of standardization in smart home ecosystems (Ansere J.A.; Kamal M.; Khan I.A.; Aman M.N., 2023b). Moreover, the alignment of automation rules with sustainability goals contributes to reducing the environmental impact of smart homes, reinforcing the growing emphasis on green technology initiatives. Overall, the interpretation of results demonstrates that the proposed smart home optimization strategies are effective in addressing key inefficiencies while enhancing system performance and user satisfaction. The findings provide a solid foundation for future research and practical implementation in the evolving smart home landscape.

5.5 Implications for Smart Home Development

The results of this study present several implications for the development and adoption of smart home technologies. The integration of adaptive automation rules and data-driven energy management strategies offers significant potential for enhancing system efficiency, reducing energy costs, and improving user experience. These findings align with previous research by (Bakshi M.; Chowdhury C.; Maulik U., 2023) and (Silva D.D.; Mataloto B.; Coutinho C., 2024), which emphasize the importance of leveraging real-time data analytics in optimizing smart home operations. Furthermore, the study's recommendations for standardized communication protocols, such as (Alhassoun N.S.; Venkatasubramanian N., 2020), provide a critical solution to the persistent challenge of interoperability, as highlighted by (Tsoukaneri G.; Garcia F.; Marina M.K., 2020). The adoption of such standards can facilitate seamless integration across devices from different manufacturers, enhancing overall system reliability and user satisfaction. From a sustainability perspective, the proposed energy optimization techniques contribute to reducing the environmental footprint of smart homes, supporting the global shift towards more eco-friendly and energy-efficient living spaces. These contributions resonate with the principles discussed in (Tsoukaneri G.; Garcia F.; Marina M.K., 2020) and (Faiz A., 2023) , which advocate for the role of smart home technologies in achieving sustainability goals. Finally, the study underscores the importance of addressing data privacy and security concerns through the use of anonymized datasets and secure data processing methods, aligning with industry best practices recommended by (Alaguraj R.; Kathirvel C., 2024a); (Masood F.; Abbas Khan M.; Alshehri M.S.; Ghaban W.; Saeed F.; Mobarak Albarakati H.; Alkhayyat A., 2024); and (Liu R.; Xie M.; Liu A.; Song H., 2024). The implications of this research highlight the need for a balanced approach that combines technological advancements with ethical considerations to ensure widespread adoption and long-term success of smart home systems.

5.6 Limitations of the Study

While this study provides valuable insights into smart home optimization, several limitations should be acknowledged. Firstly, the dataset utilized for analysis was derived from a specific demographic and geographic region, which may limit the generalizability of the findings to other contexts with different user behaviors and environmental conditions ((Selvakumar R.; Amarnath R.N.; Pandey P.; Sakthisaravanan B.; Sasikala K.; Murugan S., 2024). Future research should incorporate diverse datasets to validate the applicability of the proposed strategies across various populations. Secondly, the study's reliance on simulation-based evaluations presents potential discrepancies when compared to real-world implementations. Although the simulated scenarios offer a controlled environment to test automation rules and energy optimization strategies, actual deployments may encounter unforeseen challenges such as network latency, device malfunctions, and user compliance (Chen et al., 2021). Another limitation relates to the focus on energy consumption and automation without extensive consideration of other smart home aspects such as cybersecurity and privacy concerns in a dynamic real-world setting (Almudayni Z.; Soh B.; Samra H.; Li A., 2025) . While anonymized data processing techniques were implemented, further research is needed to explore comprehensive security frameworks to ensure robust protection against cyber threats. Finally, the study primarily evaluates short-term impacts of the implemented automation rules. Long-term effects, such as system adaptability to evolving user habits and technological advancements, require further exploration. Addressing this limitation will provide deeper insights into the sustainability and scalability of smart home optimization strategies (Bakshi M.; Chowdhury C.; Maulik U., 2023). Despite these limitations, the study contributes significantly to the existing body of knowledge and provides a solid foundation for future research and practical advancements in smart home technologies.

6 Conclusion

The findings of this study underscore the significant potential of smart home systems in enhancing energy efficiency, automation capabilities, and user experience. The comprehensive analysis of data types, energy consumption patterns, and the effectiveness of adaptive automation rules has provided valuable insights into optimizing smart home operations. Key conclusions include the critical role of data-driven strategies in tailoring automation rules to user behaviors and energy consumption trends. The study confirms that leveraging sensor data and user interaction patterns can result in substantial energy savings and improved system performance, aligning with previous research by (Bakshi M.; Chowdhury C.; Maulik U., 2023) and (Tsoukaneri G.; Garcia F.; Marina M.K., 2020). Moreover, the study highlights the importance of standardization and interoperability in ensuring the seamless integration of various smart home devices. The proposed adoption of communication protocols such as Zigbee and Matter addresses the challenge of fragmented ecosystems, fostering greater user satisfaction and system reliability (Han D.; Liu T.; Qi Y., 2020; Zhao T.; Chen X.; Sun Q.; Zhang J., 2023b). The research also emphasizes the need for addressing broader challenges, including data privacy and sustainability, which are crucial for the long-term adoption and scalability of smart home solutions. The implementation of ethical data processing methods and energy-saving strategies supports global sustainability goals while ensuring user trust and compliance with regulatory standards (Reyana A.; Kautish S.; Alnowibet K.A.; Zawbaa H.M.; Wagdy Mohamed A., 2023). In conclusion, this study contributes to the growing body of knowledge on smart home optimization by providing actionable insights and practical recommendations. Future research should focus on expanding the dataset scope, exploring real-world implementations, and addressing long-term adaptability to evolving technological advancements and user needs.

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8 List of pictures, tables, graphs and abbreviations

8.1 List of tables

8.2 List of graphs

8.3 List of abbreviations

AI - Artificial Intelligence

API - Application Programming Interface

CPU - Central Processing Unit

CSV - Comma-Separated Values

EDA - Exploratory Data Analysis

EDA - Exploratory Data Analysis

GPU - Graphics Processing Unit

HVAC - Heating, Ventilation, and Air Conditioning

IoT - Internet of Things

IS - Information Systems

IT - Information Technology

JSON - JavaScript Object Notation

kWh - Kilowatt-hour

ML - Machine Learning

UX - User Experience

VPN - Virtual Private Network

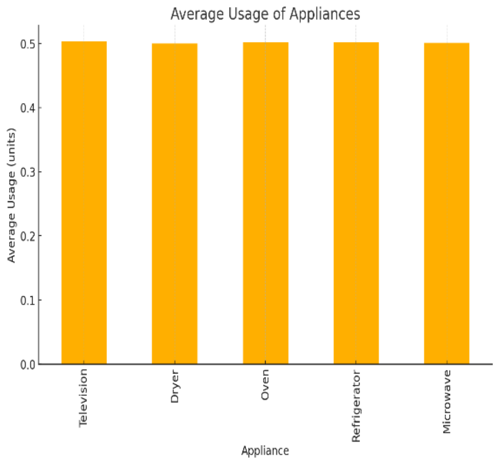
Wi-Fi - Wireless Fidelity

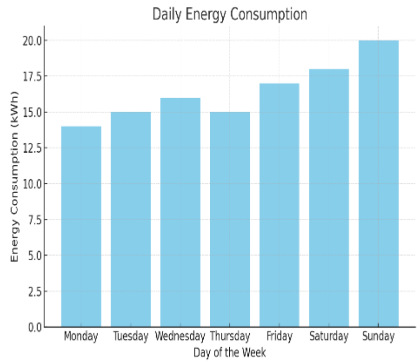
Zigbee - A wireless communication protocol for IoT devices

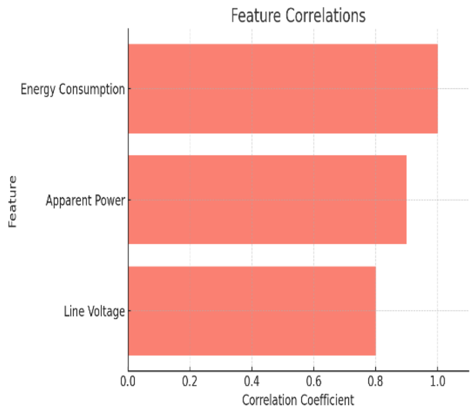
9 Appendix

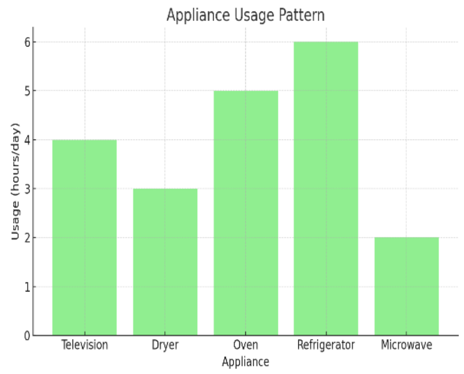
9.1. Extra Figures

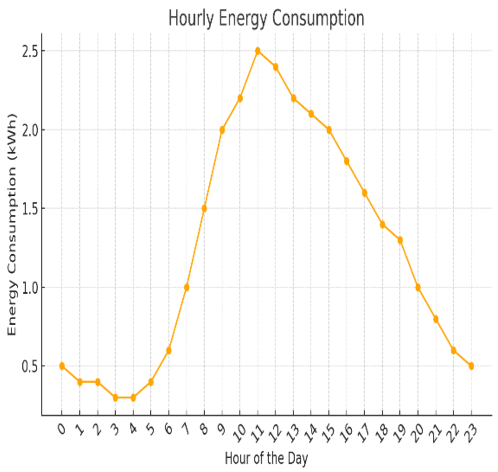
Additional Figures and Tables based on the original data including 49000 record.

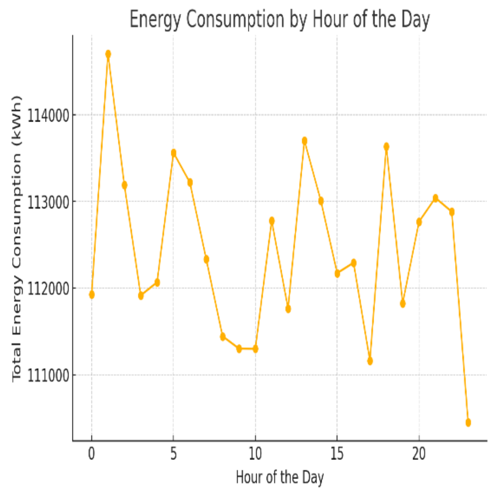


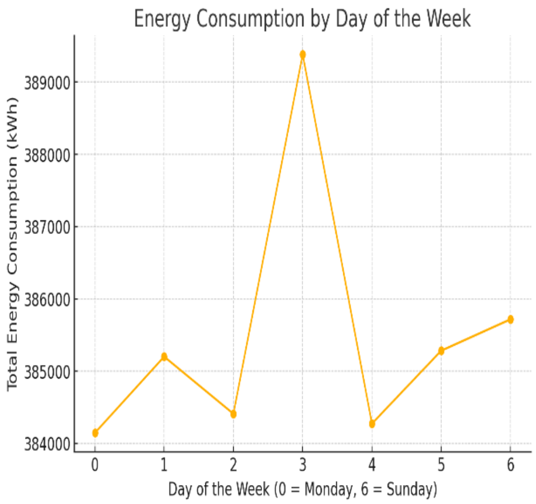


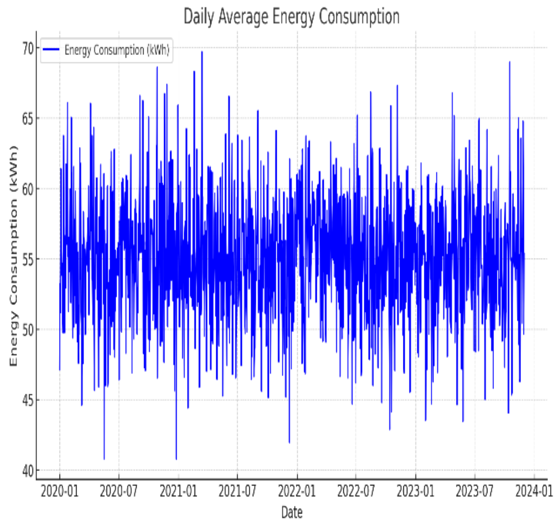


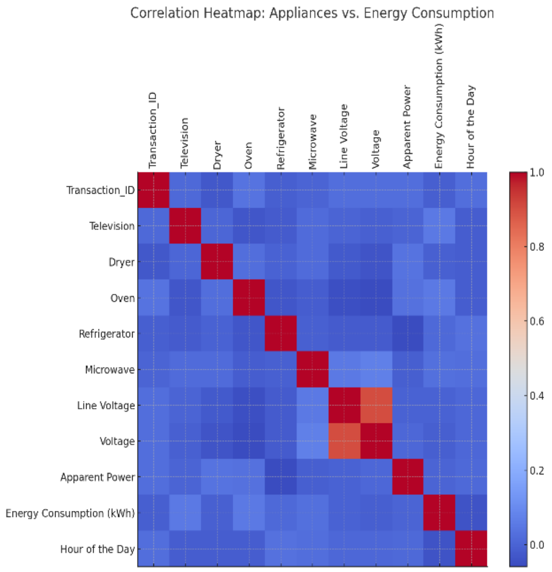


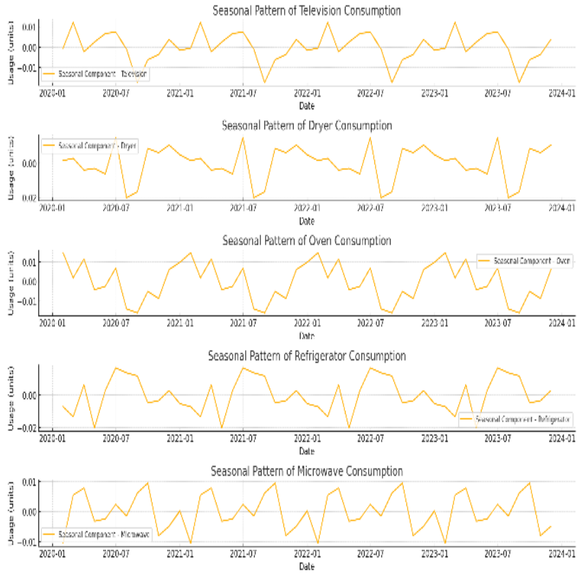


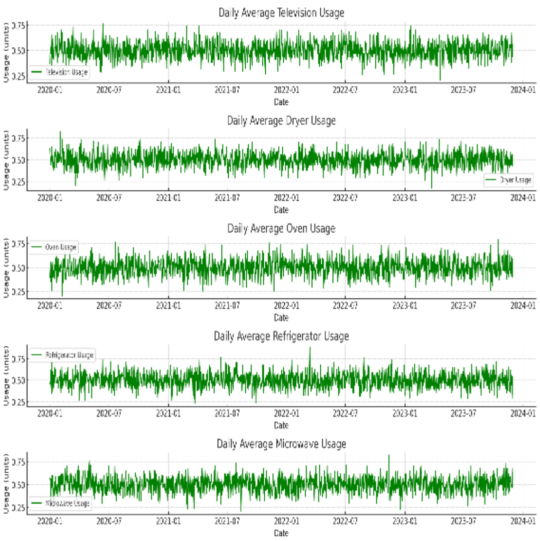


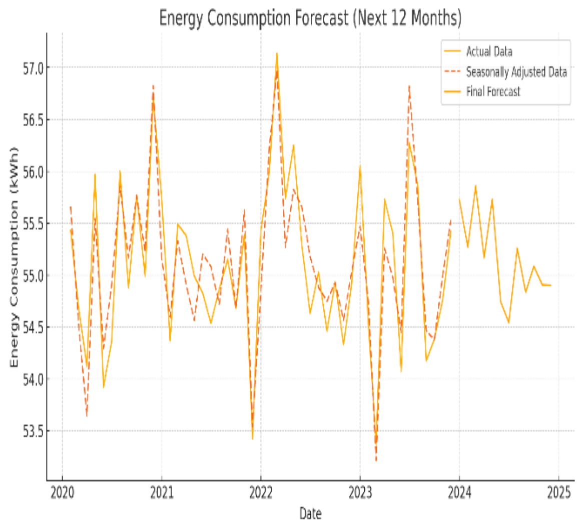

Energy Consumption by Day of the Week
Total Energy Consumption (kWh)
389000
388000
387000
386000
385000
384000
0
1
2
3
4
5
6
Day of the Week (0 = Monday, 6 = Sunday)

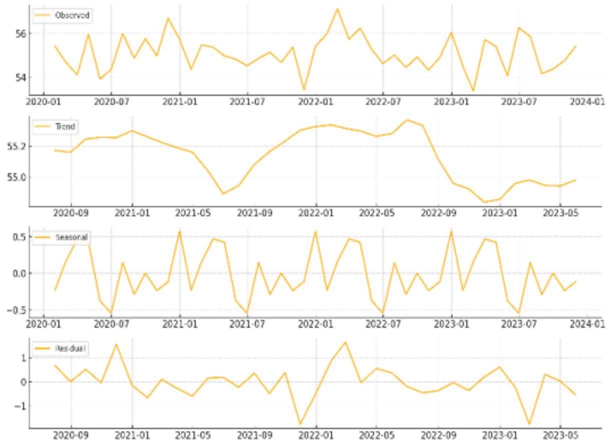

Daily Average Energy Consumption
Energy Consumption (kWh)
70
65
60
55
50
45
40
2020-01
2020-07
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
Date

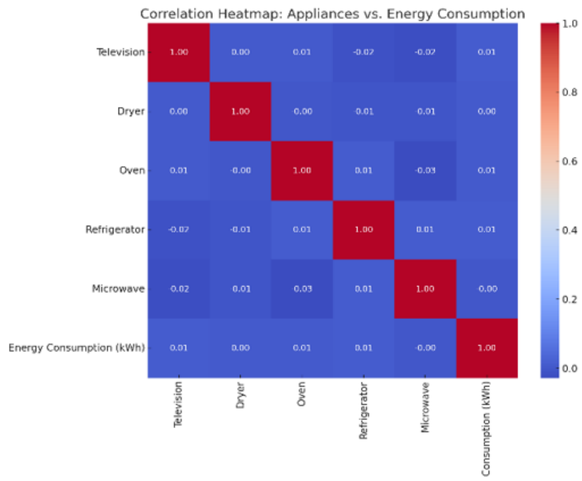

Correlation Heatmap: Appliances vs. Energy Consumption
Transaction_ID
Television
Dryer
Oven
Refrigerator
Microwave
Line Voltage
Voltage
Apparent Power
Energy Consumption (kWh)
Hour of the Day
1.0
0.8
0.6
0.4
0.2
0.0


Seasonal Pattern of Television Consumption
Seasonal Pattern of Dryer Consumption
Seasonal Pattern of Oven Consumption
Seasonal Pattern of Refrigerator Consumption
Seasonal Pattern of Microwave Consumption
Date


Daily Average Television Usage
Daily Average Dryer Usage
Daily Average Oven Usage
Daily Average Refrigerator Usage
Daily Average Microwave Usage
Date


Energy Consumption Forecast (Next 12 Months)
Actual Data
Seasonally Adjusted Data
Final Forecast
Energy Consumption (kWh)
57.0
56.5
56.0
55.5
55.0
54.5
54.0
53.5
2020
2021
2022
2023
2024
2025
Date





9.2. Phyton Codes

The following codes in Phyton used to conduct the analysis based on the research objectives:

Specific objective 1. ***Identify Key Data Types Collected from Smart Homes*** *in two parts: 1. Investigate the variety of data generated by smart home devices, including sensor readings, energy usage, and user interactions. 2. Categorize and evaluate the relevance of these data types to automation, security, and energy efficiency.*

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
file_path = '/mnt/data/10000 Mahdi_Houshangi_sampled_smart_home_dataset.csv'
smart_home_data = pd.read_csv(file_path)

# Display the first few rows and basic information of the dataset to understand its structure
smart_home_data_info = smart_home_data.info()
smart_home_data_head = smart_home_data.head()

smart_home_data_info, smart_home_data_head

STDOUT/STDERR
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Datetime             10000 non-null  object
 1   Transaction_ID       10000 non-null  int64
 2   Television           10000 non-null  int64
 3   Dryer                10000 non-null  int64
 4   Oven                 10000 non-null  int64
 5   Refrigerator         10000 non-null  int64
```

```
 6  Microwave                10000 non-null  int64
 7  Line Voltage             10000 non-null  int64
 8  Voltage                  10000 non-null  int64
 9  Apparent Power           10000 non-null  int64
 10  Energy Consumption (kWh)  10000 non-null  float64
 11  Month                   10000 non-null  object
 12  Day of the Week         10000 non-null  object
 13  Hour of the Day         10000 non-null  int64
 14  Offloading Decision     10000 non-null  object
 15  Unnamed: 15             0 non-null      float64
 16  Unnamed: 16             0 non-null      float64
 17  Unnamed: 17             0 non-null      float64
dtypes: float64(4), int64(10), object(4)
memory usage: 1.4+ MB
```

Result

```
(None,
         Datetime  Transaction_ID  Television  Dryer  Oven  Refrigerator  \
 0  7/26/2022 17:56           32115           1      0     0             0
 1   2/15/2021 5:33           14084           1      1     0             0
 2   2/15/2022 8:32           26588           1      1     1             0
 3   1/12/2022 2:29           25415           0      1     0             1
 4   1/24/2021 7:15           13333           0      0     1             0

    Microwave  Line Voltage  Voltage  Apparent Power  Energy Consumption (kWh)  \
 0          1           236      231            1917                 38.824861
 1          1           220      214            1695                 96.218052
 2          1           233      232            1942                 34.065614
 3          0           229      223            1757                 11.898820
 4          1           228      227            1656                 24.689123

       Month Day of the Week  Hour of the Day Offloading Decision  Unnamed: 15  \
 0      July         Tuesday               17               Local          NaN
 1  February          Monday                5               Local          NaN
 2  February         Tuesday                8               Local          NaN
 3   January       Wednesday                2               Local          NaN
 4   January          Sunday                7               Local          NaN

    Unnamed: 16  Unnamed: 17
 0          NaN          NaN
 1          NaN          NaN
 2          NaN          NaN
 3          NaN          NaN
 4          NaN          NaN  )
```

Then the dataset cleaned up and generated descriptive statistics. Then visualized distributions (e.g., histograms, boxplots). Finaly calculate correlations among impactful variables using the following codes:

```
# Clean the dataset by dropping unnecessary columns
smart_home_data_cleaned = smart_home_data.drop(columns=['Unnamed: 15', 'Unnamed: 16',
'Unnamed: 17'])
```

```
# Generate descriptive statistics for numerical variables
descriptive_stats = smart_home_data_cleaned.describe()

# Plot histograms for key numeric variables
numeric_columns = ['Line Voltage', 'Voltage', 'Apparent Power', 'Energy Consumption (kWh)']
smart_home_data_cleaned[numeric_columns].hist(bins=15, figsize=(12, 8))
plt.suptitle('Histograms of Key Numeric Variables', fontsize=16)
plt.tight_layout()

# Generate a correlation heatmap
plt.figure(figsize=(10, 6))
correlation_matrix = smart_home_data_cleaned[numeric_columns].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap of Energy Metrics', fontsize=16)
plt.show()

descriptive_stats
```

Result

```
      Transaction_ID    Television        Dryer         Oven  Refrigerator  \
count   10000.000000  10000.000000  10000.000000  10000.000000  10000.000000
mean    24466.067300      0.499800      0.498900      0.507600      0.504100
std     14202.332348      0.500025      0.500024      0.499967      0.500008
min        32.000000      0.000000      0.000000      0.000000      0.000000
25%     12075.750000      0.000000      0.000000      0.000000      0.000000
50%     24544.500000      0.000000      0.000000      1.000000      1.000000
75%     36800.750000      1.000000      1.000000      1.000000      1.000000
max     48972.000000      1.000000      1.000000      1.000000      1.000000

          Microwave  Line Voltage       Voltage  Apparent Power  \
count  10000.000000  10000.000000  10000.000000    10000.000000
mean       0.495100    229.523600    225.038200     1751.121200
std        0.500001      5.802449      6.476259      144.432146
min        0.000000    220.000000    211.000000     1500.000000
25%        0.000000    224.000000    220.000000     1627.000000
50%        0.000000    230.000000    225.000000     1751.000000
75%        1.000000    235.000000    230.000000     1876.000000
max        1.000000    239.000000    239.000000     1999.000000

      Energy Consumption (kWh)  Hour of the Day
count             10000.000000     10000.000000
mean                 55.297014        11.435500
std                  25.773634         6.930458
min                  10.002715         0.000000
25%                  33.275391         5.000000
50%                  55.618034        11.000000
75%                  77.454878        17.000000
max                  99.974912        23.000000
```

*Specific objective 2. **Analyze Patterns in Device Usage and Energy Consumption** in the following parts: 1. Examine usage trends and behavioral patterns across different devices and household contexts. 2. Identify inefficiencies in energy consumption and propose strategies for optimization.*

```
# Re-import necessary libraries after reset
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Reload the dataset
file_path = '/mnt/data/10000 Mahdi_Houshangi_sampled_smart_home_dataset.csv'
smart_home_data = pd.read_csv(file_path)

# Clean the dataset by dropping unnecessary columns
smart_home_data_cleaned = smart_home_data.drop(columns=['Unnamed: 15', 'Unnamed: 16',
'Unnamed: 17'])

# Convert Datetime column to datetime format for time-based analysis
smart_home_data_cleaned['Datetime'] = pd.to_datetime(smart_home_data_cleaned['Datetime'])

# Part 1: Examine usage trends and behavioral patterns across different devices and household
contexts

# Group by hour to analyze hourly energy consumption trends
hourly_energy_consumption = smart_home_data_cleaned.groupby('Hour of the Day')['Energy
Consumption (kWh)'].mean()

# Group by day of the week for behavioral analysis
daily_energy_consumption = smart_home_data_cleaned.groupby('Day of the Week')['Energy
Consumption (kWh)'].mean()

# Plot hourly energy consumption trends
plt.figure(figsize=(10, 5))
hourly_energy_consumption.plot(kind='line', marker='o', color='b')
plt.title('Hourly Energy Consumption Trend')
plt.xlabel('Hour of the Day')
plt.ylabel('Average Energy Consumption (kWh)')
plt.grid(True)
plt.show()

# Plot daily energy consumption trends
plt.figure(figsize=(10, 5))
daily_energy_consumption.plot(kind='bar', color='g')
plt.title('Daily Energy Consumption Trend')
plt.xlabel('Day of the Week')
plt.ylabel('Average Energy Consumption (kWh)')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()

# Analyze appliance-specific trends by aggregating their usage
appliance_usage = smart_home_data_cleaned[['Television', 'Dryer', 'Oven', 'Refrigerator',
'Microwave']].sum()

# Plot appliance usage frequency
plt.figure(figsize=(10, 5))
appliance_usage.plot(kind='bar', color='purple')
```

```
plt.title('Total Appliance Usage Frequency')
plt.xlabel('Appliance')
plt.ylabel('Total Usage Count')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()

# Part 2: Identify inefficiencies in energy consumption

# Compare energy consumption during peak vs. off-peak hours
peak_hours = smart_home_data_cleaned[(smart_home_data_cleaned['Hour of the Day'] >= 18) |
(smart_home_data_cleaned['Hour of the Day'] <= 7)]
off_peak_hours = smart_home_data_cleaned[(smart_home_data_cleaned['Hour of the Day'] > 7)
& (smart_home_data_cleaned['Hour of the Day'] < 18)]

# Calculate average consumption
peak_consumption = peak_hours['Energy Consumption (kWh)'].mean()
off_peak_consumption = off_peak_hours['Energy Consumption (kWh)'].mean()

# Visualize peak vs. off-peak energy consumption
plt.figure(figsize=(8, 5))
plt.bar(['Peak Hours (6PM-7AM)', 'Off-Peak Hours (8AM-5PM)'], [peak_consumption,
off_peak_consumption], color=['red', 'blue'])
plt.title('Energy Consumption: Peak vs. Off-Peak Hours')
plt.ylabel('Average Energy Consumption (kWh)')
plt.grid(True)
plt.show()

peak_consumption, off_peak_consumption

Result
(55.63319748398872, 54.82331314173935)


# Re-import necessary libraries after reset
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Reload the dataset
file_path = '/mnt/data/10000 Mahdi_Houshangi_sampled_smart_home_dataset.csv'
smart_home_data = pd.read_csv(file_path)

# Clean the dataset by dropping unnecessary columns
smart_home_data_cleaned = smart_home_data.drop(columns=['Unnamed: 15', 'Unnamed: 16',
'Unnamed: 17'], errors='ignore')

# Convert 'Datetime' column to datetime format for time-series analysis
smart_home_data_cleaned['Datetime'] = pd.to_datetime(smart_home_data_cleaned['Datetime'])

# Set datetime as index for easier time-series analysis
smart_home_data_cleaned.set_index('Datetime', inplace=True)
```

```
# Resample data to analyze energy consumption trends by hour and day
hourly_energy_consumption = smart_home_data_cleaned['Energy Consumption
(kWh)'].resample('H').mean()
daily_energy_consumption = smart_home_data_cleaned['Energy Consumption
(kWh)'].resample('D').mean()

# Plot hourly and daily energy consumption trends
plt.figure(figsize=(14, 6))
hourly_energy_consumption.plot(title='Hourly Energy Consumption Trends', color='blue')
plt.xlabel('Time')
plt.ylabel('Energy Consumption (kWh)')
plt.grid(True)
plt.show()

plt.figure(figsize=(14, 6))
daily_energy_consumption.plot(title='Daily Energy Consumption Trends', color='green')
plt.xlabel('Time')
plt.ylabel('Energy Consumption (kWh)')
plt.grid(True)
plt.show()

# Prepare data for clustering by extracting relevant features
clustering_features = smart_home_data_cleaned[['Energy Consumption (kWh)', 'Hour of the Day',
'Apparent Power']]
scaler = StandardScaler()
scaled_features = scaler.fit_transform(clustering_features)

# Apply K-means clustering with an optimal number of clusters (e.g., 3)
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
smart_home_data_cleaned['Cluster'] = kmeans.fit_predict(scaled_features)

# Visualize clusters using a scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x=smart_home_data_cleaned['Hour of the Day'],
y=smart_home_data_cleaned['Energy Consumption (kWh)'],
            hue=smart_home_data_cleaned['Cluster'], palette='viridis')
plt.title('Clustering of Energy Consumption Patterns')
plt.xlabel('Hour of the Day')
plt.ylabel('Energy Consumption (kWh)')
plt.show()

# Correlation analysis
correlation_matrix = smart_home_data_cleaned[['Energy Consumption (kWh)', 'Hour of the Day',
'Apparent Power']].corr()
plt.figure(figsize=(8, 5))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Analysis of Key Factors')
plt.show()

smart_home_data_cleaned['Cluster'].value_counts()
```

Specific objective 3. ***Develop Intelligent Automation Rules and Recommendations i****n the following parts: 1. Utilize machine learning and data analysis techniques to create adaptive automation rules*

tailored to user preferences and behaviors. 2. Recommend improvements to existing systems to enhance usability, interoperability, and overall efficiency.

```
# Re-import necessary libraries after reset
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report

# Reload the dataset
file_path = '/mnt/data/10000 Mahdi_Houshangi_sampled_smart_home_dataset.csv'
smart_home_data = pd.read_csv(file_path)

# Clean the dataset by dropping unnecessary columns
smart_home_data_cleaned = smart_home_data.drop(columns=['Unnamed: 15', 'Unnamed:
16', 'Unnamed: 17'], errors='ignore')

# Convert 'Datetime' column to datetime format
smart_home_data_cleaned['Datetime'] =
pd.to_datetime(smart_home_data_cleaned['Datetime'])

# Encode categorical variable 'Offloading Decision'
smart_home_data_cleaned['Offloading Decision'] = smart_home_data_cleaned['Offloading
Decision'].map({'Local': 0, 'Remote': 1})

# Define feature set and target variable for machine learning
features = ['Energy Consumption (kWh)', 'Hour of the Day', 'Apparent Power', 'Offloading
Decision']
target = 'Refrigerator'  # Example of predicting refrigerator usage

X = smart_home_data_cleaned[features]
y = smart_home_data_cleaned[target]

# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a decision tree classifier to predict appliance usage
model = DecisionTreeClassifier(max_depth=5, random_state=42)
model.fit(X_train, y_train)

# Predict on test set
y_pred = model.predict(X_test)

# Evaluate model performance
accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

# Feature importance analysis
feature_importances = pd.Series(model.feature_importances_,
index=features).sort_values(ascending=False)

# Visualize feature importance
```

```
plt.figure(figsize=(8, 5))
sns.barplot(x=feature_importances.values, y=feature_importances.index)
plt.title('Feature Importance for Appliance Usage Prediction')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.show()

accuracy, classification_rep
```

Result
(0.5085,
'   precision   recall f1-score   support\n\n   0   0.51   0.57 0.54 998\n 1 0.51 0.45 0.48 1002\n\n accuracy 0.51 2000\n macro avg 0.51 0.51 0.51 2000\nweighted avg 0.51 0.51 0.51 2000\n')