

Bachelorarbeit

Deutscher Titel der Bachelorarbeit	Data-Driven Insights into the Explainability of Smart Energy Systems
Englischer Titel der Bachelorarbeit	Datengestützte Einblicke in die Erklärbarkeit von intelligenten Energiesystemen
Verfasser/in Familienname, Vorname(n)	Dangl, Nicole
Matrikelnummer	12024052
Studium	Bachelorstudium Wirtschafts- und Sozialwissenschaften
Beurteiler/in Titel, Vorname(n), Familienname	Dipl.-Ing. Katrin Ehrenmüller, B.Sc.; Univ.Prof. Reka Marta Sabou, Ph.D.

Hiermit versichere ich, dass

1. ich die vorliegende Bachelorarbeit selbständig und ohne Verwendung unerlaubter Hilfsmittel verfasst habe. Alle Inhalte, die direkt oder indirekt aus fremden Quellen entnommen sind, sind durch entsprechende Quellenangaben gekennzeichnet.
2. die vorliegende Arbeit bisher weder im In- noch im Ausland zur Beurteilung vorgelegt bzw. veröffentlicht worden ist.
3. diese Arbeit mit der beurteilten bzw. in elektronischer Form eingereichten Bachelorarbeit übereinstimmt.
4. (nur bei Gruppenarbeiten): die vorliegende Arbeit gemeinsam mit

entstanden ist. Die Teilleistungen der einzelnen Personen sind kenntlich gemacht, ebenso wie jene Passagen, die gemeinsam erarbeitet wurden.

14/09/2025

Datum



Unterschrift

Bachelor Thesis

Data-Driven Insights into the Explainability of Smart Energy Systems

Nicole Dangl

Date of Birth: 21.03.2002

Student ID: 12024052

Subject Area: Information Business

Studienkennzahl: 033 561

Supervisor: Katrin Ehrenmüller, Marta Sabou

Date of Submission: 14.09.2025

Department of Information Systems & Operations Management, Vienna University of Economics and Business, Welthandelsplatz 1, 1020 Vienna, Austria

Contents

1	Introduction	7
1.1	Research Design	8
2	Literature Review	10
2.1	Smart Energy Systems	10
2.1.1	Defining Smart Energy Systems	10
2.1.2	Functionality and Requirements of SES	12
2.1.3	SES in Home Environments	13
2.1.4	Energy Communities in Austria	13
2.2	Explainable Artificial Intelligence	15
2.2.1	Theoretical Frameworks	16
2.2.2	Existing Techniques	18
2.3	User-Centered Design and Requirement Analysis	20
2.3.1	User-Centered Explanations in SES	21
2.4	User Surveys	23
3	Methodology	25
3.1	Survey	26
3.2	Analysis Methods and Algorithms	28
4	Analysis	29
4.1	User Adoption of SES	30
4.2	Motivations for SES Usage	31
4.3	Key Challenges in SES Usage	33
4.4	User Perception of Explainability Dimensions	34
4.4.1	Overall Response Distribution	35

4.4.2	Principal Component Analysis of Explainability Dimensions	36
4.5	Benefits, Trust Factors, and Preferred Formats of Explainability	38
5	Interpretation of Analysis	41
6	User Segments	45
6.1	Expert Optimisers	46
6.2	Pragmatic Cost-Savers	47
6.3	Clarity-Seeking-Non-Adopters	48
7	Discussion	50
7.1	Techniques in Relation to User Segments	51
7.2	Problems and Limitations	53
8	Conclusion	54
8.1	Future Outlook	56
	References	58
	Appendix	61

List of Figures

1	Motivations Across Age Groups	32
2	PCA Projection on Survey Items	37
3	Spearman Correlation Heatmap between Explanation Variables	40
4	Shifts in Reported Challenges by SES Usage Length .	43
5	Integration Challenges by Segment (Cramér's $V = 0.495$, $p = 0.0015$)	47
6	Motivation Profile by User Segment	50

Abstract

Smart Energy Systems (SES) promise to make homes and communities more efficient, sustainable, and flexible. Yet their success depends on more than algorithms and sensors. If people cannot understand system decisions, trust and long-term adoption are at risk. This thesis investigates how explainability can be meaningfully integrated into SES, with a focus on Austrian Energy Communities. Building on a user survey conducted in 2024, the study explores how participants perceive explainability, what motivates them to adopt SES, and which challenges they encounter. Using statistical and exploratory methods, the analysis identifies three distinct user profiles: expert optimisers, pragmatic cost-savers, and clarity-seeking non-adopters. Each group values different forms of explanation, from simple guidance to interactive and technical insights. Across all groups, clarity and transparency emerge as the strongest drivers of trust, but explainability is not a uniform need, it is shaped by expertise, adoption status, and motivational orientation. These findings underline that explainability is not just a technical feature but a social requirement that influences trust, adoption, and long-term engagement. By combining perspectives from explainable artificial intelligence and user-centred design, this thesis contributes practical guidance for developing SES that are not only intelligent but also understandable and trusted by the communities that use them.

1 Introduction

Innovative solutions are required to tackle the growing challenge of climate change, inequality, and sustainable energy security. Especially the design and operation of modern energy infrastructures, which form the foundation of a sustainable future, appear as a significant opportunity for improvement. Smart Energy Systems (SES) emerged as a promising framework that links electricity, heating, cooling, transport, and fuel networks to enable efficient and flexible energy use across regional as well as national scales [1, 2]. SES go beyond the concept of Smart Grids as the emphasis is on cross-sectoral synergies and the unified management of energy flow. In residential settings, such concepts are commonly integrated through technologies like Home Energy Management Systems (HEMS), sensors, and energy storage devices. These systems enable households to optimise their energy consumption, lower costs, as well as contribute to the stability of the broader energy grid [3, 4].

Modern tools such as Artificial Intelligence (AI) are required to create an automated and optimised Energy System like SES. Particularly Machine Learning (ML) models are enabled to forecast energy demand, manage distribution, and detect anomalies in real time [5, 6]. However, many AI-based approaches operate as so-called "Black Boxes", opaque systems working with little to no human oversight. These models make it difficult for users and regulators to understand how decisions are made. This lack of transparency can reduce trust and hinder adoption. Explainable Artificial Intelligence (XAI) addresses this challenge by developing methods and tools which can open the Black Box by enhancing interpretability, transparency, and user trust in AI-driven systems [7, 8]. To ensure system accountability, user acceptance, and long-term engagement in critical infrastructure, such as Energy Systems, explainability plays a key factor [9, 4].

Explainable SES should not be designed without constructing user requirements early in the development process to design SES that

meet user needs. User-centered design (UCD) and requirement analysis methods offer the relevant frameworks to make technical solutions align with the expectations, goals, and abilities of diverse groups of users [10, 11, 12]. Especially in smart home settings, where users have limited technical knowledge and interact with these systems directly, UCD is essential. Explanations tailored to specific user contexts, like background knowledge or age, can make a system more understandable, build trust, and improve sustained system usage [13, 14].

To make use of the full potential of SES, their users formed so-called Energy Communities (EC). Since the adoption of the Renewable Energy Expansion Act (EAG) in 2021, Austria has seen remarkable growth in these communities, as it empowers citizens to collectively be a part of the energy market by producing, sharing, and trading energy at local and regional levels [15]. SES and smart home technologies are deployed to coordinate local energy flows and enhance renewable energy integration [16]. In this context, explainability becomes a key governance tool by ensuring the understanding and trust in their collective energy management decisions made by AI-enabled systems.

Given this context, this thesis investigates how explainability can be effectively integrated into SES and HEMS. Through the analysis of user needs and preferences, it aims to determine which explanation methods will best be utilised to enhance transparency and user confidence on SES. The study builds on a survey from 2024, which explores users' perceptions of explainability in SES and was distributed among members of the Austrian EC [17]. The survey responses formed the data basis for analysing how community members experience and interact with Smart Energy Technologies.

1.1 Research Design

This thesis investigates how explainability can be meaningfully integrated into SES, with a focus on residential energy. It combines a structured literature review with an adapted user survey and applies

statistical methods to analyse user needs, expectations, and preferences toward explainability in SES.

The literature review provides the theoretical foundation for this thesis by outlining key concepts and existing research relevant to SES and explainability. It firstly covers the introduction to the world of Smart Energy, the role in home environments, and the real-world application in the form of the Austrian EC. Secondly, concepts from XAI, UCD, and user surveys are summarised to build the needed knowledge base for the following analysis.

The empirical part of this study builds on a survey originally developed by Kordulová (2024) to examine the usage of SES by members of the Austrian EC [17]. Kordulová’s survey explored how users interact with these systems and how they perceive the role and value of explainability. It combined demographic, behavioural, attitudinal, and preference-based questions, offering detailed insights into the user experience.

This thesis analyses the survey data using a combination of quantitative methods. Descriptive statistics summarise demographic characteristics and general attitudes. Cross-tabulations, t-tests, and ANOVA compare responses across user groups and test for statistical significance. Correlation analysis explores relationships between variables. Principal Component Analysis (PCA) reduces dimensionality and identifies key themes in user attitudes. Finally, K-Means clustering groups participants into potential user profiles.

These methodological steps provide the basis for answering the following research questions:

- What are the key factors influencing user trust and satisfaction in Smart Energy Systems, and how do these factors vary across different demographic groups?
- What recurring themes and sentiments emerge from user feedback on Smart Energy Systems, and how can they inform system design improvements?

- What actionable recommendations can be derived from survey data to enhance the design of user-centric, explainable Smart Energy Systems?

By combining theoretical insights with user-centered data analysis, this thesis aims to contribute practical guidance for the development of transparent and accessible Smart Energy Technologies that support long-term user trust and adoption.

2 Literature Review

This chapter presents a comprehensive literature review to provide a solid theoretical and conceptual foundation. The aim is to highlight relevant academic and practical insights that inform the understanding of SES, XAI, and UCD approaches. By examining existing research, this chapter positions the study within the broader academic discourse and establishes the basis for the subsequent survey.

2.1 Smart Energy Systems

2.1.1 Defining Smart Energy Systems

To address the challenges of climate change, energy supply, and sustainability, SES serve as a conceptual solution for designing and operating future energy infrastructures. SES introduces unified management of electricity along with heating, cooling, transport and fuel to overcome sector-specific limitations and improve coordination. The system allows for efficient, sustainable, and flexible energy use throughout national and regional scales [1].

SES are usually described as energy infrastructures that combine smart electricity, heating, and gas grids with different types of storage and control systems. Their goal is to make the most of renewable energy sources and improve the overall efficiency of the energy network. The first conceptualisation of SES took place during the early

2010s under the Coherent Energy and Environmental System Analysis project, which established economic and environmental benefits from cross-sectoral integration. For example, excess wind power can be redirected to large heat pumps that supply district heating networks. The mechanism integrates electric power systems with heating operations to balance fluctuations in renewable energy supply [1]. SES indicate a currently evolving method of designing and thinking about Energy Systems. Rather than optimising isolated sub-sectors, SES concentrates on interactions between electricity, heating, cooling, gas, transport, and storage systems. The unified vision of SES is becoming increasingly important because countries actively pursue the development of 100% renewable energy platforms, which require a high degree of flexibility and coordination between the different infrastructures [2]. This approach goes beyond the narrower concept of the Smart Grid, which focuses primarily on the digital optimisation of the electricity sector. However, in much of the academic and technical literature, the terms Smart Grid and SES are often used interchangeably, although they refer to different system scopes and levels of integration. Conflating the two terms risks overlooking the full potential of cross-sector synergies enabled by integrated infrastructures [1]. The focus of this thesis is primarily on Smart Grids as a central component of SES, including their interaction with storage technologies and end users.

In [18], a framework of a smart and sustainable Energy System is proposed. Their criteria include not only technical and economic feasibility but also energy efficiency, environmental impact, social acceptability, and integrability into existing infrastructure. From this perspective, SES must also enable multigeneration, which again includes the simultaneous production of electricity, heating, cooling, and fuels from a single source, while enhancing social welfare and minimizing resource waste [18]. An important conceptual advance within SES is the 3S framework: Source, System, Service. This emphasises the need to consider the entire life cycle of energy. From the selection of renewable energy sources to the design of multi-source

systems and the provision of energy services in a way that is consistent with societal and environmental goals [18].

2.1.2 Functionality and Requirements of SES

The successful operation of an SES depends on real-time data collection while using automated decision systems. A control management system that combines electricity with thermal and gas grids requires advanced computational intelligence capable of enabling responsive, optimised, and increasingly autonomous energy management [1]. An SES operates through enormous data streams which get collected through a broad network consisting of sensors, meters, control systems, and external platforms, including weather services and mobility monitoring. Smart meters, for example, can record household electricity consumption every 15 minutes, generating up to 35 billion data entries per year for a single utility serving one million customers. The storage system contains both details about customer consumption and interactions alongside device status data, coupled with real-time grid information and time-based price alerts and monitoring data [19].

This transition to data-centric energy management creates both opportunities and vulnerabilities. On the one hand, real-time data enables optimised forecasting, bottleneck and error detection as well as predictive maintenance across the entire energy chain, from generation to end use. Such constant monitoring of household private actions poses privacy issues, especially when the data collected achieves fine-grained tracking of daily routines [5]. At a technical level, SES are increasingly governed by ML models and AI systems capable of forecasting energy supply and demand, detecting anomalies, and automating decisions by using real-time data, collected by sensors across the system [6, 5].

As National Grid controllers, along with HEMS, increasingly use AI, the interpretability of these decisions becomes more important. Users and regulators require a full understanding of the decision-making processes. This is especially important for household-level

systems, where trust in automation is closely tied to users' ability to perceive it as transparent and fair.

2.1.3 SES in Home Environments

Smart homes are a potential solution to make energy demand and consumption visible in individuals' households. These environments are equipped with technologies that enable the monitoring, management, and optimisation of household energy use. A typical smart home setup includes various interconnected components such as smart meters, sensors, Internet of Things appliances, energy storage systems, and sometimes renewable energy sources like photovoltaic panels. These are often coordinated by a HEMS, optimising when and how devices operate based on user preferences, real-time electricity prices, and energy availability [3]. In advanced implementations, HEMS are integrated with AI systems to forecast energy demand, detect energy-intensive behaviours, and adjust consumption to maintain comfort while reducing costs. This is made possible through the interconnectivity of consumption and production, which highlights when specific devices should be operated and when it is most beneficial to reduce or shift energy use [4]. While these systems benefit individual households by lowering costs and reducing the complexity of energy saving, they contribute to higher significance by improving the stability and flexibility of the entire energy grid. With a broad implementation across the country, fluctuating supply from renewable sources can be balanced in real time [1].

2.1.4 Energy Communities in Austria

Through the concept of EC, Austria demonstrates an approach to integrate local smart systems into the broader SES framework. For creating these community networks, the European Union established basic requirements. The Clean Energy for All Europeans Package serves as the foundation for the national expansion of renewable energy through the Renewable Energy Expansion Act (EAG), which

went into effect in 2021. This legislation supports the decentralisation and democratisation of energy by allowing citizens to jointly produce, share, and trade energy at the local level [15].

There exist two uniquely defined community structures in Austrian legislation. First, the Renewable EC (Erneuerbare Energiegemeinschaften, EEGs), where the members are geographically limited. They can generate, consume, store, and sell electricity and heat from renewable sources. Membership can include individuals, small businesses, and public facilities. Their goal is regional sustainability and benefit-sharing, rather than profit. The second type is Citizen EC (Bürgerenergiegemeinschaften, BEGs). Such communities can operate through different grid zones across the country, though they are restricted to electrical energy and not necessarily bound to renewable sources. Larger companies may participate, but without a controlling interest. Since the enactment of EAG, Austria has experienced a significant expansion of its energy community sector with over 100 entities contributing and several hundred more in planning [15].

These communities implement smart home systems, including HEMS, to coordinate local energy use. This setup enables balancing supply and demand at the community level. A community sharing network enables people to exchange their excess solar power while also enabling optimised collective consumption through digital platforms. Real-time energy sharing and peer-to-peer pricing is possible, for example, through an online platform named eFriends [15]. Additionally, Austrian initiatives such as ECOSINT aim to ensure that EC remain interoperable and grid-friendly by developing standardised digital interfaces and scalable architectures that can integrate with national SES structures [16].

SES provide an integrated approach to managing electricity, heating, cooling, transport, and storage, aiming to support renewable energy use and improve overall efficiency. At the household level, smart homes and HEMS illustrate how data-driven optimisation can reduce costs and support grid stability, though they also raise concerns about privacy and transparency. In Austria, EC represent a concrete step

toward this vision, enabling citizens to collectively produce, share, and manage energy under the Renewable Energy Expansion Act.

2.2 Explainable Artificial Intelligence

The current use of AI applications utilising ML and Deep Learning (DL) techniques produces systems labelled as "Black Boxes". These models can achieve their objectives, but the reasoning behind their outputs remains opaque. Their complexity, with layered architectures and millions of parameters, makes it difficult, even for developers, to fully understand how decisions are made [7]. XAI is gaining prominence because it works to enhance AI systems with transparency features, interpretability abilities and eventually improving trustworthiness. In contrast to the Black Box models, the White Box models, like decision trees or rule-based systems, are naturally interpretable, with transparent logic and traceable decisions. The middle position in XAI forms Grey Box models that combine system complexity with improved explainability features for partially transparent systems. The key to explainability lies in adding explaining techniques to a Black Box model to understand its decision-making process. However, even with the best explanation models, a Black Box can never turn into a White Box unless the fundamental logic is directly interpretable [7, 8].

XAI contains three main terms: interpretability, transparency and explainability. The concept of interpretability is used to reveal internal mechanisms to create a human understood model, showing how inputs are processed and transformed into outputs. A transparent model is the opposite of an opaque Black Box model, since it is comprehensible on its own. Explainability, in contrast, focuses on generating understandable justifications for the model's decisions, regardless of whether the underlying model is interpretable or not. These justifications play a vital role because users need them to build trust and make informed decisions concerning AI output. For explainability to be effective, it needs to be built on a foundation of

interpretability and transparency. Otherwise, it becomes difficult to trace or correct faulty decisions, which can be particularly dangerous in high-stakes environments, like the energy sector [20, 7]. Here, AI is increasingly used to manage complex, distributed systems, often in real time. Within these operational domains, understanding the system functions alone is insufficient. Users, regulators, and stakeholders must also understand why the system behaves in a certain way. To qualify as effective, XAI needs to offer context aware information that exceeds technical interpretations [7]. For example, if a ML model reduces electricity to a neighbourhood battery system because it predicts low usage, operators must be able to explain that decision. Missing explanations can result in safety issues, public complaints or even discrimination [8]. This makes XAI directly relevant for this thesis. SES will only be effective if they not only work well but also transparently explain their decisions. Clear explanations help build trust and make adoption more likely.

2.2.1 Theoretical Frameworks

It is important to understand the broader theoretical frameworks that underpin XAI before diving into user-centered and sector specific approaches. Explainability needs to address both the internal logic of models and the diverse needs of users. By clarifying these underlying structures, we better understand why current approaches succeed or fail and where they fall short in meeting user needs. This section summarises existing XAI approaches grouped according to several key dimensions: the distinction between global and local explainability methods, the difference between perceptive interpretability and interpretability by mathematical structure, and the separation of technical XAI from human-centered XAI.

A foundational distinction in the literature is between global and local explainability methods. Global methods seek to summarise how a model behaves across a range of inputs, providing insight into its general functioning and priorities. This is particularly useful for sys-

tem designers, engineers, and policymakers overseeing larger infrastructures [8]. Local explainability, in contrast, focuses on individual predictions explaining why a model made a specific decision. In smart home contexts, local explanations help residents understand events like unexpected heating behaviour or sudden changes in energy forecasts. Both types of explanations are necessary to support the variety of stakeholders interacting with AI in Energy Systems [21].

Another categorisation consists of differentiating between perceptive interpretability and interpretability by mathematical structure. Perceptive interpretability produces human-understandable explanations through visual representations and rule-based or textual interpretation. These features are of great importance, especially among people with minimal technical experience. On the other hand, structural interpretability focuses on understanding the internal mechanisms of a ML model. Instead of just showing outcomes or visual cues, structural interpretability tries to explain how and why a model behaves the way it does by analysing its internal components like weights, gradients, activations, and feature interactions. To determine how a model came to a certain conclusion, the strength and direction of a weight are used to see which input features had the most impact. This is often done using feature importance scores or by tracing the flow of information through the network. Structural interpretability requires technical insight and often mathematical tools. Expert users tend to be the most appropriate audience for this approach because it does not work well for non-experts. The use of both interpretive approaches should be integrated through perceptive methods to build user trust and structural methods to establish robust validation, coordination, and system-level debugging [22].

In addition to these technical dimensions, recent research draws attention to the distinction between technical XAI and human-centered XAI. XAI approaches built for technical purposes focus on model enhancement and developer analysis. The techniques have three main objectives that uncover system biases, boost operational capabilities and verify stability levels. However, such methodologies are often

inaccessible to end users. Human-centered XAI tends to be overlooked in current research. It prioritises explanation formats that users can engage with, such as natural language summaries, contextual prompts, and preference-aware interactions [4].

Overall, explainability in SES should not be limited to the model level. Instead, it should be seen as a system-level design challenge involving interface design, data transparency, user feedback mechanisms, and participatory development. As SES infrastructures grow more complex and automated, explainability will become a foundational requirement for trust, compliance, and long-term system resilience [4].

2.2.2 Existing Techniques

To deliver on these goals, several model-agnostic tools are now commonly used to generate explanations in Black Box models. Model-agnostic techniques offer a flexible and powerful solution because they can be applied to any predictive model, regardless of its internal structure. Rather than relying on the model’s internal structure, they analyse input-output behaviour to generate meaningful explanations [20].

One of the most well-known is LIME (Local Interpretable Model-agnostic Explanations), which stands as one of the most recognised methods for generating Black Box explanation models. The explanation model constructs a basic surrogate model centred on a particular prediction to determine the most influential features. This method is especially suitable for local explanations and has been applied in energy forecasting, appliance control, and occupancy modelling [8]. Implementing LIME involves generating a dataset of slightly modified inputs around the prediction of interest, training a simple interpretable model, such as linear regression, on this data, and then analysing the influence of each input feature based on the resulting surrogate model [20]. Another widely used technique is SHAP (SHapley Additive exPlanations), which uses concepts from cooper-

ative game theory to assign importance values to each feature in a prediction. The technique provides global and local insight through a mathematical foundation, which makes it a popular choice for its consistent results. In SES applications, SHAP can explain complex interactions between weather data, time-of-use pricing, and user behaviour in energy forecasts or control decisions [8]. A third important model-agnostic tool is ELI5 (“Explain Like I’m Five”). This method produces understandable explanations from weighted feature lists with straightforward text outputs. ELI5 emerged as a programme designed for classifications until developers applied it to improve explainability of opaque systems [8]. In a smart home scenario, ELI5 might translate a complex energy-saving action into a straightforward message: “The heating was turned off because no one was home, and electricity was expensive.”

In addition to these, counterfactual explanations continue to attract interest as a practical way to communicate “what-if” scenarios. Counterfactual explanations provide a practical understanding of how minor changes in the model’s input data produce different output results without exploring its inner mechanisms. For example, a user might be shown that “if the outdoor temperature had been 2°C lower, the heating would have been activated.” The implementation process involves determining how a minimal modification of input values changes the prediction outcome, then generating alternative scenarios to present the user with understandable contrasts [20]. Other techniques focus more on visualisation. The predictive effect of single features on model outcomes can be illustrated using Partial Dependence Plots (PDPs) and Individual Conditional Expectation (ICE) visualisations across global and local scale. PDPs aggregate predictions across the data set to show the general effect of a feature, while ICE plots show how predictions change for individual instances [20].

Despite their strengths, these methods come with several implementation difficulties. Using SHAP or LIME without contextual adaptation can lead to miscommunication and confusion, particularly

in environments where multiple users interact with multiple system purposes. Therefore, explanation tools must be aligned with stakeholders’ goals together with technical requirements and the broader system architecture [21].

This raises the question: how can we ensure that explainability methods are designed in a way that truly meets user needs? Existing techniques are often developed from a purely technical perspective and may fail to consider the diversity of users’ expectations, experiences, and decision-making contexts. Addressing this challenge requires shifting from explanation design focused solely on models toward a more holistic, user-driven approach. In this context, requirement analysis and user-centered design are essential because they provide structured ways to capture user expectations and translate them into system features, which is directly relevant for this thesis as it aims to connect explainability in SES with concrete user needs.

2.3 User-Centered Design and Requirement Analysis

To ensure that designs align with the needs, capabilities, and expectations of their intended audience, user requirements play a critical role in shaping XAI systems. Requirements can be defined as needs that users express regarding the functionality, usability, and trustworthiness of a system. These guide the design process of a system and help developers balance technical feasibility with user needs [11, 10]. Without comparing design decisions with user requirements, XAI systems risk producing explanations that are technically accurate but unintelligible or irrelevant to end-users.

Closely related to requirements analysis is the broader concept of human-centered and UCD. Such methods put users in the center of the design process and involve iterative cycles of prototyping, feedback and improvements. Human-centered design (HCD) builds on the principle that development of a system is based upon a critical insight into users’ contexts, tasks, and goals. Each stage of the design process is improved by integrating continuous user feedback. In

this way, HCD ensures that the resulting explanations address users' actual needs and challenges [23].

UCD is based on the same philosophy but focuses even more on usability and user experience. In the context of XAI, UCD waives the implementation of one-size-fits-all approaches and rather focuses on creating the right explanation formats for specific user groups. To achieve this, designers should consider users' prior knowledge, technical expertise, and the specific context in which the explanations will be adapted [12].

Additionally, explainability is inherently contextual and goal-dependent, since users seek explanations for diverse reasons [24]. Human- and user-centered approaches are essential because they help uncover these underlying goals and translate them into specific design requirements for XAI. This iterative and participatory perspective ensures that explanations evolve in response to real-world user needs instead of remaining fixed based on initial assumptions.

By integrating requirement analysis with human- and UCD methodologies, XAI development can better address the gap between technical possibilities and user expectations. This alignment is particularly crucial for SES, where users' trust and understanding can directly impact technology adoption and long-term engagement.

2.3.1 User-Centered Explanations in SES

The level of explainability needed for SES goes far beyond general transparency in AI. SES are multi-layered environments in which AI technologies interact with physical infrastructure, human behaviour, and real-time contextual data. XAI in the energy sector has to be applicable for multiple types of stakeholders. From technical system operators to policymakers and everyday users, each of these groups requires different levels and types of explanation. The application of a standardised solution is not only ineffective, it can also reduce user trust in recommendations and results, and thereby the adoption of these systems [21]. In practice, this means that explainability in SES

has to be audience-specific. A system operator might need technical breakdowns of model confidence or feature contributions to make regulatory decisions or adjustments. In contrast, a household user simply needs to understand why their heating system did not turn on this morning. In this case, using detailed explanations about the underlying algorithm would be too complex and could lead to confusion and resistance towards the product. In fact, trust-based models of user interaction show that even technically correct decisions can reduce trust if the reasoning is not aligned with user expectations or is communicated poorly [13]. Moreover, the dynamic and distributed nature of SES makes them particularly vulnerable to errors if decisions are not transparent. A wrong AI decision might influence multiple downstream systems, like incorrectly predicting the heating needs of the evening with the result of a shut down heat pump, leading to discomfort, manual overrides, and increased energy use. The absence of explainability makes it complicated to identify where such problems originate, which makes fixing issues in real time almost impossible. Beyond being a technical feature, explainability can also be interpreted as a governance tool. It helps to ensure that systems stay transparent, compliant, and trusted by their users [9].

Another challenge is that current explainability research mostly concentrates on evaluating individual elements, like model outputs or User Interface level feedback, while neglecting system-wide decision-making processes of SES. But SES are not just collections of individual models. They are multi-layered, interconnected ecosystems where context significantly influences data interpretation, the reception of system outputs, and how users respond. System-wide explainability is required, where the explanations are meaningful and users can track decisions down to their root causes [21]. In addition, there is the issue of participation and acceptance. User acceptance forms a key requirement for smart systems to achieve success, since users do not just act as data providers, but as decision-influencers. A study by van der Werff and Steg (2016) found that participation in SES is strongly dependent on personal values and sense of control. People are more

likely to accept and support automated Energy Systems when they correspond with their environmental identity, which makes explainability not just a technological requirement, but also a psychological one [14].

In smart home environments, explainability is essential for building trust and ensuring users feel in control of the systems that manage their energy use. The primary need for household occupants goes beyond technical details since they seek easy to understand information about the automated decision of the system. When HEMS operate without clear explanations, users may feel confused, lose trust, or ignore the system altogether. Effective explainability in smart homes should contain syntactic, semantic, and pragmatic dimensions to ensure that explanations are clearly presented, cognitively accessible, and contextually meaningful. Explainable systems should also be interactive and adaptive, offering answers to questions like “Why did the heating turn on?” while tailoring explanations to individual user requirements. Explainability needs to function as an essential principle which designers should incorporate from the beginning. For example, by involving users in the development process through participatory design or other human-computer interaction methods. This improves seeing explainability as more than a technical feature and helps ensure transparent, trustworthy and supportive AI systems [4].

2.4 User Surveys

To effectively capture user requirements and needs, a common method is through user surveys. They are particularly useful when researchers need to reach a broad range of participants and collect standardised data across different user groups.

User surveys are research tools which make use of different methods like interviews, questionnaires, panel surveys, or observations to collect data from a specified sample of people. They are designed to systematically gather information about participants’ opinions, attitudes, behaviours, or experiences, usually with the goal of identifying

trends or patterns in a target population [25]. Depending on the goals of the study and the resources available, surveys can be conducted in person, over the phone, online, or via mailed forms. One of the most commonly used survey methods is the questionnaire, which provides a consistent format for asking participants standardised questions that can be compared across respondents [26].

Questionnaires are used to obtain quantitative and qualitative data efficiently, making them well-suited for large-scale studies with generalisable results. This method offers several strengths. Surveys can be done on a large scale and in a cost-effective way while collecting large datasets from diverse populations. Through the anonymity of the setup, participants respond in a more honest way. The standardised format additionally ensures comparability of results across respondents [25, 27]. At the same time, surveys do have limitations. Response rates can be low, which may affect the representativeness of the results, and questions must be carefully designed to avoid ambiguity and bias [26]. Furthermore, surveys rely on self-reported data, which means they may not always reflect actual user behaviour [27]. Nevertheless, despite these challenges, surveys are a reliable way of capturing user requirements.

To capture complex and abstract concepts like user attitudes towards explainability in SES, surveys can offer a structured way. Through targeted and specific questioning, perceived trust, challenges or worries towards AI are revealed. They also enable the analysis of how these attitudes vary across demographic groups, technical expertise levels, and usage contexts. To assess user engagement with digital energy solutions, surveys have already been widely used and have proven to be an effective tool to highlight barriers to adoption as well as opportunities for improvement [27]. Since SES technologies have a far-reaching impact on various stakeholders, surveys can detect diverse perspectives which might have been overlooked. This is helpful for ensuring that explainability is not treated as an afterthought but is part of the design process from the start.

In summary, this literature review highlights three main insights.

First, SES represent an evolving infrastructure integrating electricity, heating, cooling, transport, and storage. This offers both opportunities for efficiency and sustainability as well as challenges around complexity, privacy, and trust. Second, XAI provides a critical toolset for addressing these challenges, but its impact depends on moving beyond technical explainability. Human- and User-Centered approaches can be utilised to adapt to each user’s needs. Third, surveys emerge as an effective method for capturing these needs, helping to understand user perceptions, challenges, and preferences in relation to SES.

Together, these insights underline that explainability in SES is not simply a technical issue but a socio-technical one, requiring an understanding of how users engage with the systems in their everyday lives. The following analysis builds on survey data to explore user adoption, motivations, challenges, and perceptions of explainability, with the aim of deriving actionable insights for user-centered SES design.

3 Methodology

Building on these insights, a survey-based study was adapted to explore the perception of SES and the corresponding explainability in real-world settings. The methodological frameworks described in this chapter centre on the analysis of a structured questionnaire, designed to uncover user experiences, expectations, and preferences related to SES and explainable AI. The study is based on an existing survey developed by Kordulová (2024), created to explore these themes within Austrian EC [17]. The methodology section is divided into two parts, containing the explanation of the structure, distribution, and logic of the survey as well as details about the data preparation steps and analysis techniques employed to interpret the results.

3.1 Survey

This thesis is based on a survey originally designed by Kordulová (2024), developed to investigate the level of explainability in SES perceived by users, as well as their requirements for understandable and user-friendly energy technologies. The survey was created to give a voice to everyday users of SES within the Austrian EC. It offered a human-centered perspective in understanding how people interact with smart systems and what type of communication and decision transparency they find most useful [17].

The survey was conducted online and shared mostly through local EC across Austria in 2024. The promotion took place across community channels and social groups, which helped ensure participation from individuals who had hands-on experience with SES or were in contact with discussions around renewable energy. In total, 49 participants completed the survey. The sample was relatively diverse in terms of age, technical knowledge, and geography, though the male participant group was dominant (89.8%) [17]. Because of this imbalance, gender was not included in the analysis, as the lack of variation would have made results unreliable.

In the survey, demographic and contextual questions were combined with attitudinal and preference-based items. There were 18 questions in total, where the last two created a space for participants to leave notes and add their email address to receive updates on the survey's results. A mix of closed multiple-choice questions, 5-point Likert scales, and ranking formats was used. The first part focused on user experiences with SES, including usage patterns, motivations, encountered challenges, and views on the role and design of explainability. Demographic data, including technical expertise, age, gender, duration of membership in an energy community, and living situation, were collected in the last section [17].

In order to make the analysis relevant and properly organised, five thematic blocks of survey questions were formed. The blocks were examined in relation to the demographic and background data

(Questions 12-16), which included comparing responses based on participants' age, technical expertise, length of membership in EC, and the type of area they live in. The combined analysis of theme-specific questions with user background information helped to uncover deeper patterns and potential user segments.

The first group (Question 1) focused on how the users adapted smart systems. The Question used consists of asking whether respondents currently use any form of SES, such as smart heating, energy management software, or EV charging tools. This was used to determine the SES users and non-users and compare their responses under the following sections. The second block (Question 2) examined user motivations and was based on the question asking participants to select the most important reasons for using SES. Motivations like saving money, improving energy efficiency, or managing usage based on real-time data were being examined, which helped to uncover what people value most. The third block (Question 3) addressed user challenges when using SES. This included technical reliability, understanding the system's decisions, or compatibility with other devices.

The fourth group of questions (Questions 4-8) was formed to find out more about users' general attitude toward explainability and related system behaviours. Users were asked to rate how much they value different principles, such as clarity in energy-related decisions, system adaptability to individual needs, transparency in system functionalities, and the degree to which trust is influenced by the system's understanding of user needs. Question 8 complemented these items by directly asking how important explainability is perceived by the users overall. This group's commonality is that the questions focus more on users' conceptual orientation, attitudes, and expectations regarding the desired functionality of a SES rather than focusing on particular system features. This context is enhanced by Question 8, since it measures explainability not as a function, but as a guiding value which influences user trust and system engagement. The final set of questions (Questions 9-11) focused on how explainability can be applied in practice. Here, users were asked to select the most impor-

tant benefits of explainability, rank the factors that affect their trust in explanations, and choose preferred formats for receiving those explanations. While the fourth group looked at values and beliefs, this group captured users' concrete preferences and interaction expectations. These questions reflect a move from "what should a system ideally represent" to "how should a system actually communicate with me." These responses offer insights into how explainability features can be implemented in UCDs. The analysis of this set helped to relate user needs to the appropriate technical solutions.

3.2 Analysis Methods and Algorithms

To derive underlying information from the survey data, this study applies a combination of statistical and machine learning methods to explore user behaviour, attitudes toward SES, and preferences regarding explainability.

Data preparation ensures consistency and comparability across variables. Responses to multiple-answer questions are transformed into binary variables, while ranking questions are encoded numerically based on the order given by participants. The continuous variable age is categorised into ten-year steps to allow for grouped comparisons. No incomplete or invalid answers had to be removed. Demographic characteristics, usage behaviours, and general attitudes toward SES and explainability are summarised using descriptive statistics. Frequencies, percentages, means, and standard deviations provide an overview of the data. Relationships between categorical variables are examined with cross-tabulations, while grouped means highlight trends in attitudes across demographic groups. T-tests and one-way ANOVA tests assess whether differences in group means are statistically significant.

Correlation analysis further explores relationships between variables. Depending on data distribution, Pearson or Spearman coefficients capture patterns in how users evaluate concepts such as trust in AI-generated content. Principal Component Analysis (PCA)

reduces dimensionality and identifies hidden structures in explainability dimensions. This method allows user attitudes to be interpreted along more abstract dimensions, such as awareness and personalisation. Because of the small sample size, bootstrapping is used to test robustness. By repeatedly resampling the dataset and re-estimating component loadings, confidence intervals are generated, showing whether observed structures are stable or influenced by random variation [28]. K-Means clustering groups participants based on their selections of explainability benefits and preferred formats. This unsupervised method highlights distinct user patterns and supports the interpretation of explainability needs [29].

In addition, a simple rule-based segmentation approach defines three user profiles. These segments are validated against other survey dimensions through cross-tabulations and statistical tests.

Together, these methods provide a structured exploration of how different users perceive, experience, and value explainability in the context of SES, while highlighting the diversity of needs that inform the development of transparent, user-aligned AI tools.

4 Analysis

Following the thematic grouping of survey questions outlined in Section 3.1, the results are presented in five main parts: SES usage, motivations, key challenges, perceptions of explainability dimension, as well as benefits, trust factors and preferred formats. Each section reports the statistical findings within its thematic block and considers relevant demographic and background variables.

For each thematic block, detailed response distributions with corresponding confidence intervals are provided in the appendix. In the following, only the most relevant results are highlighted in the text, while full tables can be consulted for additional detail. Unless otherwise specified, all percentages are calculated based on the full sample ($N = 49$). For subgroup analyses, both percentages and absolute

numbers (n of N) are reported to ensure transparency, given the small sample size. For clarity, statistical values (Cramér’s V, p-values) are reported only for relationships that reached statistical significance. Where no values are provided, the corresponding associations were not statistically significant.

This section is limited to a factual presentation of the statistical results, including absolute counts, percentages, and subgroup comparisons. No interpretation is offered here, since the aim is to provide a clear and objective basis for the patterns that will be explored in Sections 5 and 6.

4.1 User Adoption of SES

Amongst our participants, SES are already widely used. Out of the 49 respondents, 34 people (69.4%) reported that they currently use SES, while 15 participants (30.6%) indicated that they do not. Looking at how long people have been using these systems, it becomes clear that adoption is still quite new. Only one participant had more than three years of experience, while most respondents fell into the “Recent Adopter” category. Specifically, 4 users (11.8%) had joined within the past six months, 11 users (32.4%) between six months and one year, and the largest group, 18 users (52.9%), reported using SES for one to three years. This means that over 95% of SES users have started their journey within the past three years.

Looking at technical knowledge shows a strong link between expertise and adoption. None of the participants without technical knowledge reported using SES (0 of 5). Among those with basic knowledge, adoption rose to 63.2% (12 of 19). The highest uptake was found among participants with higher expertise, where 88.0% (22 of 25) reported active use. Statistical tests confirm that this relationship is significant, with a strong effect size (Cramér’s V = 0.567, Spearman $r = 0.50$, $p < 0.001$).

Age also played a role in adoption. The highest usage was found among respondents aged 36–45 years (78.6%, 11 of 14) and 46–55

years (76.9%, 10 of 13). Slightly lower rates appeared among participants aged 56–65 (71.4%, 5 of 7) and those under 35 (54.5%, 6 of 11). The lowest adoption was observed in the oldest group, with only 50.0% (2 of 4) of participants aged 65 or older reporting SES use.

Settlement size revealed further variation. In small communities (<5,000 inhabitants), adoption reached 73.3% (22 of 30). Participants from small towns (5,000–20,000) showed a lower rate at 61.5% (8 of 13). Both respondents from medium-sized cities (20,000–100,000) reported using SES (100%, 2 of 2), while in large cities (>100,000), adoption dropped again to 50.0% (2 of 4). Given the small number of urban participants, results for these categories should be interpreted with caution.

4.2 Motivations for SES Usage

When asked about their reasons for using SES, participants showed a clear focus on practical benefits. The most frequently mentioned motivation was reducing energy costs, selected by 39 out of 49 participants (79.6%). Nearly as many, 34 participants (69.4%), chose optimising their energy consumption. A smaller but still substantial share of respondents named improving energy efficiency (42.9%, 21) and proactive energy management (42.9%, 21). Less common were informed decision-making (20.4%, 10), personalised energy management (8.2%, 4). In the open responses, sustainable energy use was mentioned three times and was therefore added as an additional motivation (6.1%).

Exploring differences across age groups revealed some distinct patterns (see Figure 1). Energy optimisation was most strongly emphasised among respondents aged 36–45, where nearly all participants (92.9%, 13 of 14) selected it. It was also commonly mentioned among those under 35 (72.7%, 8 of 11) and those aged 56–65 (71.4%, 5 of 7). In contrast, participants in the 46–55 age group (46.2%, 6 of 13) and in the 65+ group (50.0%, 2 of 4) chose optimisation less often. Cost reduction, on the other hand, was consistently valued across

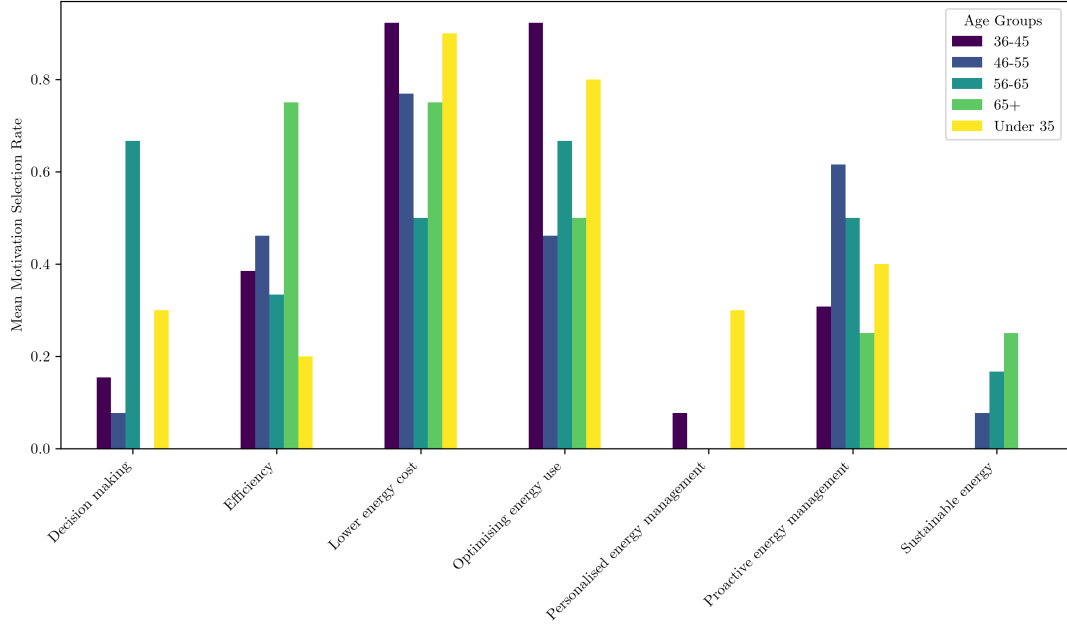


Figure 1: Motivations Across Age Groups

all ages, though to varying degrees. It was particularly high among participants aged 36–45 (92.9%, 13 of 14) and under 35 (90.9%, 10 of 11). Rates were slightly lower in the 46–55 group (76.9%, 10 of 13) and among those aged 65+ (75.0%, 3 of 4). The lowest cost-related motivation appeared in the 56–65 group, where only 42.9% (3 of 7) selected it. Statistical testing confirmed these differences, showing a moderate association between cost reduction and age group (Cramér’s $V = 0.41$ $p = 0.081$).

Settlement size also influenced motivational patterns. Respondents from large cities stood out, as half of them (50.0%, 2 of 4) named personalised energy management as a key reason for using SES. In comparison, only one participant in small towns (7.7%, 1 of 13) and one participant in small communities (3.3%, 1 of 30) mentioned this factor (Cramér’s $V = 0.46$, $p = 0.015$). Cost reduction again proved to be a universal priority across all settlement sizes. Every participant in large cities (100%, 4 of 4) mentioned it, along with 84.6% of those in small towns (11 of 13) and 76.7% of those in small communities (23 of 30). Among the very small group of medium-sized

city residents, only one of the two participants (50.0%) selected this motivation. Sustainable energy use also showed some connection to settlement size (Cramér's $V = 0.42$, $p = 0.031$).

Analysing the relationship between SES usage and motivations revealed that decision-making was particularly important for those who had only recently adopted SES. Three of seven participants (42.9%) with less than six months of experience selected it. Among participants with six to twelve months of experience, none (0 of 13) chose decision-making as a motivation. In contrast, the share rose again among those with one to three years of experience, where seven out of 26 (26.9%) selected it, before dropping back to zero among the few long-term users with more than three years of experience (0 of 3).

Technical knowledge levels showed relatively stable results in this case. Around one in five participants in each group mentioned decision-making: 20.0% (1 of 5) among those without technical knowledge, 21.1% (4 of 19) among those with basic knowledge, and 20.0% (5 of 25) among participants with higher expertise. In contrast, proactive energy management was more clearly associated with knowledge levels (Cramér's $V = 0.40$, $p = 0.021$).

Additional statistical analysis revealed connections between motivations. For instance, cost reduction and proactive energy management were negatively correlated ($\Phi = -0.38$, $p = 0.012$). A similar pattern was found between energy optimisation and sustainable energy use ($\Phi = -0.38$, $p = 0.025$).

4.3 Key Challenges in SES Usage

In question 3, most participants pointed to technical issues as a challenge when interacting with SES, which were mentioned by 36 respondents (73.5%). Other common challenges included difficulty understanding system behaviour (19 participants; 38.8%) and integration problems (18 participants; 36.7%). A smaller number of participants mentioned data protection concerns and unclear energy impacts, each reported by 15 participants (30.6%).

Technical knowledge influenced which challenges were reported. Participants with higher expertise most often named integration problems, with 60.0% (15 of 25) reporting this difficulty. By contrast, none of the respondents without technical knowledge mentioned integration (0 of 5). Statistical testing confirmed this strong link between technical knowledge and integration challenges (Cramér’s $V = 0.50$, $p = 0.002$). Furthermore, technical issues were widespread across all knowledge groups, with 80.0% (4 of 5) of participants without technical knowledge, 73.7% (14 of 19) with basic knowledge, and 72.0% (18 of 25) with higher expertise reporting them.

The length of SES usage also shaped reported challenges. Every participant with less than six months of experience (100.0%, 7 of 7) mentioned technical problems, while none in this group reported unclear energy impacts (0 of 7). Those with more than three years of experience described both technical issues and unclear energy impacts at a rate of 66.7% (2 of 3). Data protection concerns were most common among new users, with 42.9% (3 of 7) of those in the less-than-six-months group mentioning them.

Relationships between different types of challenges also became visible. Data protection concerns and unclear energy impacts were positively associated (ϕ coefficient = 0.35, $p = 0.019$). At the same time, unclear energy impacts showed a weaker but still notable association with integration challenges (ϕ coefficient = 0.28, $p = 0.053$).

4.4 User Perception of Explainability Dimensions

The explainability components in this survey were examined from multiple perspectives to capture user evaluations of clear communication and information, adaptability to individual needs, the perceived importance of explainability and the extent to which system understanding influences trust. Since explainability is a central factor for acceptance and long-term usage, this section provides an overview of participants’ ratings across the different dimensions and then explores the underlying factor structure using PCA.

4.4.1 Overall Response Distribution

Ratings for the explainability components were generally high across all categories. The most positive responses were given to the value of clear communication about system functionalities, with 35 participants (71.4%) rating it at the highest level and another 10 (20.4%) at the second level, resulting in a total of 91.8% in the top two categories. Similarly, system understanding as a driver of trust was strongly endorsed, with 33 participants (67.3%) at the highest level and 11 (22.4%) at the second, adding up to 89.8% in the top two levels.

Adaptability to user requirements received slightly lower but still positive ratings. Nearly half of the participants (49.0%, 24) gave it the highest rating, 40.8% (20) the second highest, and 10.2% (5) the third level. None of the respondents rated this aspect at the two lowest levels. Clarity of energy management decisions was rated more variably. 51.0% (25) selected the highest level, 36.7% (18 of 49) the second, 6.1% (3 of 49) the third, 4.1% (2) the fourth, and 2.0% (1) the lowest. When asked about the overall importance of explainability, 29 participants (59.2%) rated it at the highest level, 18 (36.7%) at the second highest, and 2 (4.1%) at the second lowest.

Significant relationships emerged between these variables. The strongest association was found between communication clarity and trust in system understanding (Cramér's $V = 0.66$, Spearman $r = 0.68$, $p < 0.001$), showing that participants who valued clear communication were also those most likely to report higher trust in the system. Clear information and overall explainability importance were also significantly linked (Cramér's $V = 0.62$, Spearman $r = 0.35$, $p < 0.01$), as was communication clarity and overall explainability importance (Cramér's $V = 0.54$, Spearman $r = 0.35$, $p < 0.05$). A moderately strong relationship was also present between clear information and communication ratings (Cramér's $V = 0.50$, Spearman $r = 0.42$, $p < 0.01$). Smaller, weaker effects were observed between adaptability to user requirements and communication clarity (Cramér's $V =$

0.37, $p < 0.03$).

Statistical analysis further indicated that perceptions of explainability were partly shaped by demographic factors. Clear communication varied significantly by settlement size (Cramér’s $V = 0.41$, $p = 0.003$), and was also related to membership length (Cramér’s $V = 0.33$, Spearman $r = 0.31$, $p = 0.029$). The perceived overall importance of explainability was associated with settlement size as well, though with a weaker effect (Cramér’s $V = 0.37$, $p = 0.033$).

4.4.2 Principal Component Analysis of Explainability Dimensions

To examine the underlying structure of users’ responses, a principal component analysis was first conducted on the four Likert-scale items (Q4–Q7) relating to clarity, adaptability, communication, and trust. Bartlett’s test of sphericity confirmed the suitability of the data ($p < 0.001$), and the Elbow Method indicated that two components should be retained. The resulting solution revealed a first principal component loading positively on all four items, suggesting a general “explainability and clarity” factor. The second component contrasted adaptability to user requirements with clarity of information, pointing to a potential trade-off between personalisation and transparency.

To capture the broader construct of explainability more comprehensively, an additional PCA was performed, including the global item on the importance of explainability (Q8). Bartlett’s test of sphericity again confirmed suitability ($p < 0.001$), and the Elbow Method once more supported a two-component solution. This model yielded eigenvalues of 1.24 for the first component and 0.56 for the second, explaining 47.9% and 21.9% of the variance, respectively (cumulative 69.8%). Because the overall structure was highly similar to the four-item solution, but the inclusion of Q8 reinforced the interpretability of both dimensions, the five-item model was chosen for reporting. Figure 2 presents the projection of respondents on the first two principal components (PC1 and PC2), coloured by their mean agreement score (‘Survey index’).

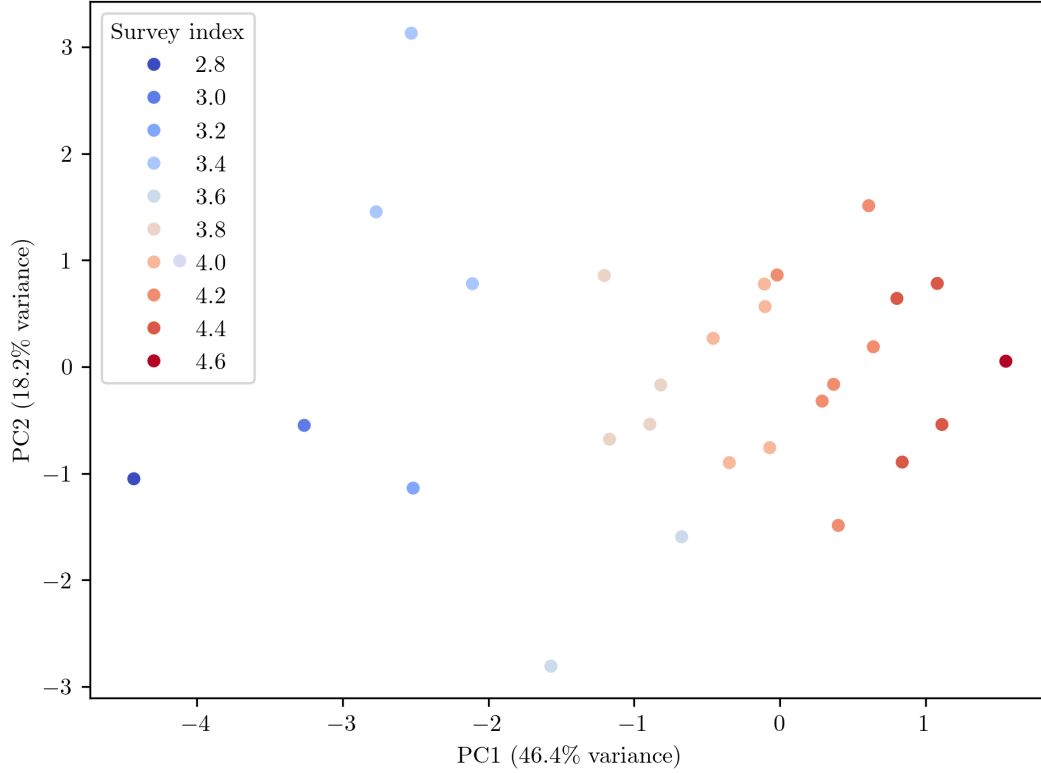


Figure 2: PCA Projection on Survey Items

The first principal component (PC1) loaded positively on all five variables, with particularly high loadings for clear communication (0.57), the importance of understanding the system (0.50) and explainability (0.41). As shown in Figure 2, respondents with higher survey indices (red tones) are positioned on the right-hand side of PC1, while those with lower scores (blue tones) cluster on the left, which shows how the component captures users' tendencies of valuing explainability and communication. The second component (PC2) showed a more differentiated structure. It was characterised by strong positive loadings for clear information (0.54) and importance of explainability (0.54), while adaptability to user requirements loaded negatively (-0.48). This indicates that PC2 reflects a contrast between transparency and adaptability.

To assess the stability of these results, a bootstrap procedure was applied. The findings confirmed that several PC1 loadings were sta-

tistically reliable, as their confidence intervals did not include zero. Clear information (loading = 0.66, CI [0.28, 0.95]), transparent communication (loading = 0.50, CI [0.16, 0.67]), understanding trust (loading = 0.42, CI [0.09, 0.62]), and the importance of explainability (loading = 0.29, CI [0.05, 0.43]) remained significant under resampling. These results strengthen the interpretation of PC1 as a robust general explainability dimension.

Associations between component scores and background variables were further tested using ANOVA. Although most results were not statistically significant, one noteworthy finding emerged: age group was significantly related to PC2 ($F = 2.74$, $p = 0.040$), suggesting generational differences in how transparency and adaptability are weighted. No significant associations were found for SES usage, technical knowledge, gender, membership length, or settlement size.

4.5 Benefits, Trust Factors, and Preferred Formats of Explainability

This final part of the analysis turns to participants' perceptions of the benefits and practical aspects of explainability. While the previous sections focused on attitudes toward and evaluations of explainability dimensions, here the emphasis lies on the functions that explainability can fulfil, the factors shaping trust and acceptance, and the preferred modes of delivering explanations. Together, these results provide a more applied perspective on how explainability can best be implemented in SES.

Understanding how the system works and makes decisions was the most frequently chosen benefit of explainability, endorsed by 65.3% (32) of participants. Almost equally important was the role of explainability in building trust and increasing acceptance of system recommendations, selected by 63.3% (31). Customisation according to individual needs was also highly valued (53.1%, 26), followed by the provision of energy consumption insights (46.9%, 23). The least frequently mentioned benefit was the identification of potential is-

sues or problems, chosen by 32.7% (16) of respondents. Statistical analysis highlighted meaningful associations within benefits. For example, the choice of energy insights was significantly related to the identification of issues ($\phi = 0.26$, Spearman $r = -0.31$, $p = 0.032$) and customisation showed a similar relationship with issue identification ($\phi = 0.26$, Spearman $r = -0.30$, $p = 0.034$). Differences also appeared by technical knowledge, with participants without any expertise unanimously prioritising system understanding (100%, 5 of 5), while none of them valued energy insights. In contrast, those with basic knowledge strongly favoured energy insights (63.2%, 12 of 19), and participants with higher expertise placed greater emphasis on trust acceptance (72.0%, 18 of 25) and on the ability to identify system issues (40.0%, 10 of 25) (Cramér’s $V = 0.36$, $p = 0.038$).

When asked what factors most influence trust in system explanations, clarity clearly dominated. Clear, concise, and easy-to-understand explanations were ranked first by two-thirds of participants (65.3%, 32) and second by another 22.4% (11). By contrast, tailoring explanations to individual needs was rarely considered most important (10.2%, 5), while many placed it second (32.7%, 16) or third (40.8%, 20). Explanations that provided insight into system reasoning were similarly ranked in the middle, while consistency with personal energy understanding was most often rated least influential, placed fourth by 55.1% (27) of participants. The relationships between these factors were also reflected in significant within-group associations. For instance, clarity and consistency were strongly associated (Cramér’s $V = 0.49$, Spearman $r = -0.51$, $p < 0.001$), as were clarity and individual tailoring (Cramér’s $V = 0.41$, $p = 0.003$) (see Figure 3). Overall, these results suggest that while tailoring and alignment may play supporting roles, clarity and simplicity remain the most decisive trust factors.

Format preferences for explanations confirmed the importance of multimodal approaches. The most popular choice was a combination of text, visual, and interactive elements, selected by 59.2% (29) of participants. Visual explanations, such as charts or dashboards, were

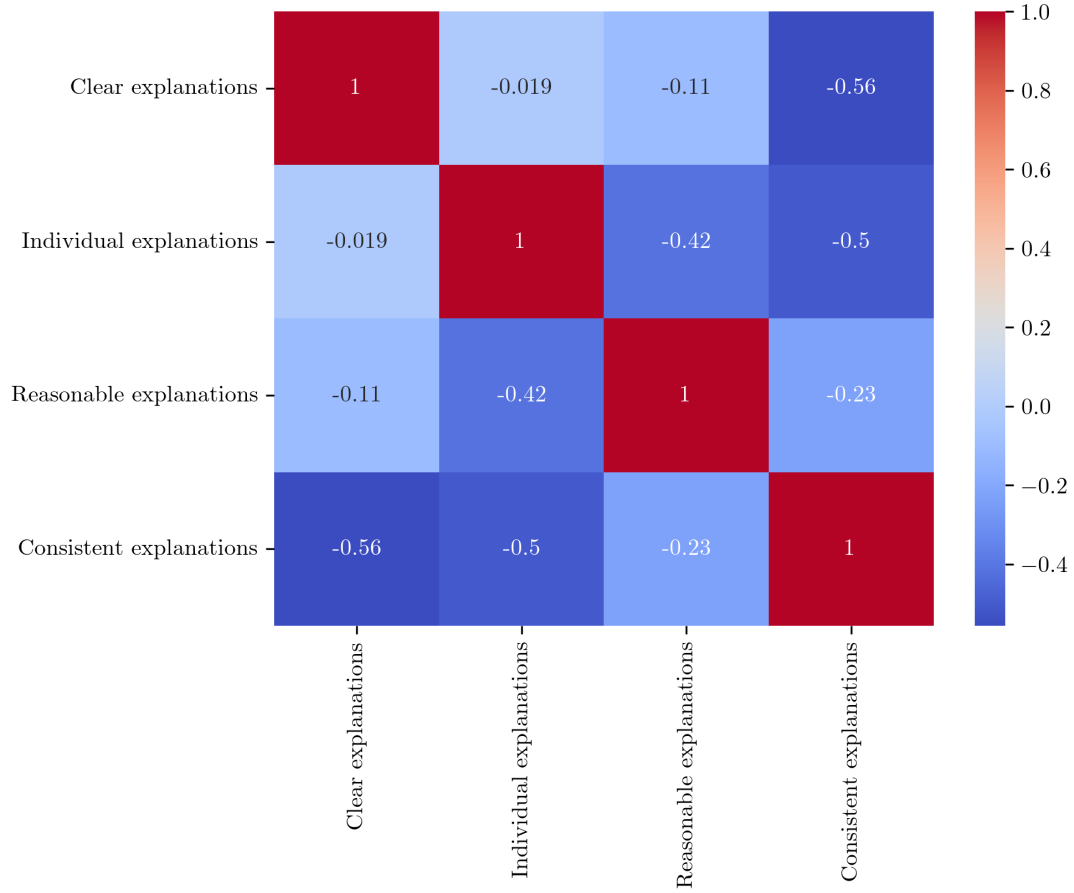


Figure 3: Spearman Correlation Heatmap between Explanation Variables

equally popular (59.2%, 29), while interactive visualisations that allow data exploration were chosen by 49.0% (24). In contrast, fewer participants opted for chatbots (28.6%, 14) or static text-based explanations (18.4%, 9). In the open responses, one participant mentioned they would prefer a video explanation, while one person suggested explanations through human conversation. At the demographic level, preferences varied. Text-based formats were significantly more common in large cities (50.0%, 2 of 4) and small towns (38.5%, 5 of 13) than in small communities (3.3%, 1 of 30) (Cramér's $V = 0.50$, $p = 0.007$). Membership length was associated with format selection as well, particularly regarding text-based explanations (Cramér's $V = 0.42$, $p = 0.035$). Within-group analysis further revealed strong links between certain format choices. Participants who valued interactive

visualisations were also significantly more likely to select visual explanations ($\phi = 0.44$, Spearman $r = 0.48$, $p < 0.001$), and those who preferred multi-modal approaches also tended to value visuals ($\phi = 0.31$, Spearman $r = -0.35$, $p = 0.013$).

Although an attempt was made to segment participants using K-Means clustering based on their selected explainability benefits as well as the preferred explanation formats, the resulting clusters were not clearly interpretable. The silhouette score was under 0.4 for all k , and visual inspection using PCA projection showed significant overlap between groups. This indicates that participants' preferences do not fall into defined categories. They reflect soft patterns and overlapping expectations, which are going to be examined by focusing on interpreting the relationships among variables instead of artificially segmenting the sample.

Taken together, the analyses provide a structured overview of how users adopt, experience, and evaluate SES, as well as how they perceive explainability. While the focus here has been on presenting the statistical patterns and relationships in the data, the next chapter moves to interpretation. The interpretation highlights what the results mean for user engagement and trust by linking these findings to broader contexts.

5 Interpretation of Analysis

This chapter provides an initial interpretation of the findings presented in the analysis. While the previous chapter focused on reporting the numerical results, the aim here is to highlight the most relevant patterns and to discuss their possible implications. The structure of this chapter follows the same contextual structure as the analysis, working through user adoption of SES, motivations for usage, key challenges, user perceptions of explainability, and finally, the perceived benefits, trust factors, and preferred formats of explanations.

Adoption rates amongst participants were relatively high, with most users having joined within the past three years, indicating that SES remain a recent development for many. The clearest pattern was that adoption was strongly tied to technical expertise. Participants with higher knowledge were far more likely to use SES, while those without any expertise did not adopt the technology at all. This points to a knowledge gap that could limit wider uptake, as SES are unlikely to have a large-scale impact if adoption remains limited to technically skilled users. Age differences suggest that adoption peaks in mid-life, where interest and resources to engage with new technology may coincide, while younger and older groups remain more hesitant. The somewhat higher adoption rates in small communities hint that local contexts also matter, though numbers for urban respondents were small.

Reducing costs and optimising energy use clearly dominated as motivations, showing that participants primarily approach SES from a practical and economic perspective. This suggests that financial savings and efficiency remain the strongest entry points for adoption, while more abstract goals such as informed decision making or personalisation play only a minor role. Age patterns indicate that younger and mid-aged users are especially focused on optimisation, while cost reduction was consistently valued across all groups. The link between technical knowledge and proactive energy management highlights that expertise does not just influence whether people adopt SES, but also how they use them. The negative correlations between motivations of proactive energy management and cost savings further suggest distinct orientations. Cost-focused users tend to prioritise straightforward savings, while proactive management with real time data is emphasised by more technically knowledgeable participants. This finding indicates that financial and expert driven orientations rarely overlap, pointing to different pathways of engagement with SES.

The main challenge amongst the participants appeared to be technical problems, showing that difficulties with system functionality

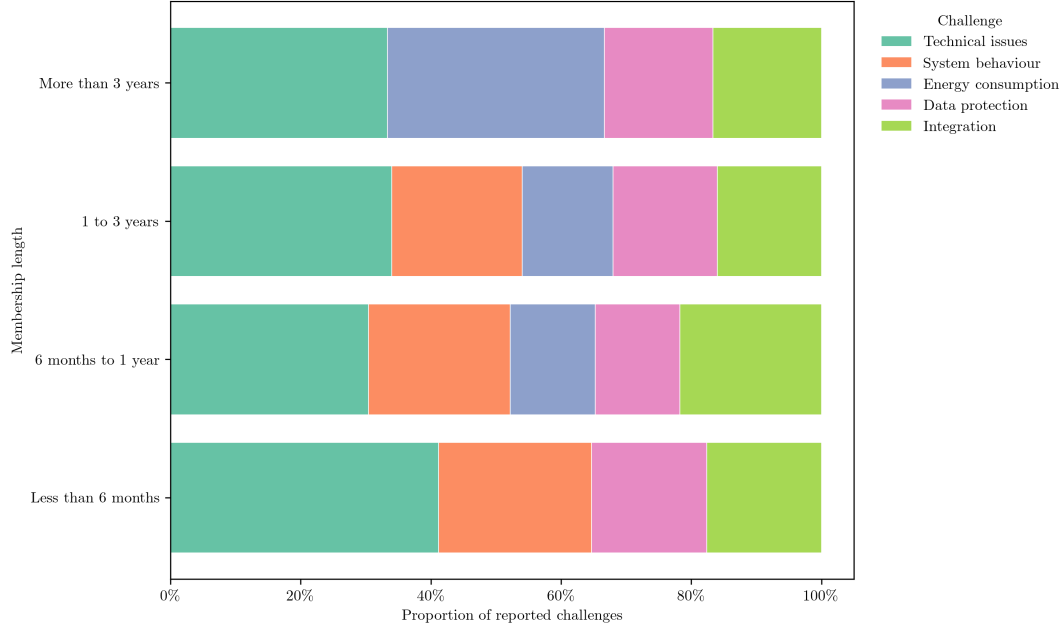


Figure 4: Shifts in Reported Challenges by SES Usage Length

remain a barrier across all user groups. However, the type of challenge varied with experience with SES and technical expertise. Users with higher technical knowledge were more likely to highlight integration problems with other smart home devices, which suggests that they engage more deeply with the technology and therefore notice system-level shortcomings. Newer users mainly reported technical difficulties, system behaviour issues, and data protection concerns, reflecting surface-level challenges at the start of adoption (see Figure 4). The fact that unclear energy impacts were reported more often among long-term users indicates that once initial technical problems are overcome, attention shifts to whether systems actually deliver understandable value. These patterns underline that challenges are not uniform but depend on knowledge and usage stage.

The descriptive analysis showed that explainability was consistently valued across all measures, with clear communication and system understanding emerging as the strongest drivers of trust. These aspects were also closely linked with one another, underlining that participants who valued clarity were the same who placed high im-

portance on trust and overall explainability. These findings show that explainability, communication, and trust are not separate dimensions but part of a shared expectation for transparency. The PCA analysis reinforces this by showing that clarity of information, transparent communication, trust in the system’s understanding, and the perceived importance of explainability all loaded strongly on the first component. This supports the notion that clarity and openness are foundational to building trust in SES. For the second component, the findings suggest that efforts to personalise or flexibly adapt systems may sometimes be perceived as reducing clarity, pointing to a design trade-off. Interestingly, age group emerged as a significant predictor of variation on this dimension. Younger and older respondents weighted transparency and adaptability differently, implying that generational preferences could shape how explainability should be communicated. The absence of associations with other background variables indicates that explainability is broadly valued across participants.

The most valued benefit of explainability was understanding how the system works, closely followed by its role in building trust. This shows that users primarily expect explainability to provide clarity about system decisions and to increase confidence in recommendations. Personalisation and energy insights mattered too, but only as secondary benefits, which suggests that while users appreciate tailoring, they first want a clear baseline of understanding and trust. Clarity clearly dominated as the trust factor, highlighting that simple and accessible explanations are decisive. Preferences for formats further underline this point. Most users wanted visual or multimodal explanations, suggesting that engagement improves when explanations are tangible and interactive. The failed attempt to segment participants based on benefits and formats is also revealing. Rather than forming distinct categories, preferences overlap and blend, meaning segmentation should focus on deeper orientations (such as motivations or knowledge levels) rather than surface-level format choices.

When combined, the results’ interpretation reveals a number of

recurring themes in the dataset. Technical knowledge emerged as the most decisive factor, shaping not only adoption but also motivations, challenges, and explainability preferences. Age and settlement size also introduced variation, particularly in adoption rates, optimisation motives, and preferred explanation formats. Across all groups, clarity and trust played central roles, both in terms of motivations for usage and in perceptions of explainability. At the same time, users differed in the extent to which they valued adaptability, personalisation, and more advanced system functions. These findings suggest the presence of distinct user types, which will be explored in the following chapter through the development of user segments.

6 User Segments

To structure the dataset into meaningful user types, different segmentation approaches were tested. Since only a small proportion of participants reported no technical knowledge (around 10%), these cases were combined with the medium-knowledge group, resulting in two categories: lower knowledge (n=24) and higher knowledge (n=25). Several attempts were made to define user groups based on motivational and benefit variables. However, these approaches proved unbalanced, as almost all participants clustered around the same two motivations, lower energy cost and optimising energy use. This meant that many respondents could not be clearly allocated to distinct groups, leaving large portions of the dataset in undefined categories.

To avoid this problem, the final segmentation was built on two dimensions that consistently differentiated participants throughout the analysis technical knowledge and SES adoption. This approach produced three stable and interpretable groups, namely Expert Optimisers (higher knowledge and adopters, n=22), Pragmatic Cost-Savers (lower knowledge and adopters, n=12), and Clarity-Seeking-Non-Adopters (lower knowledge and non-adopters, n=12). A small additional group of higher-knowledge non-adopters (Sceptical Ex-

perts) existed but was dropped from further analysis due to its very low size ($n=3$), which would not allow reliable comparisons. These groups were then tested against all other variables in the dataset using cross-tabulations and chi-square tests of independence. The results were interpreted both in terms of statistical significance and descriptive tendencies. This final solution therefore balances interpretability and robustness while ensuring that almost all respondents are meaningfully represented.

6.1 Expert Optimisers

Expert Optimisers ($n = 22$) combined higher technical knowledge with SES adoption. In terms of motivations, cost reduction was central (81,8%). Furthermore, most participants in this group reported optimising energy use (63,6%) as well as proactive energy management (63,6%) as additional motivations for SES usage. Other motivations, such as decision-making, efficiency, sustainable energy use, or personalisation, played only minor roles.

The clearest challenge for Expert Optimisers was system integration, reported by 63,6% participants (see figure 5). This was the only statistically significant result across challenges (Cramér's $V = 0.50$, $p = 0.002$), highlighting that this technically knowledgeable and experienced group may run into more complex implementation problems. Technical issues and difficulties understanding system behaviour were also widespread, but at levels similar to the other segments.

Regarding benefits, understanding the system and building trust were mentioned by around two-thirds of participants (59,1% and 68,2%). Energy insights and customisation were also noted by roughly half of the group, though without clear differences from the other segments. For format preferences, visual explanations were clearly dominant (72,7%), and interactive options were also frequently chosen (68,2%). Multi-modal explanations split the group evenly (50%). Text-based explanations and chatbots were less common.

Overall, Expert Optimisers can be described as technically con-

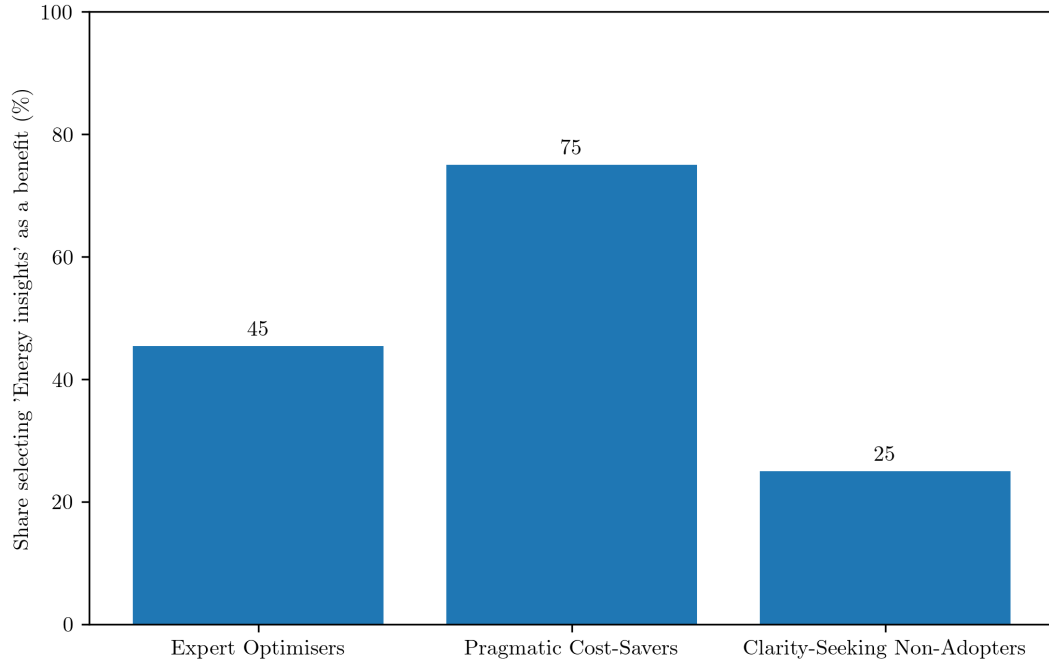


Figure 5: Integration Challenges by Segment (Cramér's $V = 0.495$, $p = 0.0015$)

fidient adopters who approach SES with a strong focus on cost reduction but also use their expertise to actively manage and optimise their energy use. Their main struggles lie not in basic technical issues, but in more advanced integration challenges, reflecting their deeper engagement with the technology. They value clear, visual, and interactive explanations that help them make sense of complex systems, while also appreciating trust and system understanding as benefits. This group represents early and knowledgeable adopters who push SES to its limits, but whose needs highlight the importance of advanced support and seamless system integration.

6.2 Pragmatic Cost-Savers

Pragmatic Cost-Savers ($n = 12$) were adopters with lower levels of technical knowledge. As expected, cost reduction was the strongest motivation (75%). Optimisation was also highly present (91,6%), although proactive energy management was far less common (25%).

Other motivations, such as decision-making, efficiency, or sustainable energy use, played a very limited role.

In terms of challenges, this group most often cited technical issues (75%). Only one participant mentioned integration, showing a sharp contrast to Expert Optimisers. Some participants reported difficulties with energy consumption (41,7%), though this result did not reach significance. When it came to benefits, Pragmatic Cost-Savers particularly emphasised energy insights (75%). This result was statistically significant (Cramér's $V = 0.30$, $p = 0.047$) and set the group apart from the others. Understanding the system and trust acceptance were mentioned by about half of the participants. For format preferences, the group was split between visual explanations (50%) and interactive formats (33,3%). Multi-modal approaches were chosen by half of the group (50%). Text-based formats and chatbots were also mentioned, but without strong consistency.

Pragmatic Cost-Savers are practical adopters who use SES mainly as a way to cut costs and optimise their energy use, without engaging too deeply in proactive management. Their limited technical knowledge makes them more vulnerable to basic technical problems, but also means they focus on tangible and straightforward benefits such as energy insights. They show some openness to different explanation formats but are less consistent in their preferences, suggesting that simplicity and clarity are more important than format itself. This group reflects a mainstream adopter type: motivated by economic value, engaged enough to optimise, but unlikely to explore more advanced functions without clear and accessible support.

6.3 Clarity-Seeking-Non-Adopters

Clarity-Seeking-Non-Adopters ($n = 12$) combined lower technical knowledge with a lack of SES adoption. Their motivations included cost reduction (83,3%) and optimisation (58,3%), though proactive energy management was rarely chosen (25%).

Challenges in this group resembled those of the Pragmatic Cost-

Savers: technical problems were common (75%), while integration issues were rare (16,7%). Difficulties with energy consumption were reported by 4 participants (33,3%). The clearest difference for this group was in benefits. Understanding the system was chosen by almost all participants (83,3%), more than in any other segment. Trust, acceptance, and customisation were also mentioned by over half of the group. Format preferences were characterised by a relative openness to multi-modal solutions: 75% of participants selected this option, more than in the other segments. Visual explanations were chosen less frequently (41,7%), and only a few participants selected text-based or chatbot formats.

Pragmatic Cost-Savers are practical adopters who use SES mainly as a way to cut costs and optimise their energy use, without engaging too deeply in proactive management. Their limited technical knowledge makes them more vulnerable to basic technical problems, but also means they focus on tangible and straightforward benefits such as energy insights. They show some openness to different explanation formats but are less consistent in their preferences, suggesting that simplicity and clarity are more important than format itself. This group reflects a mainstream adopter type: motivated by economic value, engaged enough to optimise, but unlikely to explore more advanced functions without clear and accessible support.

Taken together, the three segments highlight different ways in which users engage with or approach SES. Expert Optimisers are highly knowledgeable adopters who push the technology further but face advanced challenges such as integration. Pragmatic Cost-Savers represent more typical adopters who are motivated by financial benefits and energy insights, yet remain vulnerable to technical difficulties. Clarity-Seeking-Non-Adopters, by contrast, have not yet adopted SES but show interest if their need for trust and understanding can be met. The comparative profiles of these groups are visualised in Figure 6, which illustrates their differing priorities across motivations, challenges, benefits, and preferred formats. Together, the segments capture a spectrum ranging from expert-driven engage-



Figure 6: Motivation Profile by User Segment

ment to pragmatic mainstream usage to hesitant but interested non-adopters. They suggest that successful strategies for promoting SES adoption will need to be tailored, addressing not only technical functionality and economic incentives but also the communicative clarity that builds trust among less experienced users.

7 Discussion

This study set out to explore how users of SES differ in their motivations, challenges, and perceptions of explainability, and how these differences can be structured into meaningful user profiles. The re-

sults show that explainability is not a uniform need but is shaped by expertise, adoption status, and user orientation. Building on the EUCA framework, which emphasises the importance of tailoring explanations to end-users rather than treating them as a homogeneous group [30], the identified segments provide a concrete entry point for designing more effective and user-centered XAI strategies in the energy domain.

A key contribution of this study is the segmentation of users into three distinct profiles of engagement with SES. The EUCA framework stresses that explainable AI must be designed with end-users in mind, acknowledging their diverse roles, backgrounds, and explanation needs rather than assuming a one-size-fits-all solution [30]. From this perspective, the identified segments provide an important basis for aligning explainability strategies with concrete user characteristics.

Expert Optimisers, Pragmatic Cost-Savers, and Clarity-Seeking-Non-Adopters each represent different points along the spectrum of technical knowledge, adoption experience, and motivational orientation. According to EUCA, such variation fundamentally shapes how users interpret and benefit from explanations, meaning that explanation design cannot be detached from user profiling. In other words, segmentation translates the abstract call for “end-user-centered XAI” into a practical understanding of who the explanations are for, what they seek to achieve, and how they should be communicated [30].

7.1 Techniques in Relation to User Segments

These user segments offer a useful foundation for creating explainable SES, since they make clear that different groups value and need different forms of support. Matching appropriate techniques to each segment is therefore a promising starting point for translating user profiles into concrete design choices. The following section compares existing approaches and discusses their suitability in light of the three identified segments.

The segmentation results provide a concrete basis for matching existing explainability techniques to different user needs. As the EUCA framework emphasises, explanation design must be sensitive to user expertise, goals, and context [30]. Each of the three identified segments—Expert Optimisers, Pragmatic Cost-Savers, and Clarity-Seeking-Non-Adopters—differs in terms of technical knowledge, motivations, and adoption stage, making some techniques more suitable than others.

For Expert Optimisers, high levels of technical knowledge and proactive engagement suggest that more advanced explanation tools can be meaningfully applied. Techniques such as SHAP, which provide both local and global insights into feature importance, align with their capacity to engage with mathematical and structural interpretability [8]. LIME can also be effective for this group, particularly when used to debug and validate system decisions at a local level [20]. Visualisation techniques such as PDPs or ICE plots are also suitable, since Expert Optimisers are motivated by optimisation and proactive energy management and are likely to benefit from interactive tools that allow them to explore feature interactions.

Pragmatic Cost-Savers, in contrast, display lower technical expertise and a stronger focus on economic benefits. For this group, techniques that emphasise perceptive interpretability are more appropriate. ELI5, with its straightforward textual explanations, is well-suited to their practical orientation [8]. Counterfactual explanations can also be useful, particularly when framed in cost-related scenarios (e.g., “If you had shifted your appliance use by one hour, you would have saved X%”), since these resonate directly with their financial motivations [20]. Visual dashboards that combine energy insights with simple highlight explanations may further support their decision-making without overwhelming them.

While Clarity-Seeking-Non-Adopters are similar in their technical knowledge to Pragmatic Cost-Savers, they are not yet users of SES. Their primary barrier lies not in actionability but in trust and comprehension. For this group, explanations should focus on trans-

parency and reassurance. ELI5-style text and multimodal approaches combining visuals with natural language can address their need for clarity [4]. Counterfactuals may also help by showing that the system behaves consistently across scenarios, building reliability rather than optimising outcomes. In this sense, explanations are less about immediate benefits and more about lowering adoption barriers by fostering confidence.

Taken together, these comparisons highlight that no single explainability technique is universally suitable. Rather, their effectiveness depends on how they align with the expertise, motivations, and adoption stage of the user segment in question. This underscores the need for a user-centered approach to XAI in SES: Expert Optimisers benefit from detailed and technical interpretability, Pragmatic Cost-Savers from cost-focused and practical explanations, and Clarity-Seeking-Non-Adopters from clarity-driven and trust-building communication.

7.2 Problems and Limitations

Several limitations need to be acknowledged when interpreting the results of this study. The most important is the relatively small sample size ($n = 49$). This limited the statistical power of the analysis and likely contributed to the lack of significance in some tests. For example, linear regressions and ANOVA tests on group means did not produce significant results, which can reasonably be attributed to insufficient sample size rather than the absence of meaningful effects. In addition, the sample did not include balanced group sizes, making it difficult to draw robust conclusions across all demographics. While the patterns observed are informative, they should therefore be read as indicative rather than definitive.

A further limitation concerns the segmentation approach. The segmentation was based on a combination of technical knowledge and SES adoption, which provided a clear and interpretable structure. However, this inevitably simplifies the data and risks overlook-

ing more nuanced motivational or behavioural differences. This risk was partly mitigated by validating the segments against other variables such as motivations, challenges, and explainability preferences, but some level of simplification remains.

Finally, with a sample size of 49, the identified segments are descriptive and should not be taken as representative of the wider population. The relative sizes of the groups, in particular, cannot be generalised. Instead, the segmentation can be seen as a starting point that highlights meaningful user types and offers directions for future research with larger, more representative datasets.

8 Conclusion

This thesis aimed to explore how SES can be improved to achieve explainable and user-centered suggestions and predictions. After reviewing the literature on SES adoption, XAI, UCD, and requirement analysis, the study turned to empirical data of the survey conducted by Kordulová. The analysis combined descriptive statistics, principal component analysis, and segmentation to uncover patterns in motivations, challenges, and explainability needs. Together, these steps provided both a conceptual and data-driven foundation for answering the following research questions.

What are the key factors influencing user trust and satisfaction in SES, and how do these factors vary across different demographic groups?

The results consistently showed that clarity and transparent communication were the strongest drivers of trust and satisfaction. Clear communication received the highest ratings, together with the ability to understand system recommendations, as well as the overall value of explainability. Trust and explainability proved to be highly interconnected, which supports the idea that users perceive them as part of a shared expectation for transparency instead of separate constructs.

Although the demographic variations were limited due to the sample size, there were still noteworthy findings. Settlement size and membership length were associated with perceptions of clarity and importance of explainability, while age influenced adoption patterns. The most important value appeared to be technical knowledge shaping adoption, challenges, and motivations. This factor underlined a knowledge gap which could restrict mainstream uptake.

What recurring themes and sentiments emerge from user feedback on SES, and how can they inform system design improvements?

Several recurring themes emerged from the survey data. First, the most important motivations to adopt SES were cost reduction and energy optimisation. At the same time, challenges such as technical problems and integration issues revealed barriers depending on knowledge and experience with the technology. For example, new users reported technical issues and data protection concerns, while more advanced users noted difficulties integrating with other smart home devices and unclear energy impacts.

On the explainability side, clarity, trust, and understanding of the system's decision-making were leading themes. The principal component analysis again confirmed that these aspects are part of a broader transparency dimension. System design should prioritise clear and consistent explanations, while also acknowledging that users with different levels of expertise and experience face different challenges and expectations.

What actionable recommendations can be derived from survey data to enhance the design of user-centric, explainable SES?

The segmentation analysis distilled participants into three meaningful user groups. Each profile highlights a different orientation toward SES. Expert Optimisers are highly knowledgeable adopters

who need advanced and interactive explanations to support proactive energy management. Pragmatic Cost-Savers are driven by financial gain and prefer cost-oriented explanations. Clarity-Seeking-Non-Adopters, on the other hand, remain hesitant toward the adoption of SES but could be encouraged by explanations highlighting transparency, trust and reassurance.

These profiles provide a summarised recommendation for XAI in SES:

- For experts, integrate advanced visualisations (e.g., PDPs, ICE) and local/global explanation tools (e.g., SHAP, LIME) to enable detailed system exploration.
- For pragmatic adopters, prioritise simple textual or counterfactual explanations tied to cost and efficiency outcomes.
- For hesitant non-adopters, focus on clarity-driven, multimodal explanations that build trust and reduce perceived risks.

Taken together, the findings underline that explainability in SES is not one-size-fits-all but must be tailored to different user segments. This user-centered approach offers a practical pathway to increasing adoption, satisfaction, and trust in Smart Energy Technologies.

8.1 Future Outlook

While this thesis provided an exploratory segmentation of SES users, the limited sample size means the results cannot be generalised. Future research with larger and more representative datasets could apply cluster analysis or latent class analysis to identify segments in a more robust and confirmatory way. Such approaches would allow for testing the stability of the segments and for uncovering more fine-grained differences that may not have been visible in the present study.

Beyond segmentation, the findings highlight important next steps for the design of explainable SES. Now that user segments and their

fitting explanation techniques have been identified, the challenge is to translate these insights into concrete design choices. This could include developing adaptive interfaces that adjust explanation formats depending on the user profile, creating interactive dashboards that combine energy insights with explanation layers, or building trust-focused onboarding strategies for hesitant users. Integrating participatory design methods, where end-users are directly involved in shaping explanation features, would further ensure that explainability remains aligned with actual user needs.

This thesis showed deeper insights into how people actually meet and make sense of SES. By tracing adoption patterns, motivations, challenges, and perceptions of explainability, and finally distilling them into user segments, the study sketched out the different ways users approach these technologies. Matching these profiles with suitable explainability techniques offered a first step towards making SES not only more transparent but also more approachable and trustworthy. Since research at the intersection of SES and XAI is only at the beginning, the findings here offer a starting point for new ways of designing systems that genuinely respond to user needs and can grow into reliable companions in the transition to smarter, more sustainable energy use.

References

- [1] H. Lund, P. A. Østergaard, D. Connolly, and B. V. Mathiesen, “Smart energy and smart energy systems,” *Energy*, vol. 137, pp. 556–565, 2017.
- [2] B. V. Mathiesen, H. Lund, D. Connolly, H. Wenzel, P. A. Østergaard, B. Möller, S. Nielsen, I. Ridjan, P. Karnøe, K. Sperling *et al.*, “Smart energy systems for coherent 100% renewable energy and transport solutions,” *Applied energy*, vol. 145, pp. 139–154, 2015.
- [3] X. Kong, B. Sun, D. Kong, and B. Li, “Home energy management optimization method considering potential risk cost,” *Sustainable Cities and Society*, vol. 62, p. 102378, 2020.
- [4] M. Shajalal, A. Boden, G. Stevens, D. Du, and D.-R. Kern, “Explaining ai decisions: Towards achieving human-centered explainability in smart home environments,” in *World Conference on Explainable Artificial Intelligence*. Springer, 2024, pp. 418–440.
- [5] T. Ahmad, R. Madonski, D. Zhang, C. Huang, and A. Mujeeb, “Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm,” *Renewable and Sustainable Energy Reviews*, vol. 160, p. 112128, 2022.
- [6] E. O’Dwyer, I. Pan, S. Acha, and N. Shah, “Smart energy systems for sustainable smart cities: Current developments, trends and future directions,” *Applied energy*, vol. 237, pp. 581–597, 2019.
- [7] P. P. Angelov, E. A. Soares, R. Jiang, N. I. Arnold, and P. M. Atkinson, “Explainable artificial intelligence: an analytical review,” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 11, no. 5, p. e1424, 2021.

- [8] R. Machlev, L. Heistrene, M. Perl, K. Y. Levy, J. Belikov, S. Mannor, and Y. Levron, “Explainable artificial intelligence (xai) techniques for energy and power systems: Review, challenges and opportunities,” *Energy and AI*, vol. 9, p. 100169, 2022.
- [9] A. R. Javed, W. Ahmed, S. Pandya, P. K. R. Maddikunta, M. Alazab, and T. R. Gadekallu, “A survey of explainable artificial intelligence for smart cities,” *Electronics*, vol. 12, no. 4, p. 1020, 2023.
- [10] M. Jovanović and M. Schmitz, “Explainability as a user requirement for artificial intelligence systems,” *Computer*, vol. 55, no. 2, pp. 90–94, 2022.
- [11] M. Maguire and N. Bevan, *User Requirements Analysis*. Boston, MA: Springer US, 2002, pp. 133–148. [Online]. Available: https://doi.org/10.1007/978-0-387-35610-5_9
- [12] W. Maxwell and B. Dumas, “Meaningful xai based on user-centric design methodology,” *arXiv preprint arXiv:2308.13228*, 2023.
- [13] S. Hammer, M. Wißner, and E. André, “Trust-based decision-making for smart and adaptive environments,” *User Modeling and User-Adapted Interaction*, vol. 25, pp. 267–293, 2015.
- [14] E. Van der Werff and L. Steg, “The psychology of participation and interest in smart energy systems: Comparing the value-belief-norm theory and the value-identity-personal norm model,” *Energy research & social science*, vol. 22, pp. 107–114, 2016.
- [15] Energy Innovation Austria, “Innovations for energy communities: Research and technology development for their successful implementation in austria,” <https://www.energy-innovation-austria.at/article/innovations-for-energy-communities/>, 2023, issue 1/2023.
- [16] G. Eibl, J. Kazmi, O. Langthaler, M. Schirl, and S. Wilker, “Towards interoperable local energy communities in austria,” *e & e*

- i Elektrotechnik und Informationstechnik*, vol. 140, no. 5, pp. 432–440, 2023.
- [17] L. Kordulova, “Understanding user requirements: Exploring the significance of explainability in smart energy systems,” Ph.D. dissertation, Vienna University of Economics, 2023.
 - [18] I. Dincer and C. Acar, “Smart energy systems for a sustainable future,” *Applied energy*, vol. 194, pp. 225–235, 2017.
 - [19] K. Zhou, C. Fu, and S. Yang, “Big data driven smart energy management: From big data to big insights,” *Renewable and sustainable energy reviews*, vol. 56, pp. 215–225, 2016.
 - [20] V. Hassija, V. Chamola, A. Mahapatra, A. Singal, D. Goel, K. Huang, S. Scardapane, I. Spinelli, M. Mahmud, and A. Husain, “Interpreting black-box models: a review on explainable artificial intelligence,” *Cognitive Computation*, vol. 16, no. 1, pp. 45–74, 2024.
 - [21] S. K. Lier, J. Gerlach, and M. H. Breitner, “Who needs xai in the energy sector? a framework to upgrade black box explainability,” in *Rising like a Phoenix: Emerging from the Pandemic and Reshaping Human Endeavors with Digital Technologies, ICIS 2023*. Association for Information Systems, 2023. [Online]. Available: <https://aisel.aisnet.org/icis2023/aainbus/aainbus/19>
 - [22] E. Tjoa and C. Guan, “A survey on explainable artificial intelligence (xai): Toward medical xai,” *IEEE transactions on neural networks and learning systems*, vol. 32, no. 11, pp. 4793–4813, 2020.
 - [23] M. Brenneis and M. Mauve, “How intuitive is it? comparing metrics for attitudes in argumentation with a human baseline,” in *International Conference on Human-Computer Interaction*. Springer, 2021, pp. 125–138.
 - [24] L. Yang, H. Wang, and L. A. Deleris, “What does it mean to explain? a user-centered study on ai explainability,” in *Interna-*

- tional Conference on Human-Computer Interaction*. Springer, 2021, pp. 107–121.
- [25] T. Mathiyazhagan and D. Nandan, “Survey research method,” *Media Mimansa*, vol. 4, no. 1, pp. 34–45, 2010.
 - [26] R. Charlton, “is an ‘ideal’ questionnaire possible?” *International Journal of Clinical Practice*, vol. 54, no. 6, pp. 356–359, 2000.
 - [27] C. P. Paneru, A. K. Tarigan, and C. Toşa, “Exploring user engagement and perceptions towards smart energy applications in norway: Insights from a text mining analysis of user reviews,” *Energy Efficiency*, vol. 18, no. 4, p. 25, 2025.
 - [28] M. Greenacre, P. J. Groenen, T. Hastie, A. I. d’Enza, A. Markos, and E. Tuzhilina, “Principal component analysis,” *Nature Reviews Methods Primers*, vol. 2, no. 1, p. 100, 2022.
 - [29] T. Kanungo, D. M. Mount, N. S. Netanyahu, C. Piatko, R. Silverman, and A. Y. Wu, “The analysis of a simple k-means clustering algorithm,” in *Proceedings of the sixteenth annual symposium on Computational geometry*, 2000, pp. 100–109.
 - [30] W. Jin, J. Fan, D. Gromala, P. Pasquier, and G. Hamarneh, “Euca: The end-user-centered explainable ai framework,” *arXiv preprint arXiv:2102.02437*, 2021.

Table 1: Confidence Intervals for Selections in $SES_{Adaptiopl}Category$

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Ses Usage	Technical Knowledge	No technical knowledge	5	0	0.000	0.000	0.434
Ses Usage	Technical Knowledge	Basic knowledge of energy concepts	19	12	0.632	0.410	0.809
Ses Usage	Technical Knowledge	High level of technical expertise	25	22	0.880	0.700	0.958
Ses Usage	Membership Length	Less than 6 months	7	4	0.571	0.250	0.842
Ses Usage	Membership Length	6 months to 1 year	13	11	0.846	0.578	0.957
Ses Usage	Membership Length	1 to 3 years	26	18	0.692	0.500	0.835
Ses Usage	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Ses Usage	Age Group	Under 35	11	6	0.545	0.280	0.787
Ses Usage	Age Group	36-45	14	11	0.786	0.524	0.924
Ses Usage	Age Group	46-55	13	10	0.769	0.497	0.918
Ses Usage	Age Group	56-65	7	5	0.714	0.359	0.918
Ses Usage	Age Group	65+	4	2	0.500	0.150	0.850
Ses Usage	Population	Small municipality	30	22	0.733	0.556	0.858
Ses Usage	Population	Small town	13	8	0.615	0.355	0.823
Ses Usage	Population	Medium-sized city	2	2	1.000	0.342	1.000
Ses Usage	Population	Large city	4	2	0.500	0.150	0.850

Table 2: Confidence Intervals for Selections in Motivation Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Decision Making	Technical Knowledge	No technical knowledge	5	1	0.200	0.036	0.624
Decision Making	Technical Knowledge	Basic knowledge of energy concepts	19	4	0.211	0.085	0.433
Decision Making	Technical Knowledge	High level of technical expertise	25	5	0.200	0.089	0.391
Decision Making	Membership Length	Less than 6 months	7	3	0.429	0.158	0.750
Decision Making	Membership Length	6 months to 1 year	13	0	0.000	0.000	0.228
Decision Making	Membership Length	1 to 3 years	26	7	0.269	0.137	0.461
Decision Making	Membership Length	More than 3 years	3	0	0.000	0.000	0.561
Decision Making	Age Group	Under 35	11	3	0.273	0.097	0.566
Decision Making	Age Group	36-45	14	2	0.143	0.040	0.399
Decision Making	Age Group	46-55	13	1	0.077	0.014	0.333

Continued on next page

Table 2: Confidence Intervals for Selections in Motivation
Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Decision Making	Age Group	56-65	7	4	0.571	0.250	0.842
Decision Making	Age Group	65+	4	0	0.000	0.000	0.490
Decision Making	Population	Small municipality	30	7	0.233	0.118	0.409
Decision Making	Population	Small town	13	2	0.154	0.043	0.422
Decision Making	Population	Medium-sized city	2	0	0.000	0.000	0.658
Decision Making	Population	Large city	4	1	0.250	0.046	0.699
Efficiency	Technical Knowledge	No technical knowledge	5	3	0.600	0.231	0.882
Efficiency	Technical Knowledge	Basic knowledge of energy concepts	19	6	0.316	0.154	0.540
Efficiency	Technical Knowledge	High level of technical expertise	25	12	0.480	0.300	0.665
Efficiency	Membership Length	Less than 6 months	7	2	0.286	0.082	0.641
Efficiency	Membership Length	6 months to 1 year	13	6	0.462	0.232	0.709
Efficiency	Membership Length	1 to 3 years	26	12	0.462	0.288	0.645
Efficiency	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Efficiency	Age Group	Under 35	11	3	0.273	0.097	0.566
Efficiency	Age Group	36-45	14	6	0.429	0.214	0.674
Efficiency	Age Group	46-55	13	6	0.462	0.232	0.709
Efficiency	Age Group	56-65	7	3	0.429	0.158	0.750
Efficiency	Age Group	65+	4	3	0.750	0.301	0.954
Efficiency	Population	Small municipality	30	11	0.367	0.219	0.545
Efficiency	Population	Small town	13	7	0.538	0.291	0.768
Efficiency	Population	Medium-sized city	2	2	1.000	0.342	1.000
Efficiency	Population	Large city	4	1	0.250	0.046	0.699
Lower Energy Cost	Technical Knowledge	No technical knowledge	5	4	0.800	0.376	0.964
Lower Energy Cost	Technical Knowledge	Basic knowledge of energy concepts	19	15	0.789	0.567	0.915
Lower Energy Cost	Technical Knowledge	High level of technical expertise	25	20	0.800	0.609	0.911
Lower Energy Cost	Membership Length	Less than 6 months	7	5	0.714	0.359	0.918
Lower Energy Cost	Membership Length	6 months to 1 year	13	12	0.923	0.667	0.986
Lower Energy Cost	Membership Length	1 to 3 years	26	19	0.731	0.539	0.863
Lower Energy Cost	Membership Length	More than 3 years	3	3	1.000	0.439	1.000
Lower Energy Cost	Age Group	Under 35	11	10	0.909	0.623	0.984
Lower Energy Cost	Age Group	36-45	14	13	0.929	0.685	0.987
Lower Energy Cost	Age Group	46-55	13	10	0.769	0.497	0.918
Lower Energy Cost	Age Group	56-65	7	3	0.429	0.158	0.750

Continued on next page

Table 2: Confidence Intervals for Selections in Motivation
Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Lower Energy Cost	Age Group	65+	4	3	0.750	0.301	0.954
Lower Energy Cost	Population	Small municipality	30	23	0.767	0.591	0.882
Lower Energy Cost	Population	Small town	13	11	0.846	0.578	0.957
Lower Energy Cost	Population	Medium-sized city	2	1	0.500	0.095	0.905
Lower Energy Cost	Population	Large city	4	4	1.000	0.510	1.000
Optimizing Energyuse	Technical Knowledge	No technical knowledge	5	3	0.600	0.231	0.882
Optimizing Energyuse	Technical Knowledge	Basic knowledge of energy concepts	19	15	0.789	0.567	0.915
Optimizing Energyuse	Technical Knowledge	High level of technical expertise	25	16	0.640	0.445	0.798
Optimizing Energyuse	Membership Length	Less than 6 months	7	4	0.571	0.250	0.842
Optimizing Energyuse	Membership Length	6 months to 1 year	13	10	0.769	0.497	0.918
Optimizing Energyuse	Membership Length	1 to 3 years	26	18	0.692	0.500	0.835
Optimizing Energyuse	Membership Length	More than 3 years	3	2	0.667	0.208	0.939
Optimizing Energyuse	Age Group	Under 35	11	8	0.727	0.434	0.903
Optimizing Energyuse	Age Group	36-45	14	13	0.929	0.685	0.987
Optimizing Energyuse	Age Group	46-55	13	6	0.462	0.232	0.709
Optimizing Energyuse	Age Group	56-65	7	5	0.714	0.359	0.918
Optimizing Energyuse	Age Group	65+	4	2	0.500	0.150	0.850
Optimizing Energyuse	Population	Small municipality	30	22	0.733	0.556	0.858
Optimizing Energyuse	Population	Small town	13	7	0.538	0.291	0.768
Optimizing Energyuse	Population	Medium-sized city	2	2	1.000	0.342	1.000
Optimizing Energyuse	Population	Large city	4	3	0.750	0.301	0.954
Personalised Energymanagement	Technical Knowledge	No technical knowledge	5	0	0.000	0.000	0.434
Personalised Energymanagement	Technical Knowledge	Basic knowledge of energy concepts	19	2	0.105	0.029	0.314
Personalised Energymanagement	Technical Knowledge	High level of technical expertise	25	2	0.080	0.022	0.250
Personalised Energymanagement	Membership Length	Less than 6 months	7	1	0.143	0.026	0.513
Personalised Energymanagement	Membership Length	6 months to 1 year	13	1	0.077	0.014	0.333
Personalised Energymanagement	Membership Length	1 to 3 years	26	1	0.038	0.007	0.189
Personalised Energymanagement	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Personalised Energymanagement	Age Group	Under 35	11	3	0.273	0.097	0.566
Personalised Energymanagement	Age Group	36-45	14	1	0.071	0.013	0.315
Personalised Energymanagement	Age Group	46-55	13	0	0.000	0.000	0.228
Personalised Energymanagement	Age Group	56-65	7	0	0.000	0.000	0.354
Personalised Energymanagement	Age Group	65+	4	0	0.000	0.000	0.490

Continued on next page

Table 2: Confidence Intervals for Selections in Motivation
Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Personalised Energymanagement	Population	Small municipality	30	1	0.033	0.006	0.167
Personalised Energymanagement	Population	Small town	13	1	0.077	0.014	0.333
Personalised Energymanagement	Population	Medium-sized city	2	0	0.000	0.000	0.658
Personalised Energymanagement	Population	Large city	4	2	0.500	0.150	0.850
Proactive Energymanagement	Technical Knowledge	No technical knowledge	5	0	0.000	0.000	0.434
Proactive Energymanagement	Technical Knowledge	Basic knowledge of energy concepts	19	6	0.316	0.154	0.540
Proactive Energymanagement	Technical Knowledge	High level of technical expertise	25	15	0.600	0.407	0.766
Proactive Energymanagement	Membership Length	Less than 6 months	7	3	0.429	0.158	0.750
Proactive Energymanagement	Membership Length	6 months to 1 year	13	7	0.538	0.291	0.768
Proactive Energymanagement	Membership Length	1 to 3 years	26	10	0.385	0.224	0.575
Proactive Energymanagement	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Proactive Energymanagement	Age Group	Under 35	11	4	0.364	0.152	0.646
Proactive Energymanagement	Age Group	36-45	14	4	0.286	0.117	0.546
Proactive Energymanagement	Age Group	46-55	13	8	0.615	0.355	0.823
Proactive Energymanagement	Age Group	56-65	7	4	0.571	0.250	0.842
Proactive Energymanagement	Age Group	65+	4	1	0.250	0.046	0.699
Proactive Energymanagement	Population	Small municipality	30	14	0.467	0.302	0.639
Proactive Energymanagement	Population	Small town	13	5	0.385	0.177	0.645
Proactive Energymanagement	Population	Medium-sized city	2	1	0.500	0.095	0.905
Proactive Energymanagement	Population	Large city	4	1	0.250	0.046	0.699
Sustainable Energy	Technical Knowledge	No technical knowledge	5	1	0.200	0.036	0.624
Sustainable Energy	Technical Knowledge	Basic knowledge of energy concepts	19	1	0.053	0.009	0.246
Sustainable Energy	Technical Knowledge	High level of technical expertise	25	1	0.040	0.007	0.195
Sustainable Energy	Membership Length	Less than 6 months	7	0	0.000	0.000	0.354
Sustainable Energy	Membership Length	6 months to 1 year	13	0	0.000	0.000	0.228
Sustainable Energy	Membership Length	1 to 3 years	26	2	0.077	0.021	0.241
Sustainable Energy	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Sustainable Energy	Age Group	Under 35	11	0	0.000	0.000	0.259
Sustainable Energy	Age Group	36-45	14	0	0.000	0.000	0.215
Sustainable Energy	Age Group	46-55	13	1	0.077	0.014	0.333
Sustainable Energy	Age Group	56-65	7	1	0.143	0.026	0.513
Sustainable Energy	Age Group	65+	4	1	0.250	0.046	0.699
Sustainable Energy	Population	Small municipality	30	0	0.000	0.000	0.114

Continued on next page

Table 2: Confidence Intervals for Selections in Motivation Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Sustainable Energy	Population	Small town	13	3	0.231	0.082	0.503
Sustainable Energy	Population	Medium-sized city	2	0	0.000	0.000	0.658
Sustainable Energy	Population	Large city	4	0	0.000	0.000	0.490

Table 3: Confidence Intervals for Selections in Challenge Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Data Protection	Technical Knowledge	No technical knowledge	5	1	0.200	0.036	0.624
Data Protection	Technical Knowledge	Basic knowledge of energy concepts	19	8	0.421	0.231	0.637
Data Protection	Technical Knowledge	High level of technical expertise	25	6	0.240	0.115	0.434
Data Protection	Membership Length	Less than 6 months	7	3	0.429	0.158	0.750
Data Protection	Membership Length	6 months to 1 year	13	3	0.231	0.082	0.503
Data Protection	Membership Length	1 to 3 years	26	8	0.308	0.165	0.500
Data Protection	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Data Protection	Age Group	Under 35	11	2	0.182	0.051	0.477
Data Protection	Age Group	36-45	14	4	0.286	0.117	0.546
Data Protection	Age Group	46-55	13	5	0.385	0.177	0.645
Data Protection	Age Group	56-65	7	2	0.286	0.082	0.641
Data Protection	Age Group	65+	4	2	0.500	0.150	0.850
Data Protection	Population	Small municipality	30	7	0.233	0.118	0.409
Data Protection	Population	Small town	13	6	0.462	0.232	0.709
Data Protection	Population	Medium-sized city	2	0	0.000	0.000	0.658
Data Protection	Population	Large city	4	2	0.500	0.150	0.850
Energy Consumption	Technical Knowledge	No technical knowledge	5	2	0.400	0.118	0.769
Energy Consumption	Technical Knowledge	Basic knowledge of energy concepts	19	7	0.368	0.191	0.590
Energy Consumption	Technical Knowledge	High level of technical expertise	25	6	0.240	0.115	0.434
Energy Consumption	Membership Length	Less than 6 months	7	0	0.000	0.000	0.354
Energy Consumption	Membership Length	6 months to 1 year	13	5	0.385	0.177	0.645
Energy Consumption	Membership Length	1 to 3 years	26	8	0.308	0.165	0.500
Energy Consumption	Membership Length	More than 3 years	3	2	0.667	0.208	0.939

Continued on next page

Table 3: Confidence Intervals for Selections in Challenge Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Energy Consumption	Age Group	Under 35	11	3	0.273	0.097	0.566
Energy Consumption	Age Group	36-45	14	5	0.357	0.163	0.612
Energy Consumption	Age Group	46-55	13	4	0.308	0.127	0.576
Energy Consumption	Age Group	56-65	7	2	0.286	0.082	0.641
Energy Consumption	Age Group	65+	4	1	0.250	0.046	0.699
Energy Consumption	Population	Small municipality	30	10	0.333	0.192	0.512
Energy Consumption	Population	Small town	13	3	0.231	0.082	0.503
Energy Consumption	Population	Medium-sized city	2	1	0.500	0.095	0.905
Energy Consumption	Population	Large city	4	1	0.250	0.046	0.699
Integration	Technical Knowledge	No technical knowledge	5	0	0.000	0.000	0.434
Integration	Technical Knowledge	Basic knowledge of energy concepts	19	3	0.158	0.055	0.376
Integration	Technical Knowledge	High level of technical expertise	25	15	0.600	0.407	0.766
Integration	Membership Length	Less than 6 months	7	3	0.429	0.158	0.750
Integration	Membership Length	6 months to 1 year	13	6	0.462	0.232	0.709
Integration	Membership Length	1 to 3 years	26	8	0.308	0.165	0.500
Integration	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Integration	Age Group	Under 35	11	6	0.545	0.280	0.787
Integration	Age Group	36-45	14	5	0.357	0.163	0.612
Integration	Age Group	46-55	13	6	0.462	0.232	0.709
Integration	Age Group	56-65	7	1	0.143	0.026	0.513
Integration	Age Group	65+	4	0	0.000	0.000	0.490
Integration	Population	Small municipality	30	12	0.400	0.246	0.577
Integration	Population	Small town	13	5	0.385	0.177	0.645
Integration	Population	Medium-sized city	2	0	0.000	0.000	0.658
Integration	Population	Large city	4	1	0.250	0.046	0.699
System Behaviour	Technical Knowledge	No technical knowledge	5	3	0.600	0.231	0.882
System Behaviour	Technical Knowledge	Basic knowledge of energy concepts	19	6	0.316	0.154	0.540
System Behaviour	Technical Knowledge	High level of technical expertise	25	10	0.400	0.234	0.593
System Behaviour	Membership Length	Less than 6 months	7	4	0.571	0.250	0.842
System Behaviour	Membership Length	6 months to 1 year	13	5	0.385	0.177	0.645
System Behaviour	Membership Length	1 to 3 years	26	10	0.385	0.224	0.575
System Behaviour	Membership Length	More than 3 years	3	0	0.000	0.000	0.561
System Behaviour	Age Group	Under 35	11	5	0.455	0.213	0.720

Continued on next page

Table 3: Confidence Intervals for Selections in Challenge Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
System Behaviour	Age Group	36-45	14	6	0.429	0.214	0.674
System Behaviour	Age Group	46-55	13	4	0.308	0.127	0.576
System Behaviour	Age Group	56-65	7	2	0.286	0.082	0.641
System Behaviour	Age Group	65+	4	2	0.500	0.150	0.850
System Behaviour	Population	Small municipality	30	10	0.333	0.192	0.512
System Behaviour	Population	Small town	13	4	0.308	0.127	0.576
System Behaviour	Population	Medium-sized city	2	2	1.000	0.342	1.000
System Behaviour	Population	Large city	4	3	0.750	0.301	0.954
Technical	Technical Knowledge	No technical knowledge	5	4	0.800	0.376	0.964
Technical	Technical Knowledge	Basic knowledge of energy concepts	19	14	0.737	0.512	0.882
Technical	Technical Knowledge	High level of technical expertise	25	18	0.720	0.524	0.857
Technical	Membership Length	Less than 6 months	7	7	1.000	0.646	1.000
Technical	Membership Length	6 months to 1 year	13	9	0.692	0.424	0.873
Technical	Membership Length	1 to 3 years	26	18	0.692	0.500	0.835
Technical	Membership Length	More than 3 years	3	2	0.667	0.208	0.939
Technical	Age Group	Under 35	11	10	0.909	0.623	0.984
Technical	Age Group	36-45	14	10	0.714	0.454	0.883
Technical	Age Group	46-55	13	9	0.692	0.424	0.873
Technical	Age Group	56-65	7	6	0.857	0.487	0.974
Technical	Age Group	65+	4	1	0.250	0.046	0.699
Technical	Population	Small municipality	30	21	0.700	0.521	0.833
Technical	Population	Small town	13	11	0.846	0.578	0.957
Technical	Population	Medium-sized city	2	1	0.500	0.095	0.905
Technical	Population	Large city	4	3	0.750	0.301	0.954

Table 4: Confidence Intervals for Selections in Benefit Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Customisation	Technical Knowledge	No technical knowledge	5	4	0.800	0.376	0.964
Customisation	Technical Knowledge	Basic knowledge of energy concepts	19	9	0.474	0.273	0.683

Continued on next page

Table 4: Confidence Intervals for Selections in Benefit Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Customisation	Technical Knowledge	High level of technical expertise	25	13	0.520	0.335	0.700
Customisation	Membership Length	Less than 6 months	7	2	0.286	0.082	0.641
Customisation	Membership Length	6 months to 1 year	13	7	0.538	0.291	0.768
Customisation	Membership Length	1 to 3 years	26	16	0.615	0.425	0.776
Customisation	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Customisation	Age Group	Under 35	11	3	0.273	0.097	0.566
Customisation	Age Group	36-45	14	11	0.786	0.524	0.924
Customisation	Age Group	46-55	13	6	0.462	0.232	0.709
Customisation	Age Group	56-65	7	5	0.714	0.359	0.918
Customisation	Age Group	65+	4	1	0.250	0.046	0.699
Customisation	Population	Small municipality	30	17	0.567	0.392	0.726
Customisation	Population	Small town	13	8	0.615	0.355	0.823
Customisation	Population	Medium-sized city	2	0	0.000	0.000	0.658
Customisation	Population	Large city	4	1	0.250	0.046	0.699
Energy Insights	Technical Knowledge	No technical knowledge	5	0	0.000	0.000	0.434
Energy Insights	Technical Knowledge	Basic knowledge of energy concepts	19	12	0.632	0.410	0.809
Energy Insights	Technical Knowledge	High level of technical expertise	25	11	0.440	0.267	0.629
Energy Insights	Membership Length	Less than 6 months	7	2	0.286	0.082	0.641
Energy Insights	Membership Length	6 months to 1 year	13	7	0.538	0.291	0.768
Energy Insights	Membership Length	1 to 3 years	26	13	0.500	0.321	0.679
Energy Insights	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Energy Insights	Age Group	Under 35	11	6	0.545	0.280	0.787
Energy Insights	Age Group	36-45	14	8	0.571	0.326	0.786
Energy Insights	Age Group	46-55	13	4	0.308	0.127	0.576
Energy Insights	Age Group	56-65	7	4	0.571	0.250	0.842
Energy Insights	Age Group	65+	4	1	0.250	0.046	0.699
Energy Insights	Population	Small municipality	30	13	0.433	0.274	0.608
Energy Insights	Population	Small town	13	7	0.538	0.291	0.768
Energy Insights	Population	Medium-sized city	2	1	0.500	0.095	0.905
Energy Insights	Population	Large city	4	2	0.500	0.150	0.850
Identify Issues	Technical Knowledge	No technical knowledge	5	1	0.200	0.036	0.624
Identify Issues	Technical Knowledge	Basic knowledge of energy concepts	19	5	0.263	0.118	0.488
Identify Issues	Technical Knowledge	High level of technical expertise	25	10	0.400	0.234	0.593

Continued on next page

Table 4: Confidence Intervals for Selections in Benefit Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Identify Issues	Membership Length	Less than 6 months	7	3	0.429	0.158	0.750
Identify Issues	Membership Length	6 months to 1 year	13	6	0.462	0.232	0.709
Identify Issues	Membership Length	1 to 3 years	26	6	0.231	0.110	0.421
Identify Issues	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Identify Issues	Age Group	Under 35	11	5	0.455	0.213	0.720
Identify Issues	Age Group	36-45	14	3	0.214	0.076	0.476
Identify Issues	Age Group	46-55	13	5	0.385	0.177	0.645
Identify Issues	Age Group	56-65	7	1	0.143	0.026	0.513
Identify Issues	Age Group	65+	4	2	0.500	0.150	0.850
Identify Issues	Population	Small municipality	30	10	0.333	0.192	0.512
Identify Issues	Population	Small town	13	4	0.308	0.127	0.576
Identify Issues	Population	Medium-sized city	2	1	0.500	0.095	0.905
Identify Issues	Population	Large city	4	1	0.250	0.046	0.699
Trust Acceptance	Technical Knowledge	No technical knowledge	5	3	0.600	0.231	0.882
Trust Acceptance	Technical Knowledge	Basic knowledge of energy concepts	19	10	0.526	0.317	0.727
Trust Acceptance	Technical Knowledge	High level of technical expertise	25	18	0.720	0.524	0.857
Trust Acceptance	Membership Length	Less than 6 months	7	5	0.714	0.359	0.918
Trust Acceptance	Membership Length	6 months to 1 year	13	7	0.538	0.291	0.768
Trust Acceptance	Membership Length	1 to 3 years	26	16	0.615	0.425	0.776
Trust Acceptance	Membership Length	More than 3 years	3	3	1.000	0.439	1.000
Trust Acceptance	Age Group	Under 35	11	8	0.727	0.434	0.903
Trust Acceptance	Age Group	36-45	14	9	0.643	0.388	0.837
Trust Acceptance	Age Group	46-55	13	7	0.538	0.291	0.768
Trust Acceptance	Age Group	56-65	7	5	0.714	0.359	0.918
Trust Acceptance	Age Group	65+	4	2	0.500	0.150	0.850
Trust Acceptance	Population	Small municipality	30	18	0.600	0.423	0.754
Trust Acceptance	Population	Small town	13	8	0.615	0.355	0.823
Trust Acceptance	Population	Medium-sized city	2	1	0.500	0.095	0.905
Trust Acceptance	Population	Large city	4	4	1.000	0.510	1.000
Understand System	Technical Knowledge	No technical knowledge	5	5	1.000	0.566	1.000
Understand System	Technical Knowledge	Basic knowledge of energy concepts	19	12	0.632	0.410	0.809
Understand System	Technical Knowledge	High level of technical expertise	25	15	0.600	0.407	0.766
Understand System	Membership Length	Less than 6 months	7	5	0.714	0.359	0.918

Continued on next page

Table 4: Confidence Intervals for Selections in Benefit Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Understand System	Membership Length	6 months to 1 year	13	10	0.769	0.497	0.918
Understand System	Membership Length	1 to 3 years	26	14	0.538	0.355	0.712
Understand System	Membership Length	More than 3 years	3	3	1.000	0.439	1.000
Understand System	Age Group	Under 35	11	6	0.545	0.280	0.787
Understand System	Age Group	36-45	14	10	0.714	0.454	0.883
Understand System	Age Group	46-55	13	10	0.769	0.497	0.918
Understand System	Age Group	56-65	7	4	0.571	0.250	0.842
Understand System	Age Group	65+	4	2	0.500	0.150	0.850
Understand System	Population	Small municipality	30	19	0.633	0.455	0.781
Understand System	Population	Small town	13	9	0.692	0.424	0.873
Understand System	Population	Medium-sized city	2	2	1.000	0.342	1.000
Understand System	Population	Large city	4	2	0.500	0.150	0.850

Table 5: Confidence Intervals for Selections in Format Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Chatbot	Technical Knowledge	No technical knowledge	5	1	0.200	0.036	0.624
Chatbot	Technical Knowledge	Basic knowledge of energy concepts	19	8	0.421	0.231	0.637
Chatbot	Technical Knowledge	High level of technical expertise	25	5	0.200	0.089	0.391
Chatbot	Membership Length	Less than 6 months	7	1	0.143	0.026	0.513
Chatbot	Membership Length	6 months to 1 year	13	5	0.385	0.177	0.645
Chatbot	Membership Length	1 to 3 years	26	7	0.269	0.137	0.461
Chatbot	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Chatbot	Age Group	Under 35	11	4	0.364	0.152	0.646
Chatbot	Age Group	36-45	14	6	0.429	0.214	0.674
Chatbot	Age Group	46-55	13	2	0.154	0.043	0.422
Chatbot	Age Group	56-65	7	2	0.286	0.082	0.641
Chatbot	Age Group	65+	4	0	0.000	0.000	0.490
Chatbot	Population	Small municipality	30	6	0.200	0.095	0.373
Chatbot	Population	Small town	13	5	0.385	0.177	0.645

Continued on next page

Table 5: Confidence Intervals for Selections in Format Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Chatbot	Population	Medium-sized city	2	0	0.000	0.000	0.658
Chatbot	Population	Large city	4	3	0.750	0.301	0.954
Interactive Visual	Technical Knowledge	No technical knowledge	5	1	0.200	0.036	0.624
Interactive Visual	Technical Knowledge	Basic knowledge of energy concepts	19	8	0.421	0.231	0.637
Interactive Visual	Technical Knowledge	High level of technical expertise	25	15	0.600	0.407	0.766
Interactive Visual	Membership Length	Less than 6 months	7	3	0.429	0.158	0.750
Interactive Visual	Membership Length	6 months to 1 year	13	7	0.538	0.291	0.768
Interactive Visual	Membership Length	1 to 3 years	26	13	0.500	0.321	0.679
Interactive Visual	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Interactive Visual	Age Group	Under 35	11	4	0.364	0.152	0.646
Interactive Visual	Age Group	36-45	14	6	0.429	0.214	0.674
Interactive Visual	Age Group	46-55	13	8	0.615	0.355	0.823
Interactive Visual	Age Group	56-65	7	5	0.714	0.359	0.918
Interactive Visual	Age Group	65+	4	1	0.250	0.046	0.699
Interactive Visual	Population	Small municipality	30	15	0.500	0.332	0.668
Interactive Visual	Population	Small town	13	6	0.462	0.232	0.709
Interactive Visual	Population	Medium-sized city	2	2	1.000	0.342	1.000
Interactive Visual	Population	Large city	4	1	0.250	0.046	0.699
Multi Modal	Technical Knowledge	No technical knowledge	5	4	0.800	0.376	0.964
Multi Modal	Technical Knowledge	Basic knowledge of energy concepts	19	11	0.579	0.363	0.769
Multi Modal	Technical Knowledge	High level of technical expertise	25	14	0.560	0.371	0.733
Multi Modal	Membership Length	Less than 6 months	7	5	0.714	0.359	0.918
Multi Modal	Membership Length	6 months to 1 year	13	7	0.538	0.291	0.768
Multi Modal	Membership Length	1 to 3 years	26	14	0.538	0.355	0.712
Multi Modal	Membership Length	More than 3 years	3	3	1.000	0.439	1.000
Multi Modal	Age Group	Under 35	11	7	0.636	0.354	0.848
Multi Modal	Age Group	36-45	14	8	0.571	0.326	0.786
Multi Modal	Age Group	46-55	13	7	0.538	0.291	0.768
Multi Modal	Age Group	56-65	7	4	0.571	0.250	0.842
Multi Modal	Age Group	65+	4	3	0.750	0.301	0.954
Multi Modal	Population	Small municipality	30	16	0.533	0.361	0.698
Multi Modal	Population	Small town	13	10	0.769	0.497	0.918
Multi Modal	Population	Medium-sized city	2	1	0.500	0.095	0.905

Continued on next page

Table 5: Confidence Intervals for Selections in Format Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Multi Modal	Population	Large city	4	2	0.500	0.150	0.850
Text	Technical Knowledge	No technical knowledge	5	0	0.000	0.000	0.434
Text	Technical Knowledge	Basic knowledge of energy concepts	19	4	0.211	0.085	0.433
Text	Technical Knowledge	High level of technical expertise	25	5	0.200	0.089	0.391
Text	Membership Length	Less than 6 months	7	4	0.571	0.250	0.842
Text	Membership Length	6 months to 1 year	13	2	0.154	0.043	0.422
Text	Membership Length	1 to 3 years	26	3	0.115	0.040	0.290
Text	Membership Length	More than 3 years	3	0	0.000	0.000	0.561
Text	Age Group	Under 35	11	3	0.273	0.097	0.566
Text	Age Group	36-45	14	5	0.357	0.163	0.612
Text	Age Group	46-55	13	0	0.000	0.000	0.228
Text	Age Group	56-65	7	1	0.143	0.026	0.513
Text	Age Group	65+	4	0	0.000	0.000	0.490
Text	Population	Small municipality	30	1	0.033	0.006	0.167
Text	Population	Small town	13	5	0.385	0.177	0.645
Text	Population	Medium-sized city	2	1	0.500	0.095	0.905
Text	Population	Large city	4	2	0.500	0.150	0.850
Video	Technical Knowledge	No technical knowledge	5	0	0.000	0.000	0.434
Video	Technical Knowledge	Basic knowledge of energy concepts	19	0	0.000	0.000	0.168
Video	Technical Knowledge	High level of technical expertise	25	1	0.040	0.007	0.195
Video	Membership Length	Less than 6 months	7	0	0.000	0.000	0.354
Video	Membership Length	6 months to 1 year	13	0	0.000	0.000	0.228
Video	Membership Length	1 to 3 years	26	0	0.000	0.000	0.129
Video	Membership Length	More than 3 years	3	1	0.333	0.061	0.792
Video	Age Group	Under 35	11	0	0.000	0.000	0.259
Video	Age Group	36-45	14	0	0.000	0.000	0.215
Video	Age Group	46-55	13	1	0.077	0.014	0.333
Video	Age Group	56-65	7	0	0.000	0.000	0.354
Video	Age Group	65+	4	0	0.000	0.000	0.490
Video	Population	Small municipality	30	0	0.000	0.000	0.114
Video	Population	Small town	13	1	0.077	0.014	0.333
Video	Population	Medium-sized city	2	0	0.000	0.000	0.658
Video	Population	Large city	4	0	0.000	0.000	0.490

Continued on next page

Table 5: Confidence Intervals for Selections in Format Category

Variable	Category	Group	N	nsuccesses	Proportion	CI Lower	CI Upper
Visual	Technical Knowledge	No technical knowledge	5	2	0.400	0.118	0.769
Visual	Technical Knowledge	Basic knowledge of energy concepts	19	9	0.474	0.273	0.683
Visual	Technical Knowledge	High level of technical expertise	25	18	0.720	0.524	0.857
Visual	Membership Length	Less than 6 months	7	4	0.571	0.250	0.842
Visual	Membership Length	6 months to 1 year	13	7	0.538	0.291	0.768
Visual	Membership Length	1 to 3 years	26	16	0.615	0.425	0.776
Visual	Membership Length	More than 3 years	3	2	0.667	0.208	0.939
Visual	Age Group	Under 35	11	6	0.545	0.280	0.787
Visual	Age Group	36-45	14	6	0.429	0.214	0.674
Visual	Age Group	46-55	13	9	0.692	0.424	0.873
Visual	Age Group	56-65	7	6	0.857	0.487	0.974
Visual	Age Group	65+	4	2	0.500	0.150	0.850
Visual	Population	Small municipality	30	20	0.667	0.488	0.808
Visual	Population	Small town	13	5	0.385	0.177	0.645
Visual	Population	Medium-sized city	2	2	1.000	0.342	1.000
Visual	Population	Large city	4	2	0.500	0.150	0.850