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Date



Signature

Bachelor Thesis

An extended analysis of user requirements for explainable smart energy systems

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Abstract

Smart Energy Systems (SES) play a central role in the energy transition, as they enable the integration of renewable energies, ensure grid stability, and foster user participation in sustainable energy practices. However, their long-term acceptance depends largely on user trust - and this is strongly influenced by the explainability of system decisions. While existing research emphasises the importance of transparent and understandable communication, little is known about whether and how requirements for explanations differ between different user groups.

This thesis examines the needs and expectations of users in real-world scenarios, the role of explainability in building trust and acceptance, and whether demographic characteristics or technical background influence preferences for explanation formats.

The analysis is based on a secondary evaluation of survey data from Austrian energy communities ($n = 49$) and combines correlation and regression analyses. The results show a clear positive correlation between perceived comprehensibility of communication and trust in SES. Across all groups, combined, visual and interactive explanation formats were preferred, while purely visual formats were rarely chosen. No significant differences between age groups, genders or knowledge levels were found.

The findings make it clear that explainability is not an optional extra feature, but a fundamental prerequisite for the acceptance of SES. They provide practical recommendations for user-centred design and identify research needs for adaptive, individually tailored explanatory mechanisms.

1 Introduction

Smart Energy Systems (SES) are a vital part of the energy transition. They facilitate the integration of renewable energy sources, enhance the flexibility and stability of electricity grids, and enable consumers to consume energy more sustainably. As well as being technically relevant, SES also have great social significance: widespread acceptance of them is a key factor in achieving energy and climate policy objectives.

Although the technical development of SES has progressed rapidly in recent years, user-centred issues have not yet been adequately researched. Trust and acceptance in particular depend heavily on the explainability of the systems, i.e. the ability to make decision-making processes transparent and comprehensible. However, it is still unclear which user groups require explanations, what type of explanation is preferred and how these factors influence trust in the technology.

This thesis aims to address this research gap by investigating how different user groups perceive the explainability of SES and its impact on trust and acceptance. This gives rise to the following research questions: What are the specific needs and expectations of users when interacting with smart energy systems in real-world scenarios (RQ1)? How critical is explainability in fostering user trust and acceptance of smart energy systems? Does the importance of explainability vary among different user groups (RQ2)? How does a user's background affect their need for explainability or the types of explanations they prefer (RQ3)? Together, these questions provide a comprehensive overview of the relationship between user diversity, explainability, and trust in SES.

The empirical analysis draws on an existing survey that captured user background and context, user needs and expectations, the perceived role of explainability for trust, and preferences for explanation formats. These survey sections provide the empirical foundation for answering the research questions and will be described in detail in Chapter 4.

This thesis is based on a quantitative secondary analysis of existing survey data. This enables reliable conclusions to be drawn about the perceptions and preferences of specific user groups. However, qualitative aspects or deeper insights into individual users' decision-making processes cannot be captured. Furthermore, the results are limited to the studied sample and can only be generalised to a limited extent. Nevertheless, the results provide valuable in-

sights for the user-centred design of explainable SES and for future research.

The thesis is structured as follows: Chapter 2 presents the theoretical background and provides an overview of the literature on SES, explainability, and trust. Chapter 3 and 4 describe the methodology, particularly the survey design and analytical approach. Chapter 5 presents the results of the quantitative analysis, which are discussed in Chapter 6 in the context of existing research. Chapter 6 also summarises the most important findings, highlights limitations, and outlines implications for practice and research.

2 Literature Review

This chapter provides a comprehensive review of the existing literature relevant to understanding the landscape of intelligent energy systems, user requirements, and the application of explainable artificial intelligence principles within the context of human-computer interaction. The aim is to establish a strong theoretical foundation for this thesis, which investigates user requirements regarding the understandability and transparency of explainability in smart energy systems to foster user trust and acceptance.

2.1 Smart Energy Systems Overview

The energy sector is fundamentally transforming due to emerging technologies, renewable energy sources, and changing market trends [1]. This led to the evolution of Smart Energy Systems (SES). They differ from traditional smart grids because they adopt a complete humanistic framework that unites multiple energy sectors to discover optimal sustainable power transition methods [2]. Indeed, a smart energy system unites all network users, including generators, consumers, and prosumers, through intelligent management systems to increase economic benefits and ensure the security of electricity supply [3].

To achieve optimal results, an SES requires an understanding of energy flows and interdependencies that goes beyond the boundaries of the electricity sector. This can be accomplished by integrating heating and cooling systems into industrial operations and transport networks [4]. The main objective of SES is to improve energy efficiency while supporting sustainability goals and, thereby; enabling the integration of renewable energy into society [4]. However, to further grow green energy and smart grids, it is essential to retrieve and analyze energy data, extracting key performance indicators [5]. Overall, the demand for SES is increasing due to the growing focus on energy conservation and the projected increase in energy costs.

2.2 User Requirements in Smart Systems

SES use information and communication technologies to improve the efficiency, reliability, and sustainability of energy systems [1]. Hereby, user acceptance and trust are essential for the successful implementation of SES [6] and meeting user needs and maintaining operational transparency are directly related to acceptance and trust in complex systems such as SES [7].

It is essential to understand customer needs in order to successfully develop a product, especially in the early stages of defining user requirements [8]. Kujala (2002) defines user needs as problems that prevent users from achieving their goals or as opportunities to improve the achievement of goals [8]. User needs are the informal, often unstructured and subjective data gathered through user involvement, that should be transformed into user requirements during the requirements engineering cycle. A user requirement is any function, limitation, or feature that is necessary to satisfy a user’s needs. These requirements are raised by users and described from their perspective [8].

In the context of smart grids, it is important to promote consumer participation in regulated energy flows for a successful transition to sustainable energy and the development of smart energy systems. Therefore, it is crucial to involve consumers as active participants [9]. The development of products and services for SES requires an understanding of consumer needs and preferences in order to deliver services effectively [9].

2.2.1 Identifying User Groups

Stakeholders in Explainable AI (XAI) typically include users. They can be categorised into distinct groups such as users, developers, affected parties, operators, and regulators, whose interests sometimes collide in the integration of explainability. Different user groups naturally have diverse expectations, experiences, personal values, preferences, and needs. In order to overcome the challenges of developing effective XAI, it is necessary to consider people’s different needs for explainability, as these vary according to their goals, backgrounds, and contexts [10].

Users can be characterised according to their activity or task type, experience level, frequency of use, environment, culture, and motivation [8]. Nevertheless, it is helpful to gather personal background information such as age, occupation, technical orientation, previous computer experience, work experience, and education [8]. Additionally, different building types (e.g., office, residential, hotel) also represent various user types with different energy needs [11]. In smart energy systems, user portraits derived from large datasets can help to automatically identify user characteristics, which supports the analysis of energy demand patterns and random behavior. This is particularly relevant for developing demand-side management strategies [12].

Frequently mentioned user groups that require accountability in system decision-making and transparency of outcomes include model developers, business

owners/managers, decision-makers, affected groups, and regulators. However, this level of categorization may be too broad to fully capture the nuances of user needs [7]. Kujala (2002) provides a more detailed approach by characterizing stakeholders and their needs based on their knowledge (formal, instrumental, personal) and goals (long-term goals, immediate goals, specific tasks). Instead of studying all potential users, the recommended approach is to identify different key user types and select representative users from each essential group [8].

2.2.2 Common Needs and Expectations

Different user groups share fundamental needs such as easy access to energy data, personalised energy-saving advice, reliable system operation, and privacy protection [1]. Users require SES that can provide accurate energy usage information while also monitoring energy usage in real-time and storing historical data to simplify the decision-making process and promote behavioral changes that reduce energy use [12]. Furthermore, SES provide them with personalised recommendations that take their individual lifestyle choices and energy consumption patterns into account to help them adopt energy-saving practices [13]. However, in order to achieve widespread adoption, SES need to ensure strong security and reliability to protect user data; thereby, building trust and sustaining long-term system interaction [9].

2.3 Explainability (XAI) in Human-Computer Interaction

The explainability of systems, especially in the field of Artificial Intelligence (AI), has gained considerable importance in several research areas, including Human-Computer Interaction (HCI) [14]. HCI research and user experience (UX) design play a central role in the development and adoption of explainable AI (XAI), which is also increasingly applied in smart energy systems [7]. HCI methods such as user studies, prototyping, and heuristic evaluation provide valuable tools for generating human-centered explanations and presenting them in ways users can understand [15]. Current research focuses on how HCI can help to develop practical and explainable systems that effectively meet the needs of end users. The goal of human-centered explainability is to adapt the technical outputs of XAI systems to align with user’s cognitive processes and goals. Therefore, effective explanations must go beyond pure algorithmic transparency to be understandable and comprehensible to the respective target groups - be they end users, domain experts, or technicians in the energy sector [7].

2.3.1 Defining Explainability and its Relevance

Explainability refers to the ability of a system to explain its behavior to users [14]. According to Chazette et al. (2021), this definition is flexible, as aspects such as the explanatory content, the context, the explaining entity, and the addressees vary depending on the use case [10]. In the context of complex software systems, including smart energy systems, explainability is increasingly seen as a critical quality feature and an important non-functional requirement (NFR) [14]. It often serves to achieve other essential quality aspects such as transparency, accountability, and trustworthiness [10]. Explainability helps to overcome the “black box” nature of many modern systems, which makes it difficult for users - and often even developers - to understand how decisions are made [14]. It enables researchers, developers, and users to better interpret results, such as those generated by machine learning models in energy systems [16].

Although the terms explainability, transparency, interpretability, comprehensibility, and understandability are sometimes used interchangeably, XAI primarily aims to make AI outputs understandable to humans [7]. However, it is important to note that explainability can have both positive and potentially negative effects on a system and may require trade-offs with other NFRs [10].

2.3.2 The Role of Explainability in Building Trust and Acceptance

Explainability and interpretability are key characteristics that support trustworthiness of AI systems [1]. A primary goal of XAI is to build user trust and confidence in AI models. Explainable intelligent systems are necessary to increase user confidence and improve the acceptance of recommendations by end-users and stakeholders who rely on or are affected by these systems [17].

Research has shown that explainability can improve aspects such as trustworthiness, transparency, accountability, fairness, and ethics [14]. It influences the relationship between trust in a system and the willingness to rely on it. By making system logic understandable, explainability also increases the likelihood that users will accept recommendations. For example, empirical studies by Ribeiro et al. (2016) demonstrate the effectiveness of explanations for different models in trust-related tasks [18].

While some studies (e.g., Ribeiro et al.) confirm that explanations increase

users’ trust in AI, others like Norvig, as cited in Adadi and Berrada (2018), deny this correlation [19]. Nonetheless, explainability promotes public trust in human-AI relationship by enabling the users to monitor, understand, and potentially correct AI behavior, thereby; increasing the reliability of the combined human-AI process [20]. A deeper philosophical analysis of this relationship highlights how explainability enhances trust through contextual reasoning and persuasive feedback. This is demonstrated in explainable energy recommendation systems, where tailored explanations help users make informed decisions [13].

Shin’s (2021) study examines the effects of algorithmic explainability and causability (comprehensibility of the explanation) on user trust and acceptance. He finds that system explainability positively influences perceptions of fairness, accountability, and transparency (FAT), which in turn promotes trust. Causability not only shapes users’ perceptions of explainability but also mediates the relationship between FAT factors and trust. This study highlights the critical need to design AI explanations that are not just available, but also understandable, in order to effectively build user trust and facilitate the adoption of AI-driven systems [6].

2.3.3 User-Centered Explainability: Tailoring Explanations

The field of Explainable Artificial Intelligence (XAI) is increasingly beginning to adopt human-centered approaches [7]. Developing XAI applications is challenging because the explainability or effectiveness of an explanation is not inherent in the model, but depends on how the explanation is perceived and understood by the user. Simply making a model fully transparent does not guarantee that the recipient will understand all the information or not be overwhelmed by it [7].

A human-centered XAI approach emphasises explanations that are easy to understand for lay users - not just developers - in order to increase user satisfaction and adoption [15]. According to Liao and Varshney (2022), a proper explanation depends on several factors, including the knowledge of the recipient about AI and the specific purpose for which they seek the explanation. Therefore, the effectiveness of explanations depends on the recipient [7].

It is important to identify the specific needs of users and tailor explanations accordingly. Explanations should be adopted not only technically but also cognitively, accounting for the different backgrounds and goals of end users, technicians or domain experts. This provides a theoretical basis for

studying different user groups and their specific needs for explanations [7]. Building on this, adaptive explanatory models could provide context-sensitive explanations that adapt to changes in the environment, such as user profiles (expertise, domain knowledge, cultural background, interests, preferences) and the purpose of the explanation (justification, teaching, testing) [19].

A user’s background may influence their explanation preferences. A study by Dai et al. (2023) on smart home lighting systems emphasizes that explanations need to be carefully designed: The right type can increase trust and acceptance, while poorly worded explanations can reduce the user’s sense of control [21].

2.4 Explainability Requirements in Smart Energy Systems Context

Problems with the explainability and transparency of AI represent a significant barrier to stakeholder trust and technology acceptance in the energy sector. Explainability is an essential requirement for future smart energy grids as it establishes accountability, builds user trust and helps meet regulatory standards. The growing importance of explainability and governance in smart energy research provides the broader context for investigating specific user requirements in this thesis [1].

SES, which aim to improve the living environment and minimize energy consumption, are increasingly using AI-based decision-making. However, they face challenges due to the "black box" nature of these systems, which raises concerns about transparency and trustworthiness [1]. The work of Shajalal et al. (2021) highlights a gap between existing XAI techniques and end-user understanding in smart homes. After reviewing XAI methods and experiments in smart home scenarios, they find that many standard machine learning explanation techniques fail to effectively communicate decisions to ordinary home users, who struggle to understand and trust the system’s decisions [1].

In another study, Shajalal et al. (2024) argues for a human-centered approach to XAI for smart homes: explanations must be easy for non-experts to understand to increase user satisfaction and system adoption. Their work underscores the limitations of standard ML explanations and motivates a more targeted investigation into specific user needs in smart energy contexts [15]. Providing clear explanations, for example, for activity recognition is

considered highly valuable in smart home automation [21].

A study on context-sensitive recommendation systems for household energy efficiency showed that users were more likely to accept recommendations when provided with transparent explanations. This led to a 19 percent increase in accepted actions when economic and environmental justifications were combined [13]. This research suggests that intelligent energy applications can gain more user trust and compliance through explainable AI, as the system explains its decisions based on the user’s values [13].

2.5 Energy Communities and Survey Data

Energy communities play a central role in the energy transition, enabling local actors - such as households, small businesses, and public institutions - to generate, consume and manage renewable energy collaboratively [22]. These communities represent both technological innovations and social constructs, promoting participation, democratization, and user engagement in the energy system [22].

Integrating users into such communities provides a valuable basis for investigating real-life interaction with SES [22]. Members often have practical experience with energy management tools and are interested in the transparency and performance of these systems. Energy communities are therefore a particularly relevant user group for analyzing trust, explainability, and system acceptance.

Survey data is a suitable method for systematically recording needs, expectations, and user behavior. Structured survey data enables differentiated analysis of user groups, for example, according to age, previous technical experience, or length of membership, and helps identify patterns in the way people deal with explainable systems. Such data provide valuable insights into which types of explanation are favored and to what extent explainability is required in different contexts. This is particularly relevant for developing user-centered XAI approaches within energy communities.

3 Methodology

This chapter describes the methodological framework for investigating user requirements regarding the explainability of SES. It outlines the research design, the origin and structure of the data, as well as the steps involved in preparing the data and the statistical analysis methods employed. The aim is to present the procedure used to evaluate the existing data in a transparent and comprehensible way, in order to answer the research questions formulated in Chapter 1 (RQ1–RQ3).

3.1 Research Approach: Quantitative Analysis of Pre-existing Data

A deductive, quantitative research approach was chosen to answer the research questions. Deductive in this context means that the analysis was guided by theoretical concepts and assumptions derived from the existing literature on explainability, trust, and user diversity in SES. Based on these foundations, the study tests whether the patterns suggested by previous research can also be observed in the survey data at hand. The quantitative design refers to the systematic use of numerical survey data and statistical procedures to measure relationships between variables and to evaluate differences between user groups. This approach is well suited to address the research questions: it allows the structured examination of user needs (RQ1), the testing of the role of explainability in fostering trust (RQ2), and the analysis of whether background characteristics significantly influence preferences for explanations (RQ3).

The analysis is based on a structured dataset that was originally collected as part of Kordulova’s Bachelor’s thesis [23]. The underlying survey aimed to capture the perceptions, needs and challenges related to the explainability of SES among members of Austrian energy communities. Therefore, the data set is suitable for well-founded secondary data analysis, eliminating the need for new primary data collection.

The methodological approach consisted of several steps. First, the dataset was cleaned up by removing incomplete or irrelevant entries and coding key variables (e.g. prior technical knowledge and preferred explanation formats) uniformly. Descriptive statistics were then calculated to summarize the sample and present important distribution data (e.g., age, gender, and explainability ratings). Finally, inferential statistical methods were employed, including t-tests, analyses of variance (ANOVAs) and Pearson and Spearman

correlations. To analyse the combined influence of various predictors on trust in SES, multiple linear regression analysis was also performed. A correlation matrix was created to systematically record the correlations between central demographic variables (e.g. age, gender and prior technical knowledge) and characteristics of explainability that were evaluated (e.g. trust and comprehensibility).

This aimed to reveal both bivariate and multivariate correlations, and statistically verify the extent to which certain user characteristics significantly influence the perception and evaluation of explainable systems.

4 Data Analysis

This chapter describes the data analysis process. It focuses on the origin and structure of the data set, the structure of the questionnaire, the steps involved in data preparation, and the statistical methods used. The aim is to provide a transparent overview of the analysis process before presenting the results in the following chapters.

4.1 Origin and Context of the Survey

The survey used in this paper was originally taken from Lada Kordulova's bachelor thesis. It was designed as part of an academic research project on user-centred explainability of SES. The primary purpose of the original survey was to capture users' needs, expectations, motivations and challenges in dealing with SES - with a particular focus on the concept of explainability.

The survey was specifically targeted at members of Austrian energy communities, in particular renewable energy communities. This target group was chosen because it can be assumed that they already have some experience or interest in sustainable energy technologies. The survey was conducted online using Google Forms. Participants were recruited through targeted contact with energy community leaders who were asked to share the survey link within their community. Despite some challenges with the response rate, a total of 49 fully completed questionnaires were collected to serve as the basis for the subsequent statistical analysis.

4.1.1 Survey Design and Questions

The survey instrument used consisted of a structured online questionnaire covering various aspects of user interaction with SES. The questionnaire was

designed to systematically capture both general attitudes and specific preferences and experiences of the participants.

Close-ended questions were mainly used, particularly in the form of Likert scales to rate statements such as the perceived importance of explainability or the importance of providing clear information. Multiple-choice questions were also used to inquire, for example, about preferred formats for system explanations and perceived challenges in using intelligent energy systems. The questionnaire did not include open-ended questions. All questions were either closed-ended or predefined multiple-choice items.

Four thematic blocks of the questionnaire are of particular relevance to this study. The first block covered user background and context, including demographic information such as age and gender, self-assessed technical knowledge of energy management.

The second thematic block focused on participants' needs and expectations. Among other things, the main motivations for using SES and the subjectively perceived challenges or limitations in practical use were surveyed.

The third block focused on the importance of explainability and its influence on trust. Participants were asked to rate several statements on the importance of clear information, transparent system communication, individual adaptability, and explicitly on the explainability of decisions. A special item was also included to assess the extent to which understanding of the system influences trust in the technology. In addition, the survey contained a closed multiple-choice question in which participants were asked to select what they considered to be the most important challenges in the use of SES. The aim was to identify common barriers in terms of usability, technical reliability and system transparency.

The fourth block of questions dealt with preferences for explanation formats. Respondents were able to indicate which form of explanation they would prefer to receive from intelligent systems - for example, text-based, visual or interactive. In addition, individual trust factors related to explanations were assessed, such as clarity, understandability, comprehensibility and adaptation to individual needs and knowledge levels.

This comprehensive structure of the questionnaire allows a differentiated analysis of both quantitative patterns and qualitative insights into the expectations and requirements of potential users of SES.

4.2 Data Preparation and Cleaning

Before the actual analysis began, the survey data were systematically cleaned and prepared to ensure their usability and comparability for statistical analysis. First, all incomplete or irrelevant entries were removed, in particular free-text responses that contained no usable information (e.g. blank fields or general comments). Columns not relevant to the analysis, such as voluntary email addresses or other comments, were also excluded to focus on the research questions.

Selected variables were then coded and transformed:

1. Likert scale responses, e.g. to assess the importance of explainability, were numerically coded on a scale from 1 (“not important”) to 5 (“very important”).
2. Prior technical knowledge was extracted from the responses and categorised into three levels: 1 = low, 2 = medium, 3 = high.
3. The responses on the preferred explanation formats were thematically categorised into the groups ‘interactive’, ‘visual’ and ‘combined’.

In preparation for inferential statistical procedures (such as t-test, ANOVA and correlations), individual variables were standardised and missing values were consistently excluded if they would have affected the calculation. When grouping by gender and technical expertise, care was taken to ensure consistent internal labelling and English translation to ensure a clear basis for analysis.

4.3 Statistical Analysis Strategy

The survey data was evaluated in several steps. First, descriptive statistics were calculated to represent the composition of the sample and the central distributions of individual variables (e.g. age, gender, technical knowledge and the importance of explainability). Building on this initial analysis, various inferential statistical methods were employed to test hypotheses relating to the research questions and to identify significant correlations between user characteristics and attitudes towards the explainability of SES.

All statistical analyses were performed using the Python programming language. The following libraries were used:

1. Pandas: for data preparation and transformation
2. Matplotlib and Seaborn for visualising the results

3. SciPy.Stats for statistical testing

The specific tests selected depended on the data type and research question.

1. **T-tests** for independent samples were used to examine differences between binary groups (e.g. gender) with regard to explainability assessment. This method was chosen because the variable of interest was approximately interval-scaled (Likert scale) and the grouping variable was binary. Despite the small size of one group (female participants), the t-test was applied under the assumption of approximate normality and with cautious interpretation.
2. **One-factor analysis of variance (ANOVA)** was used to analyse differences between more than two groups, particularly when grouping according to technical prior knowledge (low, medium or high). ANOVA is appropriate for detecting group differences in a dependent variable when more than two groups are compared. Although the data stemmed from Likert-scale responses, the test was considered robust due to approximately equal group sizes and visual inspection of homogeneity of variances.
3. **Pearson and Spearman correlations** were used to analyse linear and monotonic relationships (e.g. between age and the perceived importance of explainability). Pearson's correlation was used for variables treated as interval-scaled and normally distributed, while Spearman's rank correlation served as a non-parametric alternative to confirm the robustness of the observed relationships.

To answer the second and third research questions, we also considered multivariate relationships. For this purpose, multiple linear regression analysis was performed. This aimed to analyse the combined effect of several explanatory variables on trust in SES. The dependent variable was the rating of the item 'If I understand the system, I am more likely to trust it', which was measured using a 5-point Likert scale. The independent variables included:

1. The importance of explainability in general
2. the desire for clear communication
3. the need for transparent system logic
4. the need for personalised explanations

5. and the consistency of system explanations with one's own understanding are all important factors.

All continuous predictors were standardised (z-transformed) prior to analysis to ensure comparability of regression coefficients. The regression model was calculated using the 'enter method' to comparatively examine the relative importance of the individual influencing factors on trust. The results are presented in Chapter 5.

Additionally, a correlation matrix was created to systematically relate key demographic characteristics (age, gender and prior technical knowledge) to the evaluated aspects of explainability and trust. This also formed the basis for formulating specific hypotheses for group comparison analysis (Chapters 5.2 and 5.3).

To investigate preferences for types of explanation, the distribution of response options (visual, interactive and combined) was evaluated according to knowledge level and presented graphically using a stacked bar chart (see Chapter 5.6).

All statistical results were evaluated at a significance level of $\alpha = 0.05$.

5 Results

This chapter presents the key findings of the analysis of quantitative survey data. The aim is to systematically examine the needs and expectations of different user groups in the context of SES. First, the composition of the sample is described. This is followed by analyses of the perceived importance of explainability, preferred formats of explanation, identified challenges and motives for use.

A particular focus is placed on the question of the extent to which demographic characteristics – in particular age, gender and prior technical knowledge – are related to the perception and evaluation of these aspects. The correlations are evaluated using both descriptive groupings and correlation analyses.

Descriptive statistics, such as means, medians, frequencies, and standard deviations, are employed to identify key trends and patterns within the sample. In addition, inferential statistical methods such as t-tests, analyses of variance (ANOVAs) and Pearson’s and Spearman’s correlations are used to investigate differences between groups and correlations between key variables. The results are illustrated graphically and initially interpreted with regard to the research questions.

5.1 Participants Demographics

The sample consists of 49 participants who were included in the user survey. The demographic and contextual composition are presented below, categorised by age, technical knowledge and gender.

5.1.1 Age Distribution

As shown in Figure 1, the age distribution in the survey is very diverse. The age of the participants ranges from approximately 25 to 70 years, with a majority between 30 and 60 years old.

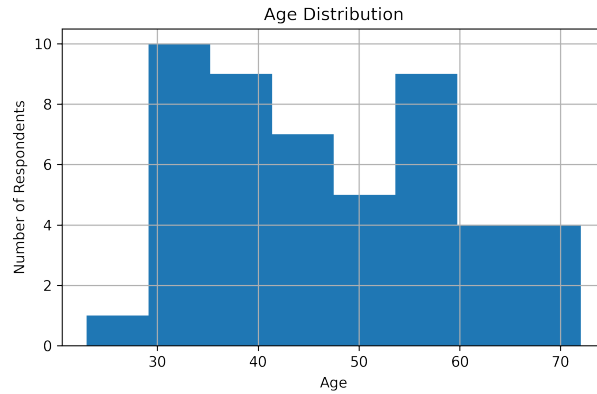


Figure 1: Age Distribution of Participants

5.1.2 Technical Knowledge

The respondents' prior technical knowledge of SES was assessed using a single stage self-assessment. They could choose from level 1 (no knowledge), level 2 (medium knowledge) or level 3 (high knowledge). As shown in Figure 2, the majority of participants rated themselves as having medium or high knowledge. Only five people stated that they had no prior technical knowledge.

This distribution suggests that the sample is generally tech-savvy. Given that all respondents are members of an energy community, this suggests that many participants have already dealt with the technological components of energy management or at least have a basic understanding of them.

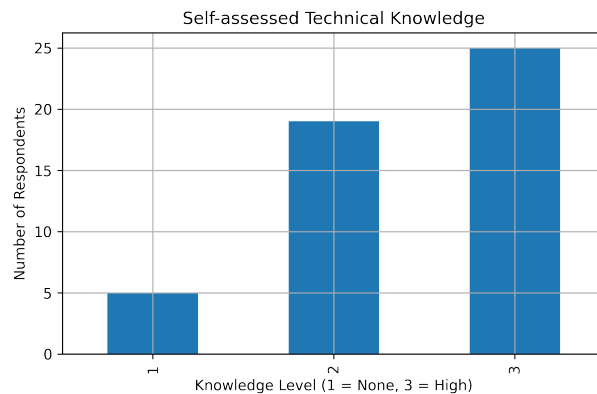


Figure 2: Technical Knowledge of Participants

5.1.3 Gender Distribution

The gender distribution within the sample is highly imbalanced. Of the 49 participants, 44 identified as male and only five as female. No further information on gender was provided. This distribution limits the comparability of gender-specific analyses. Therefore, corresponding results should be interpreted with caution.

5.2 How do demographic characteristics influence the assessment of explainability?

In order to better understand how demographic characteristics influence the perception of explainable energy systems, a correlation analysis was conducted. Figure 3 shows the correlation matrix between age, gender, technical knowledge and the following evaluation criteria:

- Perceived importance of explainability
- Trust in system decisions
- Need for transparent communication
- Consistency of system explanations with one's own understanding

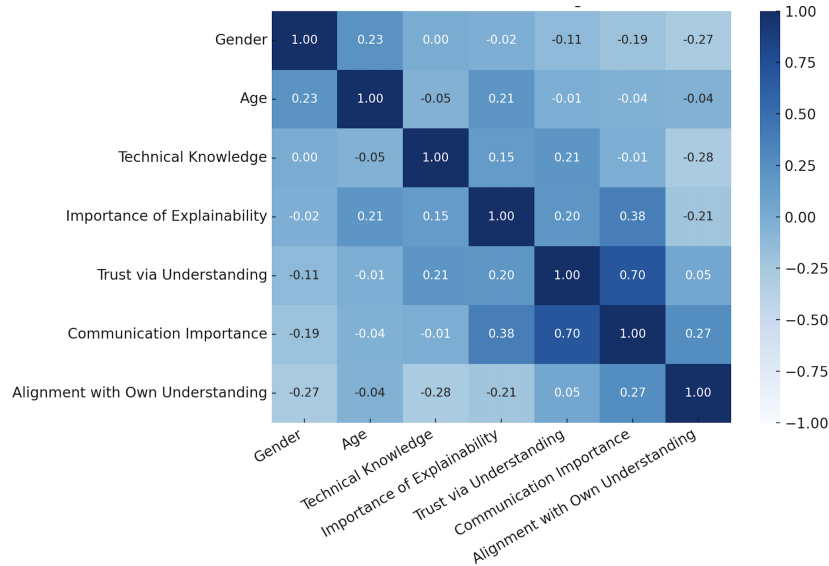


Figure 3: Correlation Matrix

The analysis revealed the following key correlations:

- Age shows a moderate positive correlation with the perceived importance of explainability ($r = 0.21$). This suggests that older participants tend to place more value on comprehensible system explanations.
- Technical prior knowledge correlates positively with the assessment that understanding creates trust ($r = 0.21$). Users with greater prior knowledge seem to trust explainable systems more.
- The strongest correlation is between the need for clear communication and trust in the system ($r = 0.70$). This underlines the central importance of transparent communication as a factor in trust.
- Gender shows no significant correlations with the evaluation criteria examined in this sample (all r values $< \pm 0.2$).

Based on this correlation analysis, the following hypotheses were formulated for further group comparisons:

- H1: There is a positive correlation between the age of the respondents and the importance they attach to the explainability of energy systems.
- H2: Respondents with greater technical knowledge rate the confidence-building effect of explainability stronger.
- H3: There is a strong positive correlation between the desire for clear communication and trust in the system.
- H4: Gender has no significant influence on the assessment of explainability and related criteria.

These hypotheses are tested in the following subsections using group analyses and inferential statistical methods (t-tests, ANOVA, Pearson and Spearman correlations). The demographic characteristics discussed above serve as the analytical framework for the following sections, in which we explore group-specific differences in the perception of explainability.

5.3 How important is explainability from the user’s perspective?

In the following, we analyse how users rate the importance of explainability – overall and in comparison across user groups. The demographic characteristics presented above – age, gender and technical knowledge – serve as key benchmarks for comparison.

To assess the relevance of explainable systems for the surveyed members of the energy community, their perception of the importance of explainability was recorded using a tailored question. This information was used as the basis for the following analyses.

5.3.1 General Perception of Explainability and Its Role in Trust

The findings indicate a clear trend in the evaluation of the explainability of SES. As illustrated in Figure 4, most participants rated explainability as very important. Around 30 participants gave it the highest rating (5 = ‘very important’), while around 20 participants rated it as moderately relevant (rating 3). Only a few participants rated explainability as less important.

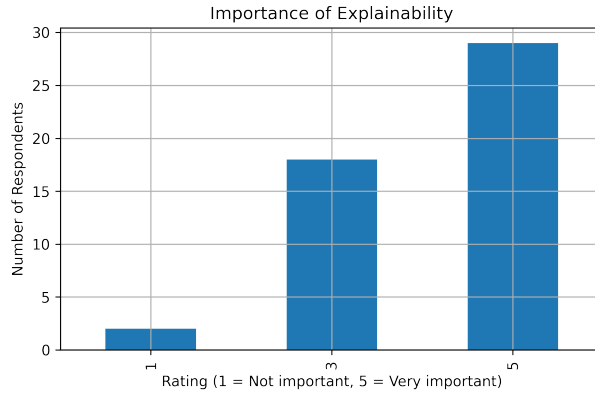


Figure 4: Explainability Importance

These results make it clear that explainability is a key feature of SES for most respondents. Users want transparent and comprehensible system communication, which should be considered when developing user-centred systems.

To better understand why explainability is perceived as so important, its connection with trust in the system was also surveyed. Figure 5 shows that most participants rated the influence of explainability on their trust as very high. Thirty-three people chose the maximum value (5 = ‘very strong’), eleven people rated it as 4, and not a single person stated that explainability had no or only a minor influence on trust.

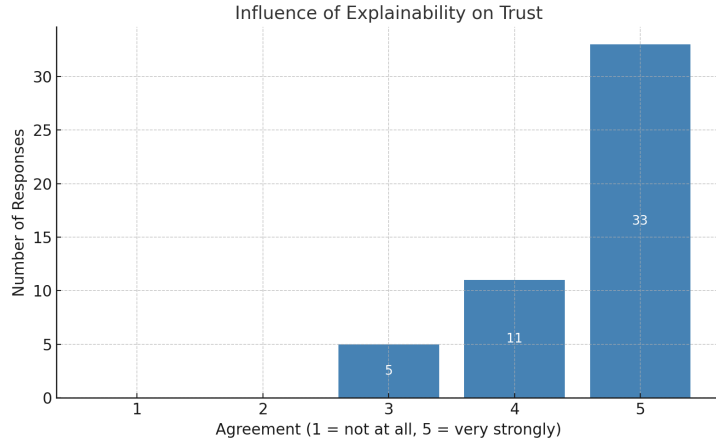


Figure 5: Influence of Explainability in Trust

These results confirm that respondents do not understand explainability as a mere comfort feature, but as an essential prerequisite for trust in SES. Users seem willing to accept automated decisions only if they are comprehensively justified.

A correlation analysis was carried out to examine this relationship in more detail. Two variables were found to be correlated: the desire for clear communication about system functions, and the belief that understanding promotes trust.

The following hypothesis was formulated for statistical testing:

1. H0 (null hypothesis): There is no correlation between the desire for clear communication and trust in the system.
2. H1 (alternative hypothesis): There is a positive correlation between the desire for clear communication and trust in the system.

The Pearson correlation revealed a significant positive correlation ($r = 0.695$; $p < 0.0001$). The null hypothesis can therefore be rejected. Participants who rated clear, transparent communication about system functions as important tended to show greater trust in the technology.

This finding highlights the central importance of explainability as a trust-promoting factor and thus supports the theoretical assumptions about the role of XAI in user-centred energy systems.

5.3.2 Are there gender-specific differences in the need for explainability?

Following the presentation of the general results, attention now turns to possible differences between user groups, beginning with an examination of differences between male and female participants.

However, the correlation analysis revealed no significant correlations between gender and the assessment of explainability. Nevertheless, a group-specific evaluation was carried out to shed more light on potential differences.

Both groups rated the explainability of SES as important overall. The average value was slightly higher for female participants than for male participants, with almost identical standard deviations – indicating comparable dispersion of assessments (see Figure 6).

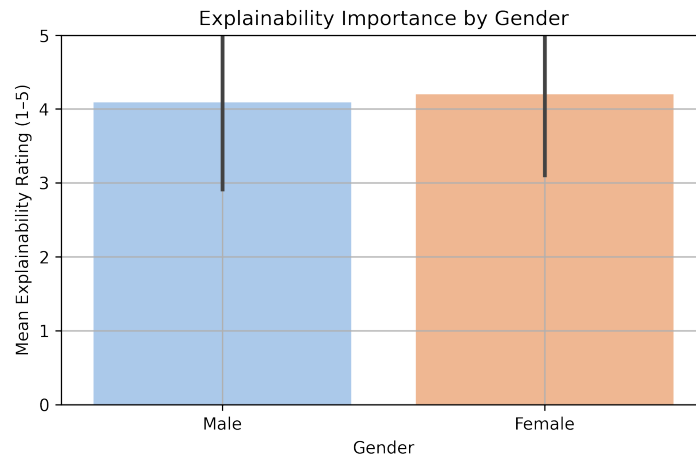


Figure 6: Explainability Importance by Gender

The following hypotheses were formulated:

1. H0 (null hypothesis): There is no significant difference between female and male participants in terms of their need for explainability.
2. H1 (alternative hypothesis): There is a significant difference between female and male participants in terms of their need for explainability.

A t-test for independent samples confirmed the null hypothesis, showing that the difference between the groups was not statistically significant ($t = -0.12$; $p = 0.91$). This suggests that, in this sample, gender has no significant influence on the assessment of explainability.

5.3.3 Does prior technical knowledge influence the assessment of explainability?

The correlation matrix showed a positive correlation between technical knowledge and trust through understanding. To examine this result more closely, the importance of explainability was evaluated separately according to knowledge level.

To investigate possible correlations between prior technical knowledge and the assessment of the importance of explainability, a grouped analysis was carried out based on the participants' self-assessment. The three groups comprised individuals with low, medium and high technical knowledge (see Figure 7).

The analysis shows that the mean values in all three groups differed only slightly. On average, individuals with high technical knowledge rated explainability slightly higher than those with medium or low knowledge. However, the differences are neither visually nor statistically significant.

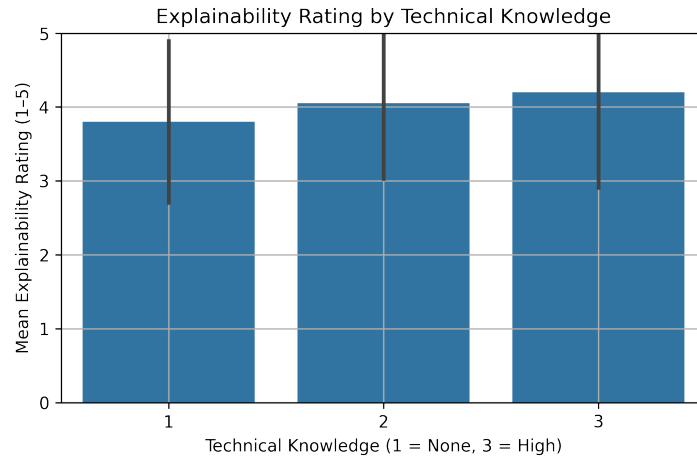


Figure 7: Explainability Importance by Technical Knowledge

To test this, the following hypotheses were formulated:

1. H0 (null hypothesis): There are no significant differences between the three groups considered in terms of their assessment of explainability.
2. H1 (alternative hypothesis): At least one of the groups differs significantly from the others in terms of the relevance of explainability.

To validate this observation, a one-factor analysis of variance (ANOVA) was chosen. The analysis revealed that there is no significant difference between the groups ($F = 0.268$; $p = 0.7662$), indicating that prior technical knowledge does not have a significant influence on the perceived importance of explainability.

In addition to the overall ANOVA, a specific comparison was conducted between participants with low (level 1) and high (level 3) technical knowledge.

The following hypotheses were tested:

1. H_0 (null hypothesis): There is no significant difference in the assessment of explainability between participants with low and high technical knowledge.
2. H_1 (alternative hypothesis): There is a significant difference in the assessment of explainability between participants with low and high technical knowledge.

An independent samples t-test revealed no significant difference ($t = -0.72$; $p = 0.496$). This further confirms the assessment that the perceived importance of explainability remains relatively constant regardless of prior technical knowledge.

These results suggest that the need for understandable and transparent system decisions is a cross-group characteristic that does not depend exclusively on prior technical knowledge.

5.3.4 Does age affect how users value explainability?

In addition to grouping participants by gender and technical knowledge, it was investigated whether there is a correlation between the age of the respondents and their assessment of the importance of explainability.

The correlation between age and assessment of explainability indicated a moderate positive relationship. Pearson and Spearman analyses were performed to validate this relationship, for which the following hypotheses were formulated:

1. H_0 (null hypothesis): There is no significant correlation between the age of the respondents and the perceived importance of explainability.

2. H1 (alternative hypothesis): There is a significant correlation between the age of the respondents and the importance they attach to explainability.

Neither method produced any statistically significant correlations. The Pearson correlation yielded a correlation coefficient of $r = 0.212$ ($p = 0.1431$), the Spearman correlation a value of $\rho = 0.208$ ($p = 0.1523$). This indicates that age has no relevant influence on the perceived importance of explainability.

It can therefore be concluded that the importance of explainability is perceived as a central usage need, regardless of age.

5.4 Which aspects of explainability promote trust?

While the previous sections analysed which user characteristics are related to the assessment of explainability, the following section examines which specific characteristics of explanations particularly promote trust. In a multiple-choice question, the participants could tick which aspects of explainability they personally consider to be particularly relevant.

As Figure 8 shows, the most common response was that explainability helps to better understand the behaviour of the system and its decision-making processes (32 responses). Almost the same number of participants (31 mentions) indicated that explainability increases trust in the system and acceptance of its recommendations.

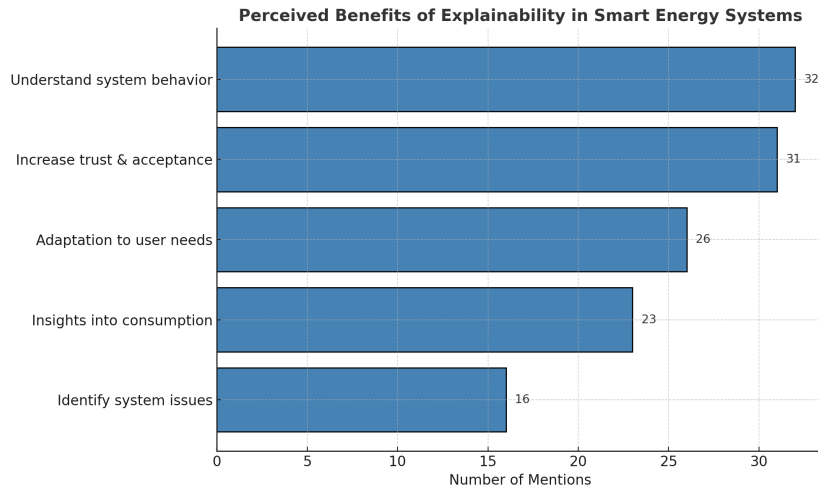


Figure 8: Perceived Benefits of Explainability in SES-Context

In addition to the general assessment of explainability, specific features of system explanations were surveyed that are intended to promote user trust in particular. Participants were asked to rate on a scale from 1 (does not apply) to 5 (fully applies) the extent to which certain characteristics of explanations promote trust.

As Figure 9 shows, the statement that explanations should reflect one’s own understanding received the highest level of agreement ($M = 3.08$). The ability to provide comprehensible explanations ($M = 2.73$) and individual adaptation to the knowledge and needs of users ($M = 2.63$) were also rated comparatively highly. In contrast, agreement with the aspect of mere clarity and simplicity was significantly lower ($M = 1.55$).

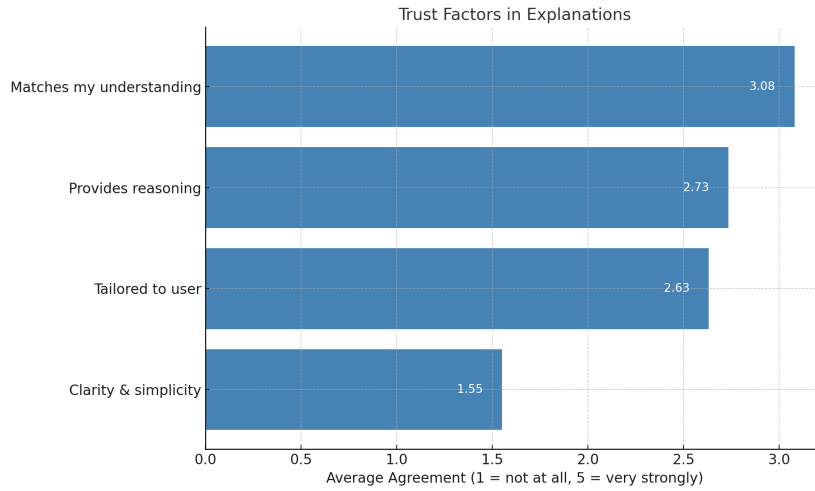


Figure 9: Trust Factors in Explanations

The analysis reveals that trust is created less by linguistic comprehensibility and more by the accuracy of content and its relevance to the user’s perspective. For the design of explainable energy systems, this means that the presentation of reasons and a context-related approach to users are more important than purely linguistic simplicity.

While this section focused on the content characteristics of explanations, the following section examines which individual assessments and requirements of users have the strongest influence on trust in SES.

5.5 Which factors have the greatest influence on trust in SES?

In addition to the individual analyses conducted to date, a multiple linear regression analysis was performed to identify the factors with the greatest influence on trust in smart energy systems (SES). Five potentially relevant predictors were included in the model:

- General importance of explainability
- Desire for clear communication
- Need for transparency in system logic
- Need for personalised explanations
- Consistency of explanations with one’s own understanding

The dependent variable was trust in the system, measured by assessing the extent to which understanding the system promotes trust.

Figure 10 shows the standardised regression coefficients of the model. The analysis is based on 49 complete datasets and results in an explained variance of $R^2 = 0.556$. This indicates that over half of the variations in trust levels can be attributed to the included characteristics.

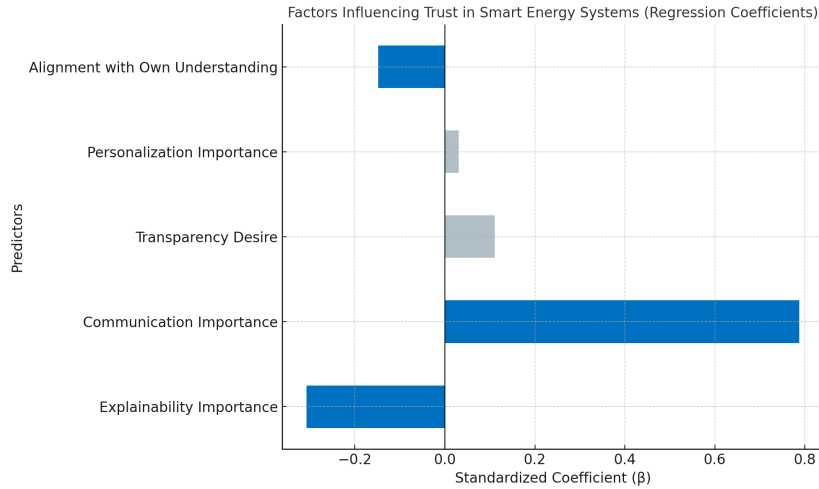


Figure 10: Factors influencing Trust

The result clearly shows that a desire for clear communication is the strongest positive predictor of trust ($\beta = 0.79$; $p < .001$). Users who value clear and

understandable communication of system functions demonstrate significantly higher levels of trust in SES.

However, surprisingly, the result for the variable 'importance of explainability' is slightly negative ($\beta = -0.13$). Although explainability was generally considered important, this finding suggests that individuals with high expectations of explainability may be more critical when explanations do not meet these expectations. A high need for transparency does not automatically lead to greater trust; rather, it can also lead to greater sensitivity to weaknesses in explanations. The other variables such as the need for transparency, the desire for personalisation, and consistency with one's own understanding had no significant influence on the model.

Overall, the analysis shows that demographic characteristics and individual attitudes are not the only decisive factors. Above all, the perceived quality of system communication, particularly its clarity, plays a central role in trust in SES. This emphasises the importance of not only creating explainable systems but also communicating them in a way that is understandable and appropriate for the target group.

5.6 Which explanation formats do users with different levels of technical knowledge prefer?

As part of the survey, participants were asked to indicate in which format they would prefer explanations by SES. The options included text-based, visual, interactive, and combined formats. The aim of this analysis was to investigate whether and how format preferences differ depending on the level of self-assessed technical knowledge.

5.6.1 Format Preferences depending on Knowledge Level

The results of the grouped analysis (see Figure 11) show clear differences in the preferred explanation formats depending on prior technical knowledge: Participants with little prior technical knowledge (level 1) predominantly favoured combined explanatory formats. Interactive formats were less frequently selected, while visual formats were hardly mentioned. The group with medium technical knowledge showed a broader distribution, with a clearer tendency towards combined and interactive formats. Participants with a high level of technical knowledge (level 3) showed a clear preference for interactive formats, followed by combined formats. Visual explanations again played a subordinate role here.

These results indicate that the requirements for suitable explanatory formats in SES gradually shift with increasing technical knowledge. In all groups, the participants show a clear preference for combined formats, a combination of visual and interactive elements. However, as technical knowledge increases, the preference for interactive formats also increases slightly, while only visual formats remain generally less favoured. This suggests that diverse, adaptively combined explanatory approaches are perceived as particularly accessible and useful – regardless of prior knowledge.

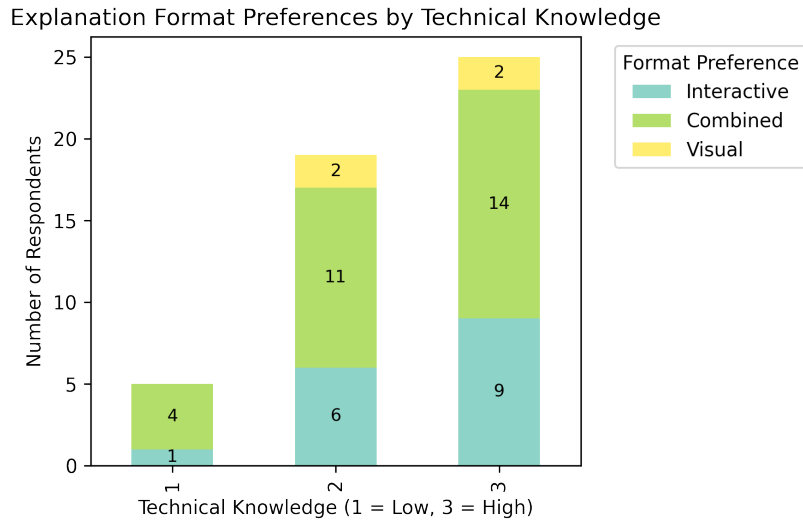


Figure 11: Format Preferences by Technical Knowledge

5.7 Identified Challenges

The survey also included a question on the biggest challenges that users experience when dealing with SES. Participants were able to choose from a list of frequently mentioned problems. The aim was to identify obstacles that potentially affect the use, understanding and trust in the systems.

5.7.1 What are the biggest challenges users face with SES?

Figure 12 illustrates the five most commonly reported challenges associated with smart energy systems (SES). Technical problems or system failures were by far the most frequently cited issue ($n = 35$). These were followed by difficulties in understanding system behaviour or recommendations ($n = 19$) and limited compatibility with other smart home devices ($n = 18$). A lack of

clarity in system communication and an unclear impact on one’s own energy consumption were also cited as key problems, with 15 citations each.

These results can be divided into three categories:

1. Technical challenges: Malfunctions, failures, and a lack of system integration dominate this category.
2. Cognitive challenges: Many users have difficulty understanding the behaviour or logic of the system.
3. Communicative challenges: Unclear information and a lack of transparency make understanding difficult.

This last aspect in particular highlights the importance of explainability: if systems communicate in an incomprehensible way, or if their recommendations are not transparent, this can lead to frustration and uncertainty, which could affect acceptance of the entire system.

The results therefore clearly demonstrate that, in addition to technical reliability, the quality and comprehensibility of system communication also plays a central role. A clear, explainable SES design can help reduce comprehension problems and boost user confidence.

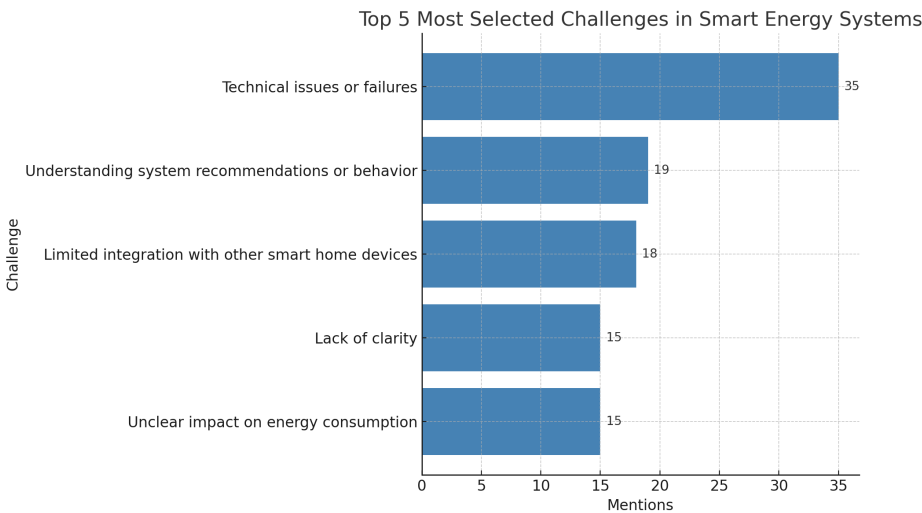


Figure 12: Most selected Challenges in SES

5.8 Summary of the Results

The results of the quantitative analysis provide comprehensive insight into the attitudes, expectations and preferences of the surveyed members of an energy community when dealing with SES. It shows that explainability is perceived by users as a key feature for acceptance of such systems – regardless of age, gender or technical knowledge. This universal relevance was confirmed both by the descriptive distribution of the ratings and by statistical tests (t-test, ANOVA, correlations).

In addition, differences in preferred explanation formats emerged: while participants of all knowledge levels predominantly preferred combined formats, the proportion of interactive formats increased slightly with increasing technical knowledge. This underscores the importance of flexible, user-centred communication strategies that take different levels of prior experience into account.

The answers to the questions about perceived challenges and motives for use also provide concrete guidance for design: users expect efficiency and sustainability but see technical complexity and a lack of comprehensibility as key obstacles.

A particularly significant correlation was found between the desire for clear communication about system functions and trust in the technology. The calculated Pearson correlation ($r = 0.695$; $p < 0.0001$) confirms that participants who considered understandable system explanations to be important also tended to show greater trust in SES. This finding underscores the central role of explainability as a trust-building factor and provides strong empirical evidence for the relevance of user-centred XAI concepts in the energy sector.

Furthermore, the results showed that none of the examined demographic characteristics – including age, gender, and technical knowledge – had a statistically significant influence on the perceived importance of explainability or related trust factors. Although some trends were observed (e.g. slightly higher trust ratings among technically experienced users), these differences were not significant. In particular, the gender distribution should be interpreted with caution due to the very small number of female participants ($n = 5$), which limits the reliability of gender-related findings. Overall, the analysis suggests that the importance of explainability is perceived as a broadly shared need - relatively independent of demographic background – and highlights the necessity of designing explainable systems.

6 Discussion

This chapter places the results presented in the previous section in a broader context to summarise the key findings, interpret them in the light of existing research, and highlight their practical and theoretical implications. In addition, the limitations of the study are discussed and possible approaches for further research outlined.

6.1 Overview of Key Findings

The analysis provides clear evidence that explainability in SES is considered a key system feature by the surveyed members of Austrian energy communities. Regardless of age, gender, or technical knowledge, they rate comprehensible and transparent system decisions as important for the use and acceptance of these technologies.

The connection between clear system communication and trust in SES was particularly evident. Indeed, the statistical analysis shows that a high value placed on comprehensible and transparent communication is the strongest positive predictor of trust. This result illustrates that it is not only the provision of explanations that is crucial, but above all their comprehensibility and alignment with the knowledge of the users.

In addition, clear preferences can be identified with regard to explanation formats. While combined formats (e.g., visual and interactive elements) are preferred across all knowledge levels, there is a slight increase in preference for interactive formats with increasing technical experience. However, visual explanations alone were chosen comparatively rarely.

Regarding the challenges identified, technical problems and system failures dominate, followed by difficulties in understanding system behaviour and logic as well as unclear communication. These findings underscore the dual challenge in designing SES: in addition to ensuring technical reliability, it is crucial to develop transparent and easily understandable communication that is tailored to the target group.

Overall, the results support the assumption that explainability in the context of SES must be viewed not as an optional add-on feature, but as a fundamental prerequisite for trust and long-term user acceptance.

6.2 Interpretation in the Context of Existing Literature

Building on these findings, the results confirm key assumptions of existing research on XAI in the context of SES. In particular, the finding that clear and understandable communication is the strongest factor influencing trust supports the statements of Liao & Varshney [7]. They emphasise that explanations must not only be available but also designed in a user-centred manner in order to be fully effective.

The universal importance of explainability, regardless of demographic factors such as age, gender, or technical knowledge, is consistent with the observations of Shin [6], according to which transparency and comprehensibility requirements exist across most groups. The fact that no significant differences between the groups studied were found in this work partly contradicts studies that identify [10], for example, age- or knowledge-related differences in the perception of system explanations. One possible explanation for this lies in the characteristics of the sample: members of energy communities often already have a certain basic interest in and understanding of energy technologies, which could mitigate group-specific differences.

It is striking that the general importance of explainability in the regression model correlates slightly negatively with trust. This apparent contradiction could be explained by an expectation gap as users with high expectations of explainability may be particularly sensitive to insufficient or unclear explanations, which can lead to a critical attitude towards the system. This phenomenon has also been observed in a similar form in studies on explainable recommendation systems, where unmet transparency requirements lead to a loss of trust [13].

The preference for combined explanation formats and the trend toward interactive formats among more tech-savvy users is consistent with findings from human-computer interaction research. Research [21] emphasises that multimedia and interactive explanations better meet the different cognitive needs of user groups than purely text- or image-based formats.

In summary, the results of this study largely confirm the theoretical assumptions and empirical findings from the literature. At the same time, they provide new insights into specific mechanisms - in particular the role of a possible expectation-disappointment dynamic - that should be investigated in more detail in future studies.

6.3 Practical Implications

The findings of this study illustrate that explainability in SES is not just a technical feature, but a central element of user-centred design. Above all, the strong correlation between clear communication and trust suggests that developers should consistently focus on this aspect. Both the survey results (see Section 5.4), which show that clarity and comprehensibility were rated as the most relevant factors for trust, and prior research on user-centred XAI (see Section 2.3) support the claim that comprehensible, structured information tailored to the prior knowledge and needs of the target group contributes significantly to acceptance. The respondents' preference for combined explanatory formats suggests that the integration of different presentation elements – such as the combination of visual and interactive components – can be particularly effective. At the same time, the survey data (Figure 12) and previous studies on SES adoption (see Section 2.2) underline that technical reliability, system compatibility, and intuitive operation are equally crucial. Close feedback with users, for example via feedback loops in energy communities, can help to identify and remedy both technical and communicative weaknesses at an early stage.

6.4 Addressing the Research Questions

Based on the above interpretations and implications, the following section explicitly addresses the research questions outlined in Chapter 1.

RQ1: What are the specific needs and expectations of users when interacting with smart energy systems in real-world scenarios?

The survey results show that users consider clear, transparent and easily understandable communication to be a key requirement when interacting with smart energy systems. In addition, technical reliability and system stability were frequently cited as expectations, with many respondents identifying technical failures as a key challenge. These results illustrate that expectations extend not only to functional performance, but also to communicative and trust-building aspects.

RQ2: How critical is explainability in fostering user trust and acceptance of smart energy systems? Does the importance of explainability vary among different user groups?

The analyses show a strong positive correlation between perceived clarity

of communication and trust in smart energy systems ($r = 0.695$, $p < 0.001$). In the multiple regression model, clarity of communication proved to be the most influential predictor and explained a considerable proportion of the variance in trust ($R^2 = 0.556$). No significant differences in the importance of explainability were found between user groups, suggesting that the correlation between clear communication and trust exists regardless of demographic or background differences.

RQ3: How does a user’s background affect their need for explainability or the types of explanations they prefer?

No statistically significant differences in the need for explainability or in the preferred explanation formats were found depending on knowledge level, age or gender. Regardless of their background, many respondents preferred clear and easy-to-understand formats, with combined formats consisting of visual and interactive elements being particularly popular. Purely visual formats were chosen comparatively rarely. More technically experienced users also showed a slight, although insignificant, preference for interactive formats. This suggests that generally accessible and multimedia-based explanatory strategies can be effective across different user groups.

6.5 Limitations

Despite clear trends, the results of this study must be interpreted with caution in several aspects. The sample size of 49 people is relatively small, which reduces its significance, especially when comparing groups. The significant imbalance in gender distribution – 44 male participants compared to only 5 female participants – also does not allow for reliable statements about possible gender-specific differences. In addition, the sample consists exclusively of members of Austrian energy communities, who generally have an above-average interest in technology. This limits the generalisability to other user groups. As this is a secondary data analysis, it was not possible to design the survey instrument itself or to supplement it with qualitative elements. Finally, all information is based on self-assessments, which may be influenced by subjective perceptual distortions.

6.6 Future Research

Future research should build on a broader and more diverse data set in order to increase generalisability and to capture possible differences between user groups more precisely. Experimental studies that specifically vary explana-

tion formats and measure their effects on trust, understanding, and usage behaviour would be particularly valuable. In addition, it would be worthwhile to explore more closely the possible expectation effect observed in this work: high demands on explainability could lead to a more critical attitude towards the system if they are not adequately met. Longitudinal approaches could complement these efforts by showing how trust and acceptance develop over time. Finally, the development of adaptive explanation mechanisms that dynamically adjust content and detail to the needs of individual users offers significant innovation potential for a truly user-centred design of SES.

7 Conclusion

This study examines the needs and expectations of users when dealing with SES, the role of explainability in building trust and acceptance, and the influence of user background on the need for explanations and preferences for explanation formats. The analysis of a survey of members of Austrian energy communities shows that clear, transparent, and easily understandable communication is considered a key system feature. Technical reliability and system stability are also among the most important expectations.

A strong positive correlation between clarity of communication and trust in SES was demonstrated, with this factor providing the largest explanatory contribution in the regression model. No differences in the importance of explainability or in format preferences between user groups (e.g. by age, gender or expertise) were found. Overall, respondents preferred combined explanation formats with visual and interactive elements.

The results make it clear that explainability should not be seen as an optional extra feature, but as a basic requirement for long-term acceptance. Developers should therefore prioritise both technical reliability and understandable, target group-oriented communication. Future research should verify these findings with larger, more diverse samples, pursue experimental approaches to different explanation formats, and develop adaptive explanation mechanisms that dynamically adapt to individual needs.

References

- [1] R. Alsaigh, E. Glaab, and E. Curry, “Ai explainability and governance in smart energy systems: A review,” *Energy Informatics*, vol. 6, no. 1, pp. 1–25, 2023.
- [2] A. Wazeer and A. Das, “Recent developments in the smart energy systems,” *Handbook of Smart Energy Systems*, pp. 1–19, 2022.
- [3] D. Moneta, “Smart grids: enabler for the energy transition,” in *EPJ Web of Conferences*, vol. 189. EDP Sciences, 2018, p. 00012.
- [4] H. Lund, P. A. Østergaard, D. Connolly, and B. V. Mathiesen, “Smart energy and smart energy systems,” *Energy*, vol. 137, pp. 556–565, 2017.
- [5] D. Bonino, F. Corno, and L. De Russis, “Home energy consumption feedback: A user survey,” *Energy and Buildings*, vol. 47, pp. 383–393, 2012.
- [6] D. Shin, “The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable ai,” *International Journal of Human–Computer Studies*, vol. 146, p. 102551, 2021.
- [7] Q. V. Liao and K. R. Varshney, “Human-centered explainable ai (xai): From algorithms to user experiences,” *arXiv preprint arXiv:2110.10790*, 2021.
- [8] S. Kujala, *User studies: A practical approach to user involvement for gathering user needs and requirements*. Helsinki University of Technology, 2002.
- [9] G. Schweiger, L. V. Eckerstorfer, I. Hafner, A. Fleischhacker, J. Radl, B. Glock, M. Wastian, M. Rößler, G. Lettner, N. Popper *et al.*, “Active consumer participation in smart energy systems,” *Energy and Buildings*, vol. 227, p. 110359, 2020.
- [10] L. Chazette, W. Brunotte, and T. Speith, “Exploring explainability: a definition, a model, and a knowledge catalogue,” in *2021 IEEE 29th international requirements engineering conference (RE)*. IEEE, 2021, pp. 197–208.
- [11] Y. Xu, C. Yan, H. Liu, J. Wang, Z. Yang, and Y. Jiang, “Smart energy systems: A critical review on design and operation optimization,” *Sustainable Cities and Society*, vol. 62, p. 102369, 2020.

- [12] H. Zhu, H. H. Goh, D. Zhang, T. Ahmad, H. Liu, S. Wang, S. Li, T. Liu, H. Dai, and T. Wu, “Key technologies for smart energy systems: Recent developments, challenges, and research opportunities in the context of carbon neutrality,” *Journal of Cleaner Production*, vol. 331, p. 129809, 2022.
- [13] C. Sardinios, A. Symeonidis, and P. Chatzimisios, “The emergence of explainability: Delivering explainable and personalised recommendations for energy efficiency,” in *Proceedings of the 23rd International Conference on Model Driven Engineering Languages and Systems (MODELS)*, 2020, pp. 139–148.
- [14] M. Unterbusch, M. Sadeghi, J. Fischbach, M. Obaidi, and A. Vogel-sang, “Explanation needs in app reviews: Taxonomy and automated detection,” in *2023 IEEE 31st International Requirements Engineering Conference Workshops (REW)*. IEEE, 2023, pp. 102–111.
- [15] M. Shajalal, R. Gutiérrez, A. Dengel, and S. Ahmed, “Explaining ai decisions: Towards achieving human-centered explainability in smart home environments,” *Proceedings of the 3rd International Workshop on eXplainable Artificial Intelligence (xAI 2024)*, 2024.
- [16] R. Machlev, L. Heistrene, M. Perl, K. Y. Levy, J. Belikov, S. Manor, 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.
- [17] V. Hassija, V. Chamola, A. Mahapatra *et al.*, “Interpreting black-box models: A review on explainable artificial intelligence. *cogn comput* 16, 45–74 (2024),” 2024.
- [18] M. T. Ribeiro, S. Singh, and C. Guestrin, ““ why should i trust you?” explaining the predictions of any classifier,” in *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 2016, pp. 1135–1144.
- [19] A. Adadi and M. Berrada, “Peeking inside the black-box: a survey on explainable artificial intelligence (xai),” *IEEE access*, vol. 6, pp. 52 138–52 160, 2018.
- [20] A. Ferrario and M. Loi, “How explainability contributes to trust in ai,” in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. ACM, 2022, pp. 1457–1466.

- [21] J. Dai, M. Düring, and A. Schmidt, “The effect of explanation design on user perception of smart home lighting systems: A mixed-method investigation,” in *Proceedings of the CHI Conference on Human Factors in Computing Systems*. ACM, 2023, pp. 1–13.
- [22] A. C. Lazaroiu, M. Roscia, G. C. Lazaroiu, and P. Siano, “Review of energy communities: Definitions, regulations, topologies, and technologies,” *Smart Cities*, vol. 8, no. 1, p. 8, 2025.
- [23] L. Kordulova, “Understanding user requirements: Exploring the significance of ex-plainability in smart energy systems.”