

Article

Motivational, Sociodemographic, and Housing-Related Determinants of Smart Technology Adoption in German Households [†]

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Abstract

Alongside technological innovations, the energy transition requires notable behavioral changes in the residential sector. Smart technologies (STs) can support this shift by promoting transparency, energy-conscious behavior, and automated efficiency gains; their adoption depends on user acceptance. This study investigates the determinants shaping adoption patterns of different STs in German households. Based on a standardized online survey of 284 participants within the SmartQuart project (2022 and 2023), the analysis examined the motivational, sociodemographic, and housing-related factors influencing usage. The investigation was guided by a conceptual framework adapted from the Unified Theory of Acceptance and Use of Technology 2. The results revealed that efficiency- and control-related motives mainly drive the adoption of energy-oriented technologies, such as energy monitoring and home energy management systems. In contrast, indoor air quality monitoring and smart home systems are primarily used to enhance residential comfort. Regression analyses demonstrated that education and building type have a significant impact on energy-oriented technologies, while income, age, and living space influence comfort-oriented applications. The findings highlight the importance of differentiated communication and user-centered technology design. Despite limited generalizability, this study offers relevant insights into the target group-specific adoption dynamics essential for promoting behavioral energy efficiency in the residential sector.

Keywords: smart technologies; energy monitoring; home energy management systems; indoor air quality monitoring; smart home; UTAUT2; sociodemographic and housing factors; motivational factors; technology adoption; behavioral energy efficiency



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1. Introduction

In the energy transition context, reducing energy consumption and enhancing energy efficiency in the building sector play crucial roles. A substantial proportion of total energy consumption in Germany results from private residential properties. The two main sectors contributing to this consumption are heating and hot water supply [1]. Beyond technical measures such as energy-efficient renovation or renewable source utilization, effectively reducing energy demand in this area requires active user behavior modification. Behavioral measures offer considerable energy-saving potential, which remains largely underutilized

to date. Active user behavior, including optimized heating and ventilation, reduced standby losses, and adjusted room temperature, can yield substantial energy savings [2–4]. However, implementing these measures necessitates a high motivation level, awareness, and continuous engagement with personal energy consumption—requirements that are challenging to achieve in everyday practice.

In this context, smart technologies (STs) play a pivotal role, functioning as information tools and control–automation instruments. The integration of smart heating controls, adaptive thermostats, smart meters, and connected household appliances facilitates the detailed recording, visualization, and optimization of energy consumption. These systems introduce transparency, promote conscious behavior, and enable user-independent efficiency gains through automated processes. Furthermore, so-called feedback systems, which provide real-time feedback on consumption values, can support the development of energy-efficient habits [5–7].

The investigation of these technologies is particularly relevant amid the ongoing digital transformation of the building sector. As part of this transformation, buildings are becoming “smart buildings”, in which information and communication technologies play a pivotal role. This digitalization enables greater data transparency and connectivity between system components and facilitates the development of data-based applications that optimize energy and load management. Thus, STs act as an interface between technical energy efficiency and digital innovation [8,9]. Thus, ST integration into private households opens new perspectives for behavior-based energy savings and should be considered part of the digitization of the building sector and a complementary strategy to technical modernization.

1.1. Description of Investigated STs

The technologies examined in this study fall into two categories: First, monitoring systems for recording and analyzing consumption and comfort data, including energy and indoor air quality monitoring (IAQM); second, intelligent control systems such as smart home applications and home energy management systems (HEMS). Relevant terms are briefly described below.

Energy monitoring involves the continuous, systematic recording and evaluation of energy consumption, including electricity, heat, and water. Its primary objective is to create transparency in consumption, identify potential savings, and derive optimization measures. Energy monitoring is typically achieved by utilizing smart meters and sensors, which facilitate the real-time transmission of consumption data to centralized platforms. The information obtained is used to analyze user behavior and to comply with legal requirements [10,11]. The practice of IAQM complements energy monitoring by evaluating indoor climate parameters, aiming to identify those parameters that have a notable impact on the well-being and performance of occupants. These include temperature, humidity, and carbon dioxide concentration. The data is collected using specialized sensors and used to optimize the indoor climate. The overarching objective is to enhance the quality of stay, minimize health risks, and increase individual residential comfort [12,13]. Smart home applications also enable automated control of building services, including lighting, heating, shading, security, and household appliances. The implementation of customizable scenarios and centralized control, frequently facilitated through mobile devices or voice assistants, has been demonstrated to enhance comfort, energy efficiency, and security. The underlying infrastructure is based on networked sensors and control units that interact via common communication protocols [14,15]. HEMS are defined by their capacity to extend beyond the scope of conventional monitoring techniques, thereby facilitating intelligent, automated control of energy flows within the confines of buildings. Energy

generators (e.g., photovoltaics), storage systems (e.g., battery storage), and consumers (e.g., heat pumps and electric vehicles) are networked and operated in an optimized manner. The overarching aims are to optimize self-consumption, reduce peak loads, and utilize energy cost-effectively. This is achieved by considering user behavior, weather data, and electricity tariffs. The integration of such systems is imperative for the successful implementation of decentralized energy generation and active participation in future smart grids. Unlike monitoring systems and smart home applications—whose radio-based meters, sensors, and control units are generally retrofittable in existing buildings with minimal effort—retrofitting energy management systems demands greater system integration and configuration effort [11,16].

The technologies described herein offer various potential for reducing energy consumption and increasing living comfort. Empirical field studies have shown that intelligent heating controls and automated indoor climate regulation can reduce heating energy consumption by up to 30% [17]. Energy monitoring systems can also markedly increase energy awareness and change consumption patterns in the long term [18,19]. Furthermore, HEMS facilitate flexible load shifting, particularly when used alongside photovoltaic systems or electromobility [20]. This helps to ensure grid stability and facilitates the integration of decentralized energy sources.

Despite this technical potential, empirical evidence indicates that the impact of STs relies on their acceptance and utilization by end consumers [21]. However, the simple existence of these systems does not guarantee their utilization or the emergence of sustainable behavioral modifications [22,23]. Empirical studies have demonstrated that individual-level motives markedly influence technology adoption decisions [24]. The underlying motives are technology-specific.

1.2. Motivation and Objectives of the Study

Against this background, the present study aims to investigate the determinants of acceptance and use of various STs in private households in Germany, as well as to identify and theoretically explain similarities and differences in adoption patterns. The study considers motivational factors—such as economic, control-related, ecological, and comfort-oriented motives—derived from previous empirical and theoretical studies. These are complemented by structural factors, such as sociodemographic and housing characteristics, which may also influence technology use.

Building on the theoretical foundations of established technology acceptance models, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2), these factors are embedded in a conceptual framework that describes the relationships between individual motivations, structural conditions, behavioral intention to use, and actual usage. This framework forms the basis for the empirical analysis of adoption patterns and facilitates a nuanced examination of influencing factors.

The present study, therefore, pursues three specific objectives: (1) to identify and compare motivational determinants across users of different STs, (2) to determine the direct effects of sociodemographic and housing characteristics on actual usage, and (3) to analyze the influencing effects of these characteristics on motivational factors. Finally, the study examines the determinants that commonly influence the adoption of all considered STs and identifies technology-specific differences, aiming to determine adoption patterns.

This integrated analytical approach contributes to the expansion of existing theory formation on technology acceptance and provides practical insights for developing target group-specific products, designing effective information and communication materials, and politically establishing funding measures for energy transition and digitalization in the residential sector. The results deepen the understanding of how specific motivations,

sociodemographic, and housing conditions shape ST adoption, strengthen the scientific basis for user-centered research, and support the digital transformation of residential environments to enhance building energy efficiency.

Building on this foundation, the following chapter describes the theoretical assumptions of technology acceptance models. Subsequently, the results of the literature review are presented, and the conceptual model developed in this study is described, combining motivational, sociodemographic, and housing determinants as a guiding framework for empirical investigation.

2. Theoretical Background and Literature Review

2.1. Technology Acceptance Models

The acceptance and use of STs in private households are predominantly determined by cognitive and motivational processes. The Technology Acceptance Model (TAM), developed by Davis [25], has been established as the central theoretical framework for explaining these relationships. TAM posits that perceived usefulness and perceived ease of use determine users' attitudes toward a technology and ultimately its actual usage. These attitudes, in turn, influence users' behavioral intention to use technology, which can be defined as an individual's deliberate readiness to engage with it. Ultimately, the actual usage of technology is determined by its users' attitudes and behavioral intentions.

While TAM provides a robust basis for examining technology-related acceptance processes, it only partially accounts for social and contextual determinants. Extended models, such as the UTAUT [26] and its further development, UTAUT2 [27], integrate the concept of behavioral intention more explicitly and incorporate additional determinants and moderating variables—such as age, gender, or experience.

These extensions enable a more nuanced analysis by capturing interindividual differences in the strength of the relationships between cognitive evaluations, behavioral intentions, and actual technology usage. Integrating motivational, social, and structural determinants is particularly relevant in the context of energy-related digitalization in private households, as technology adoption decisions are influenced not only by individual values and needs but also by demographic and housing-related conditions.

2.2. Motivational and Demographic Influencing Factors

A comprehensive literature review was conducted to identify the potential factors influencing the use of STs in private households. Results indicate that, while adoption motives vary depending on the technology, they can be systematically categorized into overarching motivational dimensions that have been consistently discussed and documented in technology acceptance and energy use research [20,22–24,28–38]. Based on prior empirical findings, four central motivational determinants are identified:

2.2.1. Economic Motivation

Economic motives are among the most frequently identified drivers of technology acceptance in the field of energy-related applications. The expectation of reducing energy costs or achieving long-term financial savings by using STs plays a central role in the adoption decision. Users perceive economic benefits as an immediate, measurable outcome of technology use, linking individual cost reduction with efficiency gains and contributing significantly to perceived usefulness [23,28,30,39].

2.2.2. Control- and Autonomy-Related Motivation

A further key motive is the desire for control and autonomy over one's energy consumption. Users aim to monitor energy demand, understand usage patterns, and actively

influence consumption. This motive is frequently linked to perceived self-efficacy, defined as confidence in one's ability to manage energy-related actions effectively. Energy monitoring and HEMS provide technical support for this, offering transparency and individualized control options. Control over energy flows fosters autonomy and efficiency, reinforcing the cognitive evaluation of the technology as useful [23,32,40].

2.2.3. Ecological Motivation

Ecological motivation reflects the desire to reduce one's environmental footprint and contribute to sustainable energy use through ST adoption. Research indicates that users with pronounced environmental awareness perceive STs as tools for promoting energy efficiency and resource conservation. Energy monitoring and smart home systems are regarded as instruments for the implementation of environmentally friendly behaviors and the support of energy transition. This motive reflects a value-based orientation geared toward long-term ecological goals and has a positive effect on the behavioral intention to use the technologies [20,29].

2.2.4. Health- and Comfort-Related Motivation

In the domain of IAQM and smart home technologies, extant studies have demonstrated that health and comfort considerations are critical determinants of adoption. Users value improvements in air quality, indoor climate, and overall living environment, which enhance physical and emotional well-being. Beyond functional benefits, hedonic components, such as convenience, living quality, and emotional satisfaction, play an important role. This motive extends beyond efficiency considerations, addressing subjective quality of life as a central utility aspect [31,32].

2.2.5. Demographic Influencing Factors

Beyond motivational factors, earlier studies have demonstrated that sociodemographic characteristics exert various effects on ST utilization. Education positively influences technical understanding and environmental–health awareness and correlates positively with adoption willingness [32]. Income plays a particularly relevant role in cost-intensive technologies, whereas age, household size, and marital status exert distinct technology-specific effects. For instance, IAQM is more prevalent in households with children or older people, groups for whom preventive healthcare is particularly relevant [31].

2.3. Conceptual Framework and Model Assumptions

Building on the theoretical framework of TAM, UTAUT, and UTAUT2, and the determinants identified in Section 2.2, this study develops an integrative adoption model explaining ST use in private households. The model integrates individual motivations and structural conditions, such as sociodemographic and housing-related factors, into a cohesive theoretical framework (see Figure 1).

At the model core is the concept of behavioral intention to use, which functions as the central cognitive mediator between individual motivations and actual usage. The four motivational factors—economic, control, ecological, and comfort—shape behavioral intention to use through value-based, rational, autonomy-related, and hedonic evaluations, respectively.

The model further accounts for sociodemographic factors (e.g., age, gender, education, and income) and housing-related factors (e.g., homeownership status, building type, living space, and household size). These factors have direct effects on ST usage and indirect effects via the motivational dimension. These factors are assumed to influence motivation, which then indirectly influences behavioral intention and use through differences in education, income, household structure, and living environment, for example.

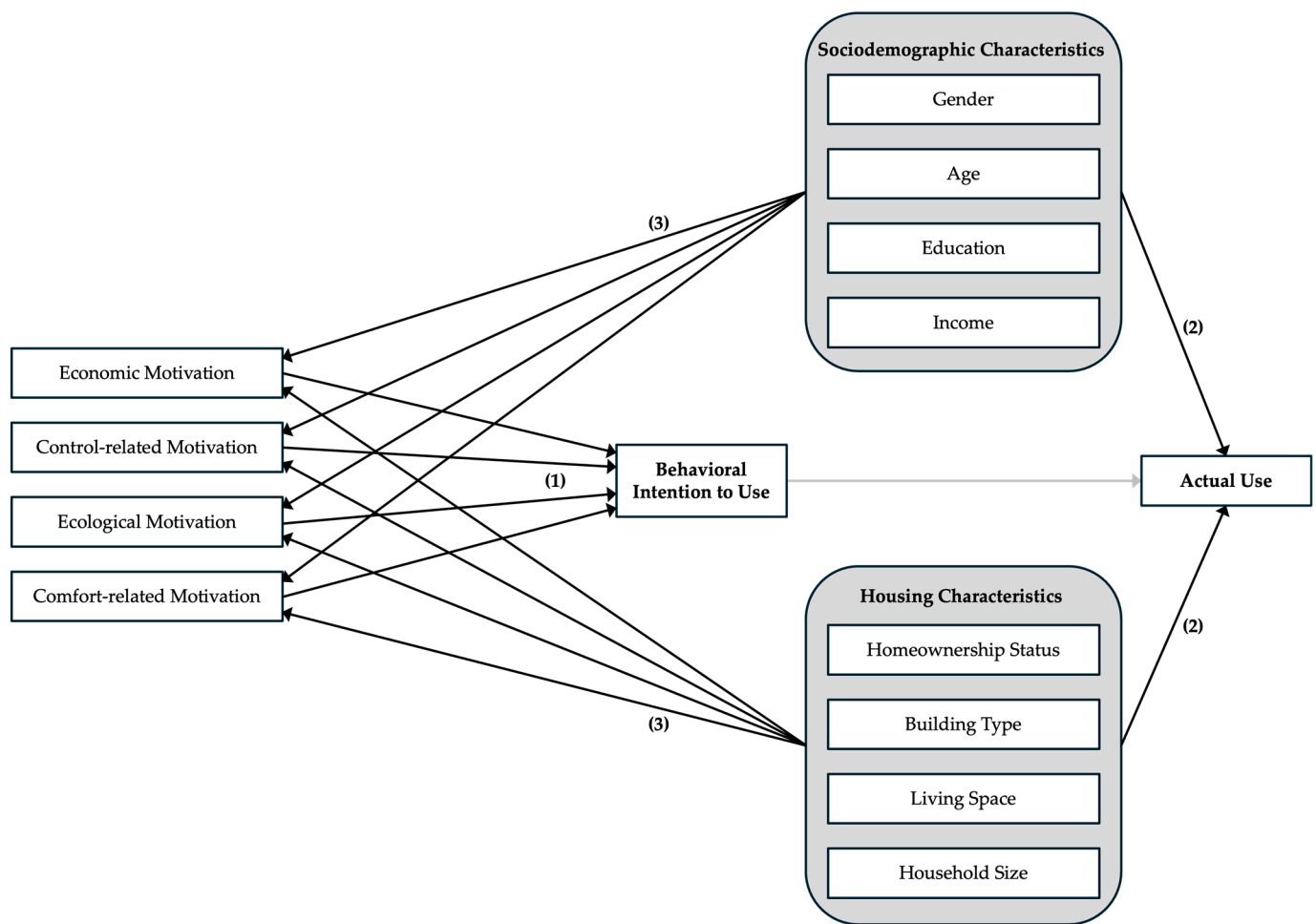


Figure 1. Conceptual model linking motivational, sociodemographic, and housing-related factors to ST use. The numbered arrows correspond to the key assumptions described in Section 2.3.

The conceptual framework is predicated on the following key assumptions:

- (1) Motivational factors (ecological, economic, control/autonomy, health/comfort) influence the behavioral intention to use STs.
- (2) Sociodemographic and housing-related factors exert direct effects on actual ST usage.
- (3) Sociodemographic and housing-related factors influence motivation, which indirectly influences behavioral intention and usage.

In summary, the proposed framework integrates motivational, sociodemographic, and housing-related determinants of technology acceptance. It extends existing models by incorporating user needs and housing-related dimensions, which have been underexplored in the context of the energy-related digitalization of residential environments.

Overall, the study contributes to theoretically extending UTAUT2 by integrating motivational determinants as external predictors and sociodemographic and housing-related characteristics as direct and indirect influencing factors. This integration results in a theoretically grounded and empirically testable framework for explaining ST adoption in German households within the energy transition context.

3. Materials and Methods

The study is based on a survey conducted within the regulatory sandbox for the energy transition SmartQuart, funded by the German Federal Ministry for Economic Affairs and Energy (BMWE). Since 2020, the project has pursued energy transition implementation in three structurally different German districts [41,42]. In accordance with the aforemen-

tioned process, the socioeconomic and technical capacities and challenges of the various stakeholders were identified and examined. The subsequent section outlines the methodological approach used to examine the acceptance of the energy transition process within the SmartQuart project.

3.1. Survey Design and Data Collection

Based on a systematic literature review, a structured and standardized online questionnaire was developed. The survey addressed several thematic areas related to the acceptance of the energy transition in the building sector. The present study focuses on the section of the questionnaire dealing with the use of STs in private residential settings, as well as on the supplementary sociodemographic and housing-related characteristics of the respondents.

Initially, participants were asked about their current utilization of STs to differentiate between users and non-users. The questionnaire was standardized across subgroups. Users responded to items measuring motivational factors for each technology, while non-users received questions regarding perceived barriers and adoption obstacles (the latter are not analyzed in this paper). Within each subgroup, all participants received identical questions in the same order and with consistent response options, ensuring the comparability and reproducibility of the data.

The motivational items for users were derived from the four central motivation dimensions identified in the literature review. The respondents evaluated the extent to which each factor influenced their use of STs on a four-point Likert scale (1 = “not at all,” 4 = “very strong”). Sociodemographic and housing characteristics (e.g., age, income, building type, and household size) were recorded categorically using established empirical social research survey standards to ensure comparability with other studies.

To ensure content and linguistic validity, the questionnaire was subjected to a pretest with experts and potential respondents. Feedback was used to optimize the questionnaire in terms of content, technical aspects, and language, and to ensure that the items were comprehensible.

The data were collected from September 2022 to December 2023 using the SoSci Survey platform (version 3.3.19) [43]. The online survey employed an open-access approach, making it available to all interested individuals in Germany, not only those directly involved in the SmartQuart project. This inclusive strategy was developed to capture a broad perspective on ST use and acceptance.

A multichannel recruitment strategy was implemented to maximize sample heterogeneity. Survey dissemination employed digital and analogue channels—targeted email lists, specialist forum postings, and promotion at in-person events. The latter included public citizen events and industry-specific trade fairs. The strategy targeted interested private individuals and professionally involved actors to capture a broad spectrum of potential users.

Participation in the online survey was voluntary and anonymous. All participants were informed in advance about the purpose of the study and the use of their data only for research purposes. No sensitive personal data was collected.

3.2. Data Analysis

To obtain differentiated insights into the factors influencing ST adoption, a three-stage analytical approach was applied using quantitative survey data. The data were evaluated using statistical methods, with all analyses performed in IBM SPSS Statistics (version 29).

First, the internal consistency of the four items measuring behavioral intention to use for each technology was tested using Cronbach's α . Values above 0.70 were interpreted as indicating satisfactory reliability [44]. Subsequently, mean value analyses of the mo-

tivational items were conducted to identify which factors most strongly influenced the behavioral intention to use each technology within the respective user groups. No statistical significance tests were performed, as the user groups of STs were not mutually exclusive and often overlapped, limiting the applicability of group-based inferential tests.

Second, the impact of sociodemographic and housing-related variables on the actual use of STs (1 = use, 0 = non-use) was examined using binary logistic regression. The objective of this study was to identify the factors that influence the probability of adoption. Predictor variables included sociodemographic characteristics (gender, age, educational attainment, and annual net household income) and housing characteristics (homeownership status, building type, living space, and household size).

Third, the influencing effects of sociodemographic and housing characteristics on users' motivational factors were examined using multiple linear regression analyses. For each of the four motivational dimensions—economic, control-related, ecological, and comfort-related—separate regression models were estimated for each ST under consideration. This methodological approach provides a differentiated analysis of how user and housing characteristics influence individual motivational dimensions toward the respective technologies.

The combined use of reliability testing, descriptive analysis, binary logistic regression, and multiple linear regression provides a multidimensional framework for analyzing behavioral aspects of ST adoption—without distorting the data structure or comparability between user and non-user groups.

The following section provides a detailed explanation and classification of the sample composition and background. The survey results on the current use of the STs examined are also included.

3.3. Background of the Sample

This research is based on survey responses from 284 private users in Germany collected between September 2022 and December 2023. Participant background analysis covered sociodemographic and housing characteristics, which were examined as influencing factors, as well as the current use of the various STs. Table 1 presents the descriptive statistics for the respondents' sociodemographic, housing characteristics, and ST adoption. Cases with missing responses (“no answer”) were excluded from the respective analyses, resulting in varying totals.

Table 1. Overview of the Participants' Background.

		Variable	<i>n</i>	Valid (%)
Sociodemographic characteristics	Gender	Male	205	74.5%
		Female	70	25.5%
		Total	275	100.0%
	Age	<34 years	83	29.5%
		35–49 years	68	24.2%
		50–65 years	100	35.6%
		>65 years	30	10.7%
		Total	281	100.0%
	Highest Educational Qualification	Secondary school certificate	17	6.0%
		Vocational training	23	8.2%
		University entrance qualification	50	17.8%
		University degree	191	68.0%
		Total	281	100.0%
	Annual Household Income	<25,000 euros	41	16.4%
		25,000–50,000 euros	60	24.0%

Table 1. Cont.

		Variable	<i>n</i>	Valid (%)
Sociodemographic characteristics	Annual Household Income	50,000–75,000 euros	72	28.8%
		75,000–100,000 euros	42	16.8%
		>100,000 euros	35	14.0%
		Total	250	100.0%
Housing characteristics	Homeownership Status	Homeowner	108	52.4%
		Tenant	98	47.6%
		Total	206	100.0%
	Building Type	Detached single-family home	45	21.7%
		Row house (townhouse)	26	12.6%
		Semi-detached/two-family house	22	10.6%
		Apartment in multi-family building	114	55.1%
		Total	207	100.0%
	Living Space	<50 m ²	30	15.0%
		50–100 m ²	78	39.0%
		101–150 m ²	59	29.5%
		151–200 m ²	24	12.0%
		>200 m ²	9	4.5%
		Total	200	100.0%
Adoption of STs	Energy Monitoring	1 person	58	21.1%
		2 persons	113	41.1%
		3–5 persons	97	35.3%
	Household Size	>5 persons	7	2.5%
		Total	275	100.0%
	IAQM	Yes	128	45.6%
		No	153	54.4%
		Total	281	100.0%
	Smart Home	Yes	71	25.0%
		No	213	75.0%
		Total	284	100.0%
	HEMS	Yes	82	28.9%
		No	202	71.1%
		Total	284	100.0%

Sociodemographic data indicated a predominance of male participants, with 74.5% ($n = 205$) male and 25.5% ($n = 70$) female. The sample's age distribution was: <34 years, 29.5% ($n = 83$); 35–49 years, 24.2% ($n = 68$); 50–65 years, 35.6% ($n = 100$); and >65 years, 10.7% ($n = 30$). Educational attainment was predominantly academic: 68.0% ($n = 191$) held a university degree, 17.8% ($n = 50$) a university entrance qualification, 8.2% ($n = 23$) vocational training, and 6.0% ($n = 17$) a secondary school certificate. Income distribution showed a considerable disparity, with approximately 16.4% ($n = 41$) of respondents indicating an annual net household income of less than 25,000 euros and 14.0% ($n = 35$) reporting an income exceeding 100,000 euros. The largest group was the income bracket between 50,000 and 75,000 euros (28.8%, $n = 72$), followed by the bracket between 25,000 and 50,000 euros (24.0%, $n = 60$) and 75,000–100,000 euros (16.8%, $n = 42$).

The housing structure data showed that residential property ownership was evenly split: homeowners 52.4% ($n = 108$), tenants 47.6% ($n = 98$). The building type currently

occupied was dominated by apartments in multi-family houses (55.1%, $n = 114$), followed by single-family houses (21.7%, $n = 45$), terraced houses (12.6%, $n = 26$), and semi-detached/two-family houses (10.6%, $n = 22$). Around 15.0% ($n = 30$) of the respondents lived in spaces of less than 50 m². The largest proportion (39.0%, $n = 78$) had 50–100 m² of living space, and a further 29.5% ($n = 59$) had 101–150 m². Only 12.0% ($n = 26$) of respondents lived in spaces measuring 151–200 m², while 4.5% ($n = 9$) had spaces exceeding 200 m². Household size also varied: 21.1% ($n = 58$) of the respondents lived alone, 41.1% ($n = 113$) lived in households of two people, and 35.3% ($n = 97$) lived in households of three to five people. Households with more than five members were underrepresented, accounting for just 2.5% ($n = 7$) of the sample.

Examining the current use of various STs revealed the highest acceptance and usage for energy monitoring, with 45.6% ($n = 128$) of respondents using this technology. IAQM systems were used by 25.0% ($n = 71$), smart home applications by 28.9% ($n = 81$), and HEMSs by 37.9% ($n = 106$).

The sample is not representative of the general population due to the overrepresentation of male participants and individuals with higher education and income levels. Instead, it reflects a user group characterized by these attributes. These structural conditions should be considered when generalizing the results.

4. Results

4.1. Influence of Motivational Factors on Behavioral Intention

To examine the behavioral intention to use the investigated STs, motivational factors were analyzed based on four theoretically and empirically derived motivational dimensions: economic, control-related, ecological, and comfort-related motivation. These dimensions reflect the most frequently reported reasons for ST adoption in the extant literature and were operationalized using four corresponding items:

- (1) Reducing energy costs (economic motivation),
- (2) Controlling energy consumption (control-related motivation),
- (3) Saving energy (ecological motivation), and
- (4) Enhancing residential comfort (comfort-related motivation).

As all four items were designed to capture the common construct of behavioral intention to use, the internal consistency of the scale was initially assessed using Cronbach's α for each technology. The obtained α values ranged from 0.72 to 0.88, indicating good internal consistency [44] (see Table 2). This outcome validates the notion that the four items collectively constitute a coherent construct of behavioral intention to use.

Table 2. Reliability analysis of behavioral intention to use constructs for STs.

Smart Technology	Cronbach's α
Energy monitoring	0.878
IAQM	0.785
Smart Home	0.815
HEMS	0.722

Subsequently, mean comparisons of the four motivational dimensions were conducted to determine which motives were most strongly expressed for each technology. The responses were measured on a four-point Likert scale (1 = “not at all” to 4 = “very strong”). The mean values were interpreted as follows: mean values < 1.50 indicated “not at all”,

1.50–2.49 “little”, 2.50–3.49 “strong”, and >3.50 “very strong” influence. Table 3 shows a comparison of the mean values for the various STs.

Table 3. Mean values of motivational factors across different STs.

Motivational Factors	Energy Monitoring			IAQM			Smart Home			HEMS		
	Mean	<i>n</i>	SD	Mean	<i>n</i>	SD	Mean	<i>n</i>	SD	Mean	<i>n</i>	SD
Reducing energy costs	3.10	115	1.046	2.99	69	0.833	2.62	78	1.084	3.46	103	0.751
Controlling energy consumption	3.23	120	0.991	2.88	69	0.932	2.51	79	1.073	3.29	103	0.800
Saving energy	3.06	117	1.028	2.94	70	0.931	2.65	79	1.075	3.48	103	0.669
Enhancing residential comfort	2.40	114	1.070	3.38	69	0.730	3.47	81	0.672	3.02	102	0.944

The results of the data analysis indicate that economic motivation (“reducing energy costs”) was rated as a strong influence factor for the use of energy monitoring (mean = 3.10; SD = 1.05; *n* = 115), IAQM (mean = 2.99, SD = 0.83, *n* = 69), and HEMS (mean = 3.46, SD = 0.75, *n* = 103). For smart home applications, the evaluation was more ambivalent (mean = 2.62, SD = 1.08, *n* = 78), indicating only the moderate relevance of economic considerations.

A similar pattern emerged for the control-related motivation (“controlling energy consumption”). This factor was perceived as a strong motivator for energy monitoring (mean = 3.23, SD = 0.99, *n* = 120), IAQM (mean = 2.88, SD = 0.93, *n* = 69), and HEMS (mean = 3.29, SD = 0.80, *n* = 103). In contrast, smart home technologies again showed mixed evaluations (mean = 2.51, SD = 1.07, *n* = 79).

Ecological motivation (“saving energy”) was also identified as a strong influence factor for energy monitoring (mean = 3.06, SD = 1.03, *n* = 117), IAQM (mean = 2.94, SD = 0.93, *n* = 70), and HEMS (mean = 3.48, SD = 0.67, *n* = 103). The evaluation for smart homes was again ambivalent, with a slight tendency toward a strong influence (mean = 2.65, SD = 1.08, *n* = 79).

Finally, the comfort-related motivation (“enhancing residential comfort”) was rated as a strong driver for IAQM (mean = 3.38, SD = 0.73, *n* = 69), smart home (mean = 3.47, SD = 0.67, *n* = 81), and HEMS (mean = 3.48, SD = 0.67, *n* = 103). In contrast, energy monitoring was the only technology for which comfort was evaluated as a minor motivational factor (mean = 2.40, SD = 1.07, *n* = 114).

Overall, the findings suggest that economic, control-related, and ecological motives play a particularly important role in the adoption of energy- and management-oriented technologies, while comfort-related motives are more dominant in applications with a direct impact on living quality, such as smart home and IAQM systems.

4.2. Influence of Sociodemographic and Housing Factors on Usage

In line with the assumption that sociodemographic and housing-related characteristics influence ST use and adoption, binary logistic regression analyses were conducted, with separate models estimated for each application. The dependent variable was dichotomously coded to indicate whether the system was used in the household (1 = use, 0 = non-use). All independent variables were included in the model as categorical predictors, including sociodemographic factors such as gender (male and female), age group, highest education level, annual household income, and housing-related factors such as homeownership status (tenant and owner), building type, living space, and household size.

Prior to conducting the binary logistic regression analysis, multicollinearity among the independent variables was examined. As SPSS does not provide direct variance inflation factor (VIF) statistics for logistic regression models, an auxiliary linear regression was performed using the same set of predictors to obtain tolerance and VIF values. In accordance with the widely accepted thresholds proposed by Field et al. [45], tolerance values below 0.10 and VIF values above 10 were interpreted as potential indicators of multicollinearity. In the present analysis, all tolerance and VIF values were within acceptable limits, suggesting that no substantial multicollinearity issues were present. Table 4 presents the multicollinearity diagnostic results.

Table 4. Tolerance and VIF values for predictors included in the binary logistic regression models.

	Predictor	Tolerance	VIF
Gender	Gender (1 = female)	0.739	1.353
Age	<34 years (Ref)	-	-
	35–49 years	0.506	1.974
	50–65 years	0.390	2.562
	>65 years	0.568	1.759
Education	Secondary school certificate (Ref)	-	-
	Vocational training	0.503	1.987
	University entrance qualification	0.381	2.623
	University degree	0.333	3.001
Income	<25,000 euros (Ref)	-	-
	25,000–50,000 euros	0.374	2.677
	50,000–75,000 euros	0.376	2.663
	75,000–100,000 euros	0.395	2.531
	>100,000 euros	0.421	2.376
Homeownership status	Homeownership status (1 = tenant)	0.249	4.008
Building Type	Detached single-family home (Ref)	-	-
	Row house (townhouse)	0.685	1.460
	Semi-detached / two-family house	0.628	1.594
	Apartment in multi-family building	0.279	3.583
Living space	<50 m ²	-	-
	50–100 m ²	0.225	4.453
	101–150 m ²	0.134	7.464
	151–200 m ²	0.240	4.172
	>200 m ²	0.310	3.222
Household size	1 person (Ref)	-	-
	2 persons	0.340	2.943
	3–5 persons	0.353	2.834
	>5 persons	0.720	1.388

4.2.1. Energy Monitoring

The regression model for energy monitoring use was statistically significant ($\chi^2(22) = 41.024$, $p = 0.008$), with an acceptable level of variance explained by Nagelkerke's $R^2 = 0.298$, in accordance with the recommendations of Backhaus et al. [46]. The Hosmer–Lemeshow test was used to check the goodness of fit, showing a high level of fit ($\chi^2(8) = 7.852$, $p = 0.448$). The overall percentage of correct classifications was 73.6%, with a sensitivity of 83.5% and a specificity of 61.1%. Table 5 presents the binary logistic regression results for energy monitoring use, revealing significant effects for several predictors. Compared to the lowest educational attainment reference category (secondary school certificate), the probability of

use decreased with higher educational attainment. Participants with a university degree were significantly less likely to use an energy monitoring system ($B = -1.838$, $SE = 0.908$, $p = 0.043$). Building type was also a significant predictor. Those living in a row house (townhouse) were significantly less likely to adopt an energy monitoring system than those in a single-family house (reference category) ($B = -1.493$, $SE = 0.709$, $p = 0.035$). Gender, age, income, homeownership status, living space, and household size showed no significant effects. However, certain distinctions were observed in favor of larger residential units, a factor that could be further explored in subsequent analyses.

Table 5. Results of Binary Logistic Regression for Energy Monitoring Use.

	Predictor	B	SE	Wald	df	Sig.	Exp (B)
Sociodemographic Factors							
Gender	Gender (1 = female)	−0.007	0.451	0.000	1	0.988	0.993
Age	<34 years (Ref)			0.655	3	0.884	
	35–49 years	−0.016	0.627	0.001	1	0.979	0.984
	50–65 years	0.271	0.559	0.236	1	0.627	1.312
	>65 years	0.470	0.719	0.427	1	0.513	1.600
Education	Secondary school certificate (Ref)			4.186	3	0.242	
	Vocational training	−1.789	1.061	2.841	1	0.092	0.167
	University entrance qualification	−1.856	0.978	3.599	1	0.058	0.156
	University degree	−1.838	0.908	4.098	1	0.043 *	0.159
Income	<25,000 euros (Ref)			6.019	4	0.198	
	25,000–50,000 euros	−0.402	0.621	0.418	1	0.518	0.669
	50,000–75,000 euros	−0.248	0.599	0.172	1	0.678	0.780
	75,000–100,000 euros	−0.080	0.706	0.013	1	0.910	0.923
	>100,000 euros	1.829	1.000	3.346	1	0.067	6.230
Housing Factors							
Homeowner-ship status	Homeownership status (1 = tenant)	−0.238	0.685	0.120	1	0.729	0.788
Building Type	Detached single-family home (Ref)			4.810	3	0.186	
	Row house (townhouse)	−1.493	0.709	4.434	1	0.035 *	0.225
	Semi-detached /two-family house	−0.607	0.686	0.783	1	0.376	0.545
	Apartment in multi-family building	−1.040	0.703	2.188	1	0.139	0.353
Living space	<50 m ²			3.214	4	0.523	
	50–100 m ²	0.099	0.675	0.021	1	0.884	1.104
	101–150 m ²	1.022	0.881	1.345	1	0.246	2.778
	151–200 m ²	0.247	1.014	0.059	1	0.807	1.281
	>200 m ²	0.774	1.312	0.348	1	0.555	2.168
Household size	1 person (Ref)			0.972	3	0.808	
	2 persons	−0.196	0.563	0.121	1	0.728	0.822
	3–5 persons	−0.578	0.651	0.788	1	0.375	0.561
	>5 persons	−0.046	1.421	0.001	1	0.974	0.955
	Constant	2.167	1.333	2.641	1	0.104	8.732

Statistical significance was defined as $p < 0.05$ (*).

4.2.2. Indoor Air Quality Monitoring (IAQM)

The binary logistic regression model for predicting IAQM utilization was also statistically significant ($\chi^2(22) = 56.040$, $p < 0.001$). The explained variance, Nagelkerke's R^2 , was found to be 0.438, which, according to Backhaus et al., can be considered good. The model fit was tested using the Hosmer–Lemeshow test ($\chi^2(8) = 5.904$, $p = 0.658$). The model's overall classification accuracy was 82.9%, with a sensitivity of 92.9% and a specificity of

50.0%. Table 6 reports the binary logistic regression results for the predictors of IAQM usage. Significant effects were observed in IAQM use across different age and income categories. IAQM systems were used less frequently by people aged 50–65 than by people younger than 34 years (reference category) ($B = -1.678$, $SE = 0.771$, $p = 0.030$). This trend was also evident in the other age groups. However, this could not be proven to be significant. Similarly, higher household incomes ($>150,000$ euros) were significantly more positively associated with use than the lowest income class of less than 25,000 euros (reference category) ($B = 3.553$, $SE = 1.135$, $p = 0.002$). Additionally, living space was a significant predictor: households with over 200 m² of living space were significantly more likely to use the technology than those with under 50 m² (reference category) ($B = 3.975$, $SE = 1.798$, $p = 0.027$). However, no significant influence was found for gender, educational attainment, homeownership status, building type, or household size.

Table 6. Results of Binary Logistic Regression for IAQM Use.

Predictor		B	SE	Wald	df	Sig.	Exp (B)
Sociodemographic Factors							
Gender	Gender (1 = female)	−1.194	0.709	2.834	1	0.092	0.303
Age	<34 years (Ref)			4.742	3	0.192	
	35–49 years	−1.090	0.813	1.799	1	0.180	0.336
	50–65 years	−1.678	0.771	4.731	1	0.030 *	0.187
	>65 years	−22.263	8023.436	0.000	1	0.998	0.000
Education	Secondary school certificate (Ref)			0.975	3	0.807	
	Vocational training	−0.036	1.380	0.001	1	0.979	0.965
	University entrance qualification	0.759	1.156	0.431	1	0.511	2.136
	University degree	0.697	1.107	0.396	1	0.529	2.008
Income	<25,000 euros (Ref)			14.161	4	0.007 *	
	25,000–50,000 euros	0.139	0.914	0.023	1	0.879	1.149
	50,000–75,000 euros	1.379	0.889	2.409	1	0.121	3.972
	75,000–100,000 euros	1.926	0.996	3.740	1	0.053	6.859
	>100,000 euros	3.553	1.135	9.802	1	0.002 *	34.917
Housing Factors							
Homeowner-ship status	Homeownership status (1 = tenant)	1.477	0.995	2.206	1	0.138	4.381
Building Type	Detached single-family home (Ref)			3.781	3	0.286	
	Row house (townhouse)	0.046	0.837	0.003	1	0.957	1.047
	Semi-detached/two-family house	−1.306	0.943	1.916	1	0.166	0.271
	Apartment in multi-family building	−1.520	0.955	2.533	1	0.111	0.219
Living space	<50 m ²			8.027	4	0.091	
	50–100 m ²	0.488	0.927	0.277	1	0.599	1.629
	101–150 m ²	2.197	1.179	3.470	1	0.063	8.997
	151–200 m ²	1.313	1.474	0.793	1	0.373	3.716
	>200 m ²	3.975	1.798	4.887	1	0.027 *	53.248
Household size	1 person (Ref)			2.050	3	0.562	
	2 persons	−0.653	0.747	0.764	1	0.382	0.521
	3–5 persons	−0.687	0.805	0.728	1	0.394	0.503
	>5 persons	1.101	1.621	0.461	1	0.497	3.008
Constant		−2.324	1.653	1.976	1	0.160	0.098

Statistical significance was defined as $p < 0.05$ (*).

4.2.3. Smart Home

The regression model for predicting the use of smart home applications was statistically significant ($\chi^2(22) = 52.254, p < 0.001$) and demonstrated good explanatory power (Nagelkerke's $R^2 = 0.402$), aligning with the recommendations of Backhaus et al. The model's fit was evaluated using the Hosmer–Lemeshow test, revealing satisfactory results ($\chi^2(8) = 5.198, p = 0.736$). The model had a predictive accuracy of 79.3%, with a sensitivity of 92.6% and a specificity of 40.5%. Table 7 summarizes the binary logistic regression results for smart home application usage. Annual household income was also a significant predictor of smart home system use. Compared to the reference category of less than 25,000 euros, both income classes of 50,000–75,000 euros ($B = 2.440, SE = 1.205, p = 0.043$) and >100,000 euros ($B = 3.022, SE = 1.333, p = 0.023$) had a significantly positive effect on usage. Another influencing factor was ownership status: homeowners used smart home systems significantly less often than tenants ($B = -1.644, SE = 0.835, p = 0.049$). The predictors age and education were not significantly associated with usage; however, effects can be seen in both categories that warrant further investigation. The same applies to building type, living space, and household size.

Table 7. Results of Binary Logistic Regression for Smart Home Use.

Predictor		B	SE	Wald	df	Sig.	Exp (B)
Sociodemographic Factors							
Gender	Gender (1 = female)	−0.491	0.624	0.619	1	0.431	0.612
Age	<34 years (Ref)			3.411	3	0.332	
	35–49 years	−0.334	0.758	0.194	1	0.660	0.716
	50–65 years	−0.855	0.730	1.371	1	0.242	0.425
	>65 years	−1.841	1.054	3.052	1	0.081	0.159
Education	Secondary school certificate (Ref)			2.740	3	0.433	
	Vocational training	−1.290	1.099	1.378	1	0.240	0.275
	University entrance qualification	−1.463	0.970	2.277	1	0.131	0.231
	University degree	−1.394	0.862	2.613	1	0.106	0.248
Income	<25,000 euros (Ref)			11.058	4	0.026 *	
	25,000–50,000 euros	0.805	1.239	0.422	1	0.516	2.237
	50,000–75,000 euros	2.440	1.205	4.098	1	0.043 *	11.474
	75,000–100,000 euros	2.257	1.271	3.155	1	0.076	9.559
	>100,000 euros	3.022	1.333	5.139	1	0.023 *	20.527
Housing Factors							
Homeowner-ship status	Homeownership status (1 = tenant)	−1.644	0.835	3.873	1	0.049 *	0.193
Building Type	Detached single-family home (Ref)			3.341	3	0.342	
	Row house (townhouse)	−0.115	0.692	0.028	1	0.868	0.892
	Semi-detached/two-family house	−1.339	0.780	2.942	1	0.086	0.262
	Apartment in multi-family building	−0.753	0.757	0.987	1	0.320	0.471
Living space	<50 m ²			3.852	4	0.426	
	50–100 m ²	0.962	1.249	0.594	1	0.441	2.618
	101–150 m ²	0.750	1.365	0.301	1	0.583	2.116
	151–200 m ²	0.103	1.508	0.005	1	0.946	1.108
	>200 m ²	2.262	1.778	1.619	1	0.203	9.603
Household size	1 person (Ref)			0.824	3	0.844	
	2 persons	−0.421	0.791	0.283	1	0.595	0.657
	3–5 persons	−0.681	0.862	0.625	1	0.429	0.506

Table 7. Cont.

	Predictor	B	SE	Wald	df	Sig.	Exp (B)
Household size	>5 persons	−1.106	1.552	0.508	1	0.476	0.331
	Constant	−0.135	1.894	0.005	1	0.943	0.874

Statistical significance was defined as $p < 0.05$ (*).

4.2.4. Home Energy Management System (HEMS)

The logistic regression model used to explain the use of HEMS was statistically significant ($\chi^2(22) = 59.750$, $p < 0.001$). The explained variance was Nagelkerke's $R^2 = 0.419$. The model's goodness of fit was assessed using the Hosmer–Lemeshow test ($\chi^2(8) = 9.505$, $p = 0.301$). The proportion of cases correctly classified was 73.8%, with a sensitivity of 83.8% and a specificity of 55.9%. Table 8 presents the logistic regression results. The findings for HEMS were similar to those for the use of energy monitoring systems. Once again, people with a university degree were significantly less likely to use such systems than participants with a secondary school certificate (reference category) ($B = -1.694$, $SE = 0.816$, $p = 0.038$). Building type also played a role: residents of semi-detached/two-family houses ($B = -1.804$, $SE = 0.716$, $p = 0.012$) and apartments in multi-family houses ($B = -1.714$, $SE = 0.729$, $p = 0.019$) were significantly less likely to use such systems than residents of detached houses (reference category). Living space showed a positive but statistically insignificant trend. Age, gender, household income, ownership status, and household size had no significant influence in this model.

Table 8. Results of Binary Logistic Regression for Use of HEMS.

	Predictor	B	SE	Wald	df	Sig.	Exp (B)
Sociodemographic Factors							
Gender	Gender (1 = female)	0.626	0.535	1.367	1	0.242	1.870
Age	<34 years (Ref)			2.857	3	0.414	
	35–49 years	−0.425	0.729	0.340	1	0.560	0.654
	50–65 years	−0.641	0.669	0.919	1	0.338	0.527
	>65 years	0.545	0.822	0.441	1	0.507	1.725
Education	Secondary school certificate (Ref)			6.559	3	0.087	
	Vocational training	−0.466	0.999	0.217	1	0.641	0.628
	University entrance qualification	−1.814	0.928	3.826	1	0.050	0.163
	University degree	−1.694	0.816	4.313	1	0.038 *	0.184
Income	<25,000 euros (Ref)			4.246	4	0.374	
	25,000–50,000 euros	−1.019	0.763	1.782	1	0.182	0.361
	50,000–75,000 euros	−0.140	0.740	0.036	1	0.850	0.869
	75,000–100,000 euros	−0.244	0.819	0.089	1	0.765	0.783
	>100,000 euros	0.458	0.983	0.217	1	0.641	1.581
Housing Factors							
Homeowner-ship status	Homeownership status (1 = tenant)	−1.331	0.745	3.192	1	0.074	0.264
Building Type	Detached single-family home (Ref)			7.983	3	0.046 *	
	Row house (townhouse)	−1.117	0.691	2.611	1	0.106	0.327
	Semi-detached/two-family house	−1.804	0.716	6.341	1	0.012 *	0.165
	Apartment in multi-family building	−1.714	0.729	5.520	1	0.019 *	0.180
Living space	<50 m ²			5.580	4	0.233	
	50–100 m ²	1.990	1.171	2.888	1	0.089	7.313

Table 8. *Cont.*

	Predictor	B	SE	Wald	df	Sig.	Exp (B)
Living space	101–150 m ²	2.145	1.325	2.621	1	0.105	8.542
	151–200 m ²	1.112	1.417	0.616	1	0.433	3.041
	>200 m ²	2.687	1.813	2.197	1	0.138	14.684
Household size	1 person (Ref)			2.253	3	0.522	
	2 persons	−0.497	0.686	0.526	1	0.468	0.608
	3–5 persons	0.098	0.772	0.016	1	0.899	1.102
	>5 persons	−1.285	1.517	0.718	1	0.397	0.277
	Constant	1.527	1.653	0.853	1	0.356	4.606

Statistical significance was defined as $p < 0.05$ (*).

4.3. Influence of Sociodemographic and Housing-Related Factors on Motivational Dimensions

After examining the relative strength of individual motivational factors and the influence of sociodemographic and housing characteristics on the use of STs, the analysis further explored whether these characteristics affect the level of motivation associated with their adoption. For this purpose, separate multiple linear regression analyses were conducted for each investigated ST. For each technology, a distinct model was estimated for every motivational dimension, namely economic, control-related, ecological, and comfort-related motivation.

The aim of this analysis was to determine whether user characteristics such as age, gender, household income, educational level, or housing characteristics such as homeownership status, building type, living space, or household size influence the strength of these motivational factors. However, the results indicated that none of the regression models reached statistical significance. Consequently, no systematic influence of sociodemographic or housing-related factors on the motivational dimensions could be identified across the technologies investigated.

5. Discussion

5.1. Motives for Adoption and Acceptance

The analysis of motivational factors influencing behavioral intention to use based on the mean value comparison reveals that, although the strength of these effects varies across technologies, certain overlaps can be identified. In the context of energy monitoring systems, control-related motives exert the strongest influence, while economic and ecological dimensions also show substantial effects. A similar pattern emerges for HEMS. Here, the most prominent motivations are energy conservation (ecological) and cost reduction (economic), followed by the control of energy consumption. Additionally, enhancing residential comfort is perceived as a significant driver.

Although the dominant motives differ slightly between technologies, the findings indicate that both energy monitoring and HEMS are primarily adopted for economic and usage-related reasons, such as controlling energy consumption and reducing energy costs. These results align with previous studies emphasizing the importance of energy and cost transparency as key motivational drivers [17,18,29,30]. While energy savings are crucial, their significance appears to be closely linked to financial benefits, suggesting that purely ecological considerations play a subordinate role in adoption decisions.

In the case of IAQM, the primary motivation is comfort-related, particularly improving residential comfort through enhanced air quality and climate control. This finding supports existing research highlighting comfort enhancement as a central motivation [31]. Nevertheless, economic and ecological factors also exert notable, albeit weaker, influences.

The control of energy consumption is still relevant, though less dominant than in energy-oriented systems such as energy monitoring and HEMS.

For smart home applications, comfort-related motives also prevail. The other motivational dimensions—economic, ecological, and control-related—are evaluated more ambiguously and cannot be identified as strong predictors. This ambivalent assessment indicates that comfort and lifestyle considerations are more influential than energy efficiency-related aspects [33].

Overall, two overarching trends can be identified:

- (1) Economic and ecological motivations are closely interrelated and often occur simultaneously, implying that energy savings are primarily interpreted through their economic benefits.
- (2) The comparison of mean values demonstrates that control over energy consumption, primarily for economic reasons, and the enhancement of residential comfort are central drivers of the behavioral intention to use STs. Consequently, the adoption of such systems is motivated less by purely ecological reasoning and more by pragmatic utility aspects such as cost efficiency, control, and comfort.

5.2. Influence of Sociodemographic and Housing Characteristics on Usage

The binary logistic regression analysis results complement the motivation-oriented perspective by showing that sociodemographic and housing factors influence the actual usage of STs. These analyses clearly demonstrate that usage frequencies are significantly influenced by structural characteristics.

When considering sociodemographic variables, age was found to have a significant influence on the use of IAQM systems. Older respondents reported a lower level of use compared to younger ones. This finding contrasts with previous assumptions in the literature suggesting that IAQM technologies are often adopted by older individuals primarily for health-related reasons [31]. A potential explanation for this discrepancy may be found in the focus of the present study, which emphasizes the comfort-related dimension of IAQM rather than its health-related benefits. Consequently, younger users—who tend to associate STs with convenience, automation, and lifestyle enhancement—may perceive greater utility in such systems compared to older users.

Unexpectedly, energy monitoring and HEMS are negatively correlated with academic qualifications (university degree), challenging the assumption that education drives technology acceptance [32]. One possible explanation is that individuals with higher educational attainment may adopt a more critical or selective attitude toward new technologies, reflecting greater expectations regarding data security or verifiable efficiency gains. Moreover, highly educated respondents might already rely on alternative or more specialized means of energy management, or they may perceive limited personal benefit from additional technological support. This suggests that education does not necessarily increase acceptance but rather that acceptance is influenced by cognitive evaluation.

However, income has been demonstrated to exhibit a positive correlation with system utilization, suggesting that individuals with higher income levels are more inclined to adopt IAQM. This finding aligns with prior research linking higher income to a technology-oriented, health-conscious, and affluent lifestyle [31,32], which is also reflected in the present study. Income was also identified as a significant predictor of the adoption of smart home systems: individuals with medium to high income levels tend to use these technologies more frequently. This suggests that smart home systems may be associated with a lifestyle-oriented pattern of technology adoption, where convenience and social signaling play a role beyond functional utility.

Furthermore, the findings indicate that housing characteristics have a direct influence on ST adoption. The impact of homeownership status is significant only in the context of smart home systems. A notable observation is that tenants exhibit a higher frequency of utilization of these systems than homeowners. This phenomenon suggests that certain smart home components are perceived as easily retrofittable, thereby negating the need for ownership to justify investment or installation.

Building type has been identified as a relevant factor in the context of energy monitoring and HEMS. The analysis reveals that residents of single-family houses use these systems significantly more often than those living in multi-family, semi-detached/two-family, or row houses. This pattern may be indicative of infrastructural or technical prerequisites that are more easily implemented in single-family homes than in more complex residential settings.

Living space also shows a positive, though not always statistically significant, association with energy-oriented technology use. However, a significant effect of living space was identified for IAQM: households with larger living areas are more likely to adopt such systems than those with smaller ones. This finding suggests that, at a certain point in living size, the monitoring of indoor comfort is perceived as more necessary or practical. This is because maintaining consistent comfort conditions becomes increasingly challenging without technological support.

5.3. Influence of Sociodemographic and Housing Characteristics on Motivational Dimension

This study could not confirm the assumption that sociodemographic and housing-related characteristics influence the motivational dimensions of ST adoption. Possible explanations include the limited variance observed within the investigated motivational dimensions and the homogeneity of the sample, which lacks representativeness, particularly regarding gender, income, and education. Such sample characteristics may have attenuated potential interaction effects.

Moreover, previous studies within the UTAUT2 framework suggest that the moderating effects of sociodemographic variables are context-dependent and may not be observable across all application domains [27]. Accordingly, the present findings suggest that the direct influence of sociodemographic and housing-related factors on usage intention and behavior is more relevant than their indirect effects on motivational dimensions.

5.4. Identification of Adoption Patterns of STs

When considered collectively, the identified motivational, sociodemographic, and housing-related factors together, distinct adoption patterns and overarching effects become evident across the examined STs. The findings suggest that motivational drivers and structural conditions exert influence on user behavior, though in technology-specific ways.

In the context of energy-oriented systems, such as energy monitoring and HEMS, the primary motivations for usage are identified as being control-related, economic, and ecological. In such cases, educational level and building type have emerged as significant structural determinants. A notable finding is that individuals with higher educational attainment exhibit a lower frequency of system adoption. This observation may indicate that more highly educated users evaluate the potential benefits of such technologies more critically or may already rely on alternative strategies for energy conservation and consumption management. Lower adoption rates among this group may also reflect heightened sensitivity to issues of data privacy or technology acceptance. Conversely, residents of single-family homes are significantly more likely to use energy-oriented systems, suggesting that infrastructural and technical preconditions are generally more favorable in this type of housing compared to multi-family or terraced dwellings. The identified effects of

energy-oriented technologies (energy monitoring and HEMS) on adoption are summarized in Figure 2, highlighting consistent influences.

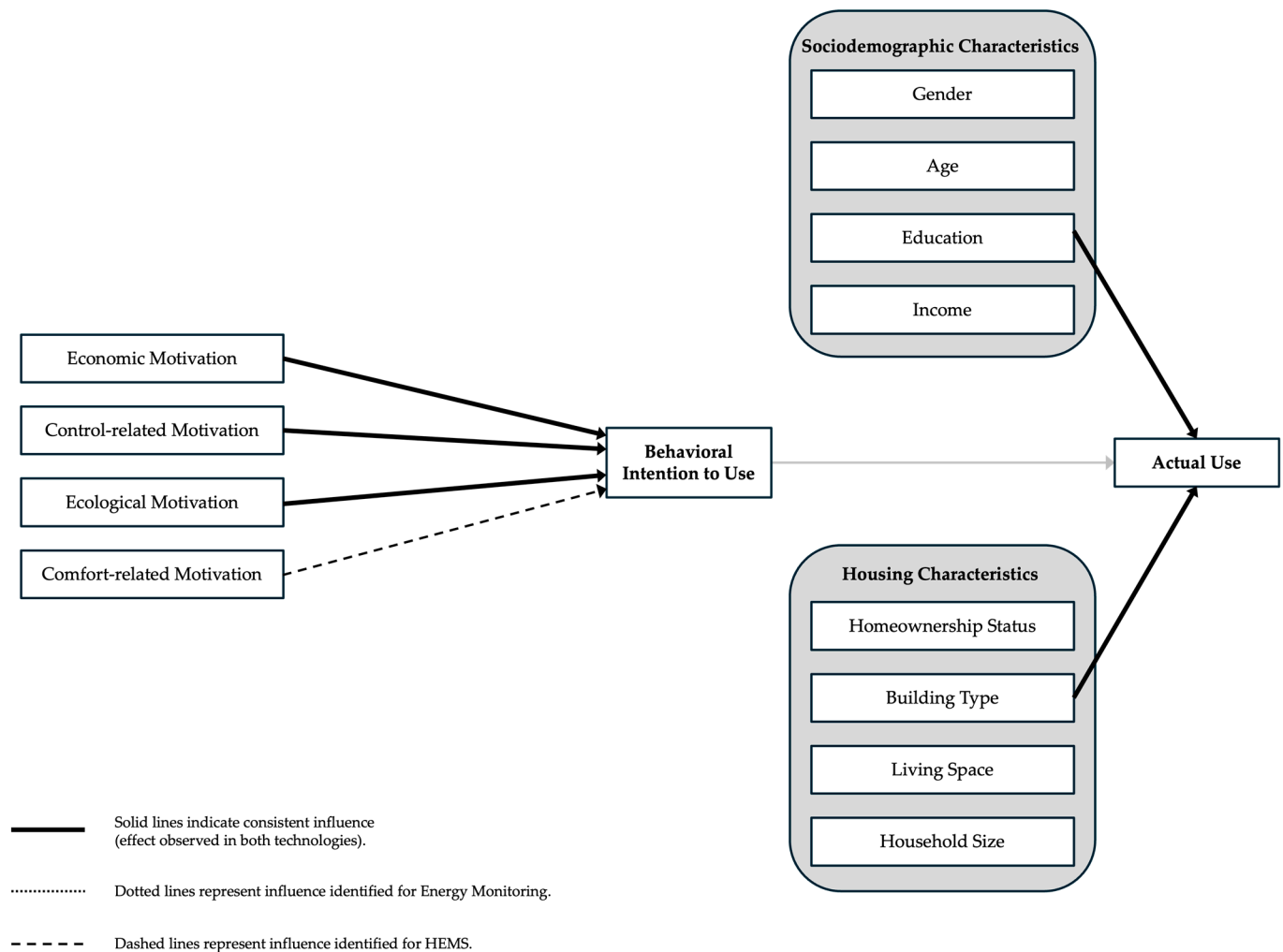


Figure 2. Impact diagram illustrating the identified effects of energy-oriented technologies (energy monitoring and HEMS), including consistent influences on adoption.

In contrast, technologies primarily motivated by comfort-related factors, such as IAQM and smart home, show a significant influence of household income. This finding suggests that comfort-oriented technologies are still predominantly perceived as lifestyle products, with greater accessibility to higher-income households.

The adoption of IAQM systems, which are closely associated with perceived residential quality and comfort, is further influenced by age and living space. Younger individuals and households with larger living areas are more likely to use IAQM systems. This finding suggests that such technologies serve as both a symbol of a technology-oriented, modern lifestyle and a practical method for managing the complexity of comfort regulation in larger living spaces. In more spacious homes, air quality and comfort monitoring appear to be perceived as functional components of technologically enhanced living environments. In contrast, younger users may associate these technologies more strongly with innovation and smart-living ideals. Figure 3 summarizes the identified effects of comfort-oriented technologies (IAQM and smart home) on adoption, highlighting consistent influences.

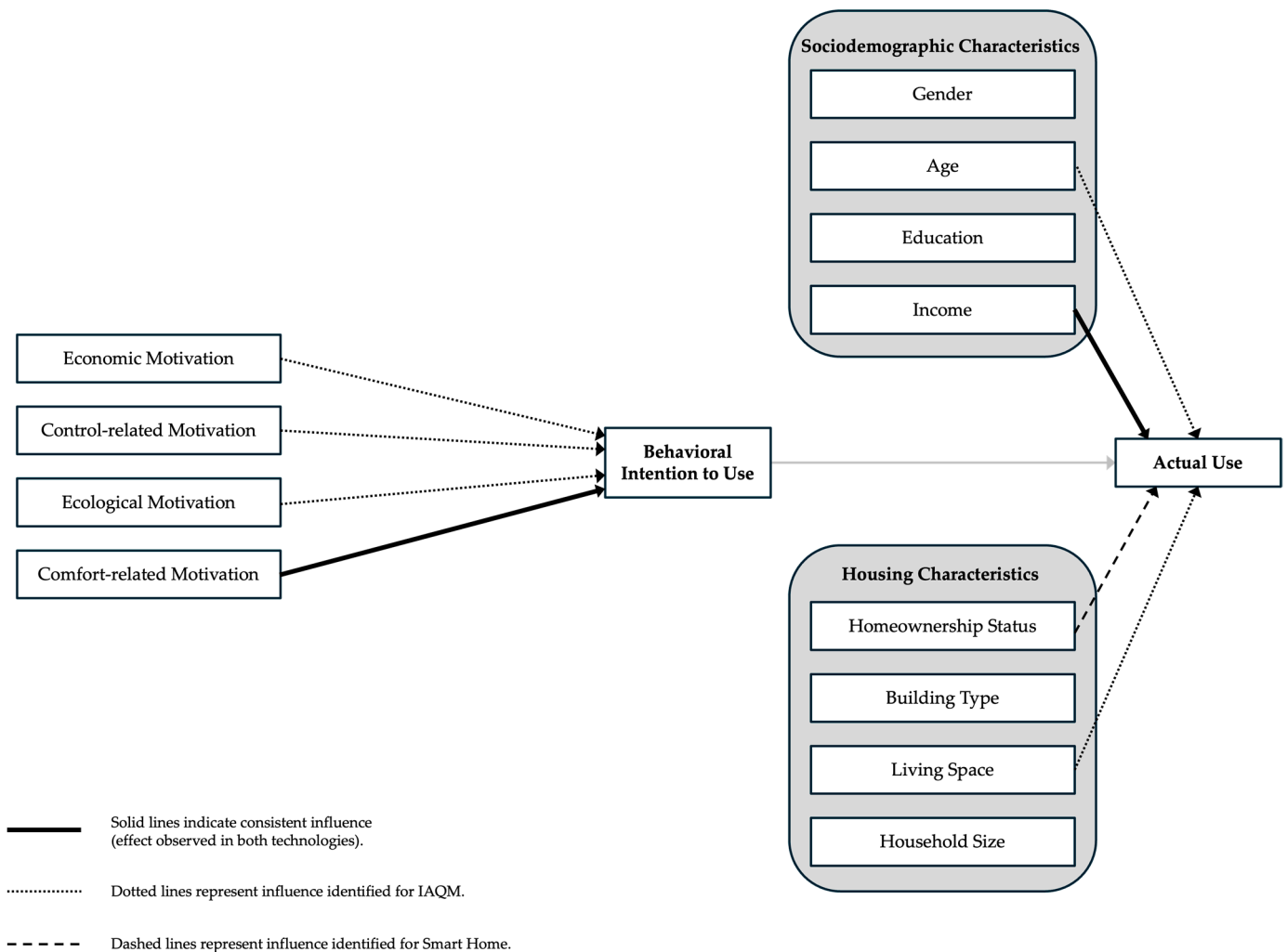


Figure 3. Impact diagram illustrating the identified effects of comfort-oriented technologies (IAQM and smart home), including consistent influences on adoption.

Contrary to the findings of previous studies, gender was not found to have a significant effect. This suggests a potential decline in gender-specific barriers to technology adoption and indicates that technological competence and accessibility are becoming increasingly gender-neutral.

5.5. Limitations and Implications for Future Research

The results are limited in terms of their significance and generalizability due to the selective participant structure. The overrepresentation of men and households with high levels of education and income could distort the effects of education and income, thus explaining the discrepancies with previous research results. Future studies should investigate these conflicting relationships in greater depth using more representative samples. In particular, the negative correlation between high educational attainment and usage requires further investigation. This could be due to different perception patterns, technophobia, or information deficits, all of which could be explored through in-depth qualitative studies.

Moreover, the statistical analyses were limited by the sample composition. As the motivational dimensions were evaluated exclusively among ST users and not among non-users, comparative analyses between these groups could not be conducted. Consequently, motivational factors could not be incorporated into the binary logistic regression models to examine their direct influence on the likelihood of technology use.

Furthermore, the assumption that sociodemographic and housing-related characteristics affect motivational dimensions could not be confirmed, as none of the estimated models reached statistical significance. This outcome may have resulted from the limited variability within the sample, which potentially reduced the explanatory power of the analyses. Consequently, the conceptual model proposed in this study could not be fully validated empirically.

Future research should include user and non-user groups and adopt broader methodological approaches. This would allow for more comprehensive validation of the conceptual framework and to uncover potential interaction effects between motivational, sociodemographic, and housing-related determinants.

Nevertheless, this study contributes markedly to our understanding of target group-specific dynamics in the context of digital transformation within the private home environment.

6. Conclusions

Overall, this study showed that the adoption of STs in private households in Germany is influenced by various factors, including application-specific motivations and structural conditions. Table 9 provides an overview of the motivational, sociodemographic, and housing-related variables that influence the use of various STs.

Table 9. Comparative overview of motivational, sociodemographic, and housing-related factors associated with ST adoption.

		Energy-Oriented Technologies		Comfort-Oriented Technologies	
		Energy Monitoring	HEMS	IAQM	Smart Home
Motivational Factors	Reducing energy costs	X	X	X	
	Controlling energy consumption	X	X	X	
	Saving energy	X	X	X	
	Enhancing residential comfort			X	X
Sociodemographic Factors	Gender				
	Age			X	
	Highest Educational Qualification	X	X		
	Annual Household Income			X	X
Housing Factors	Homeownership Status				X
	Building Type	X	X		
	Living Space			X	
	Household Size				

Note: X indicates that a influence of the factor on technology adoption was observed.

Efficiency and control were the main motives for energy monitoring and HEMS, while well-being and comfort primarily influenced IAQM and smart home adoption. These results suggest that users selectively evaluate the specific value propositions of different technologies based on personal needs and living contexts.

Sociodemographic and housing-related factors such as education, income, age, homeownership status, and building type also play an important role in actual use, sometimes in unexpected ways. Notably, highly qualified individuals showed lower ST use, suggesting

the existence of potential unexplored barriers. The results also suggest that comfort-related technologies are particularly prevalent in resource-rich and tech-savvy households with large living spaces. Meanwhile, systems driven solely by energy efficiency are used by less-educated groups.

Collectively, these results emphasize that the adoption of STs in private households is a multidimensional process shaped by individual motivations and contextual user and living conditions. This provides valuable insight for the design of user-centered, socially inclusive strategies to promote the use of technology in residential environments.

6.1. Theoretical Implications

Theoretically, this study extends existing technology acceptance models such as TAM, UTAUT, and UTAUT2 by integrating motivational, sociodemographic, and housing-related determinants into a unified framework for ST adoption in private households. Empirical testing confirmed that motivational factors influence behavioral intention, while sociodemographic and housing characteristics impact actual usage. However, the influencing effects of structural condition (sociodemographic and housing characteristics) on motivational dimensions could not be identified, likely due to limited variability in the sample. These findings suggest that motivational and structural determinants largely operate in parallel rather than interactively, highlighting the need to distinguish between cognitive drivers and contextual constraints. Future research should refine the model by incorporating multi-level and context-specific perspectives, including those of non-user groups, in order to better capture the complex interplay between individual motivations, structural conditions, and adoption behaviors.

6.2. Practical Implications

From a practical perspective, the findings highlight the need for ST manufacturers, developers, and policymakers to consider the diversity of user needs and household contexts more carefully. Targeting specific user segments is essential for product design, such as visualization tools, automation functions, and system integration, as well as for communication strategies. Energy-related systems that emphasize efficiency and control benefits appeal to different audiences than technologies that offer hedonic or comfort-oriented benefits. For less widespread technologies, such as IAQM or smart home applications, intuitive, scalable solutions combined with personalized guidance could help to reduce barriers to acceptance.

Furthermore, policy instruments and market communication strategies should reflect technological diversity and social heterogeneity. Support measures should not only focus on high-cost technologies or homeowners, but also address tenant households, technologically disadvantaged users, and those with medium levels of education. This could be achieved through standardized tenant models, smart plug-and-play solutions, and publicly funded advisory or information services. Collaborating with local energy consultants, housing associations, and municipal utilities can further enhance outreach and foster the socially inclusive diffusion of STs.

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Abbreviations

The following abbreviations are used in this manuscript:

HEMS	Home energy management system
IAQM	Indoor air quality monitoring
ST	Smart Technology
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
VIF	Variance Inflation Factor

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