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Behavioral Intentions to Use Energy Efficiency Smart Solutions under the Impact of Social Influence: An Extended TAM Approach

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Abstract: The role of social influence (SI) as a determining factor in accepting new technologies has been addressed in several studies using the initial or extended technology acceptance model (TAM). This research uses an adaptation of the extended technology acceptance model (TAM) to analyze the behavioral intention of Romanian consumers regarding the use of energy efficiency smart solutions (EESS) under the effect of social influence. Data were processed with the structural equation modeling technique (PLS-SEM). The sample consisted of 302 domestic electricity consumers in Romania. The study's findings show that the respondents' perceptions of the two social influence dimensions—network of friends, colleagues, or family (SI_FF); and public space (SI_PS)—and their effects on other conceptual model variables are significantly different. The main implications highlight that the proposed model addresses social influence on two levels (SI_FF and SI_PS), to highlight not only the differences in users' perceptions, but also the main directions in which efforts to promote these technologies should be focused more intensively, in the context of implementing European policies regarding the reduction of energy consumption at the level of household consumers. An important component of the proposed model is the analysis of the role of hedonic motivation constructs, expected performance, perceived usefulness, and perceived ease of use in mediating the relationship between social influence and behavioral intention to use.

Keywords: social influence; social norms; EESS; TAM; hedonic motivation; technology acceptance; UTAUT; UTAUT 2; social networks; smart home; smart connected objects; behavior intention

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Citation: Cioc, M.M.; Popa, Ș.C.; Olariu, A.A.; Popa, C.F.; Nica, C.-B. Behavioral Intentions to Use Energy Efficiency Smart Solutions under the Impact of Social Influence: An Extended TAM Approach. *Appl. Sci.* **2023**, *13*, 10241. https://doi.org/10.3390/app131810241

Academic Editors: Antonio Fernández-Caballero, António Pereira and Nuno Alexandre Ribeiro Costa

Received: 2 August 2023
Revised: 5 September 2023
Accepted: 6 September 2023
Published: 12 September 2023

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1. Introduction

Voluntary change in the consumption behavior of household users is an ongoing concern at the European level in order to increase energy efficiency, an aspect highlighted by key policy documents such as the REPowerEU Program [1] or the "Playing my part" plan [2]. On the other hand, digital transformation is now imperative for all businesses willing to adapt to the rapidly changing business environment [3], including EU strategic directions on energy efficiency. Among the concrete measures proposed at the strategic level are those aimed at the adoption of new intelligent devices to control energy consumption. It is estimated [2] that these measures would lead to a 15% reduction in energy consumption. Given the voluntary nature of these measures, this research examines how the generalization of green technologies such as smart meters, smart light bulbs, or smart sockets (hereafter referred to as EESS—Energy Efficiency Smart Solutions), could be stimulated at the public level based on social influence relationships that have a significant impact on users' behavioral adoption intentions.

The perspective of the determinants influencing the adoption of technology can be found in research that addresses various technologies attributed to EESS, such as smart energy technologies (SET), which integrate various energy-saving technologies based on automatic sensor control [4–6]; smart home solutions, including automation and control solutions for energy or lighting systems [7–9]; home energy management system (HEMS) technologies [10–12]; building energy management systems (BEMS) [11]; smart connected objects (SCO) [13]; or even electric vehicles [6]. Most of the analyzed studies are based on the variables of the technology acceptance model (TAM) in the initial variants [14], the extended Unified Theory of Acceptance and Use of Technology (UTAUT) [15], and UTAUT2 [16], using main constructs such as behavioral intent, social influence, or hedonic motivation. The availability of users in the direction of accepting EESS technologies is also addressed under the influence of other varied determinants, such as awareness of the benefits of using energy-efficient technologies [9,17], the attitude towards environmental protection [4,5,18], internalizing objectives [11], trust in technology [8], or public policies to stimulate the adoption of EESS technologies [4,6,19].

Among the above mentioned elements, social influence (SI) is a construct of the technology acceptance model developed within the UTAUT variants [15] and UTAUT2 [16], in addition to the four main constructs of the original model [14]—the attitude regarding the use, perceived utility, intention, and ease of use. In the context of the model of acceptance of technology, social influence is defined as "the degree to which an individual perceives that important others believe he or she should use a particular technology" [15] (p. 451). In fact, UTAUT2 is the model that highlights the important role of social influence [13]. Other authors [20] approach social influence from the perspective of social pressures that individuals perceive, and on the basis of which they approach a certain way of action. Social influence directs users to specific behavioral patterns under the impact of individuals, groups and societal norms [21].

From the perspective of EESS technologies, the analysis of the specialized literature revealed a series of studies based on the TAM model that use social influence as the main construct. According to Billanes and Enevoldsen [22], social influence is among the top 10 factors that decisively influence the acceptance and adoption of energy technologies. Social influence is one of the main determinants of the acceptance of smart meters, an aspect less addressed in previous research in the field [18]. The study by Girod, Mayer, and Nagele [4] indicated the relevance of beliefs related to social influence as a factor in the adoption of new green technologies. In the United Kingdom, social influencing factors such as image, social norms, or voluntariness, have been identified [11] as predictors of perceived utility (PU), which is the perceived ease of use or intention to use HEMS for technologies. Another study applied in Denmark [23] addresses the impact of consumer networks on consumer behavior from the perspective of social influence. In a systematic review based on previous research [24], three types of social influences have been identified that affect the decision to adopt vehicles based on alternative fuels: interpersonal communication, neighborhood effect, and conformity with social norms. Humeres' study [25] showed the impact of public policies on the social acceptance of smart meters in the population of Chile. Last but not least, Chen et al. [12] assigns an essential role underlying social motives and social norms in the adoption of energy efficient technologies, showing that social influence, along with behavior and attitude, are the strongest predictor of the intention to adopt.

The review of specialized literature reveals certain research gaps. As previously shown, in the majority of TAM-based approaches, social influence is treated as a global variable, although the impact of social influence on technology adoption intention is differentiated according to the channels through which it is exerted. In this context, as an element of novelty, the conceptual model proposed in this paper distinctly approaches the impact of social influence on the following dimensions—network of friends, colleagues or family, and public space—regarding the process of adopting EESS technologies. Also, the role of public policies in the exercise of social influence is a topic that is not frequently addressed in specialized literature, as most research is focused on the perspective of friends, family, colleagues or social networks. In the case of the adoption of technologies aimed at increasing energy efficiency, such as in the case of EESS, public policies constitute one of the main avenues for voluntary modification of the consumption behavior of household users, including through the exercise of social influence, which is why this paper gives major importance both in the direction of the research of these influences, as well as with a view to formulating proposals to improve policies aimed at the degree of adoption of EESS.

In continuation of the above approaches, this research proposes an adaptation of the extended technology acceptance model (TAM) to analyze the behavioral intention to use EESS technologies under the effect of social influence at the level of the domestic energy consumer sector in Romania. In the context of this main objective, the major contributions of the paper aim to:

- highlight the strong direct effect of social influence on perceived ease of use, perceived usefulness, hedonic motivation, and expected performance;
- demonstrate the indirect role of social influence on the behavioral intention to use EESS;
- formulate a set of proposals in the direction of improving marketing strategies and public policies for increasing the degree of assimilation of EESS solutions by maximizing the role of social influence.

Research is structured as follows: after the introduction section, Section 2 comprises the conceptual model and the development of the research hypotheses using the extended TAM model. Section 3 includes the materials and methods used in the research. Section 4 contains the results obtained. Section 5 includes a discussion and analysis of the implications of the results obtained in the previous section. Section 6 contains the research conclusions.

2. Conceptual Model and Research Hypotheses

2.1. Conceptual Model

Approaching the role of social influence as a determining factor in the adoption of EESS technologies presents a series of distinctiveness related to the channels for both exercising social influence and socio-cultural factors. Some research [11] also showed the less relevant role of subjective norms in the adoption of assimilated EESS technologies (such as HEMS), provided that the intention to adopt is based on utility rather than on the social status conferred by the acquisition of those technologies. Other authors [20] demonstrate the link between social influence and perceived social value of EESS technologies, raising an argument that the public needs to be made aware through online or offline promotion of the benefits of adopting new energy-efficient technologies. An important role in interpreting the adoption of energy-efficient technologies is played by cultural differences [12]. In the meta-analysis realized by Schepers and Wetzels [26], after comparing several Western and non-Western studies, they show that subjective norms had a greater impact on behavioral intent in Western studies. Other authors [27] researched the use of social influence or social norms (SN) as preachers in the TAM model, in correlation with the cultural dimensions defined by Hofstede [28]. However, Pettifor et al. [24] explain the significant heterogeneity between studies based on social influence in terms of cultural receptivity in relation to the effects of social influence, while Schepers and Wetzels [26] analyze the moderating role of demographic factors in exercising social influence, showing—for example—that young people are more easily influenced by the characteristics of technology and the opinions of colleagues than older users. Nusir, Alshirah, and Alghsoon [29] argue that gender, age, education, information technology and communications (IT&C) experience, and monthly income significantly moderate the relationship between perceived ease of use and both social influence and behavioral intention. The role of age and education is also highlighted in the research of Dinu, Lazăr, and Pop [30].

Other authors argue that IS-based approaches should include components to stimulate the environmental component in the context of certain users, such as those who already use assimilated EESS technologies (electric vehicle) and are predisposed to adopt new technologies [31]. In this context, Ru, Wang, and Yan [32] show that organizations concerned with environmental protection should stimulate the intention to save energy as a popular social trend. In another study [17], it is shown that people concerned with environmental issues experience social pressure when it comes to adopting energy-efficient technologies as a result of social influence. However, according to other authors [19], social pressure to buy green technologies is less important. Also, while people with high environmental values have similar beliefs about price value or performance, they exercise a less positive vision from the perspective of the compatibility of new technologies with the social environment of which they are part [4]. Another recent study on user confidence in new technologies [33] indicates a strong relationship between social influence and two other determinants of accepting new technologies: perceived security and perceived trust. Last but not least, the collaborative experience of using EESS is relevant, given that communication between users based on social influence can increase their level of interest in new technologies [34].

The outline of the concept model related to the present research is based on the study of conceptual models presented in the analyzed studies, taking into account social influence as a determining factor for the adoption of EESS technologies. A study by Billanes and Enevoldsen [22] in the field of using TAM for the analysis of acceptance of energy technologies shows that social influence has the highest impact on perceived usefulness (PU), attitude, perceived ease of use (PEOU), behavioral intention (BI), and actual use. Attié and Meyer-Waarden [13] show the important role of social image in the early stages of adopting smart connected objects (SCO) as well as the positive influence on PU and PEOU. Schepers and Wetzels [26] show the influence of subjective norms on both the attitude toward use and the behavioral intention to use. Other studies [35] approached social influence from the perspective of social networks, demonstrating the positive impact of social media features (SMF) above perceived usefulness (PU) and perceived ease of use (PEOU). The correlation between social influence and PU is also highlighted in the research of Nath, Bhal, and Kapoor [36]. Chen et al. [12] shows that social norms have a strong impact on the behavioral intention to use HEMS technologies in Japan and the USA. However, another study [37] shows, that social influence does not have a significant effect on the behavioral intention to use artificial intelligence (AI)-based technologies, in the context of the still insufficient level of maturity of these solutions. This hypothesis is also supported by Chaveesuk et al. [38], in a TAM-based research on the adoption of autonomous vehicles (AVs). Based on the models analyzed, this research proposes a conceptual model that includes seven main constructs and eight hypotheses (Figure 1).

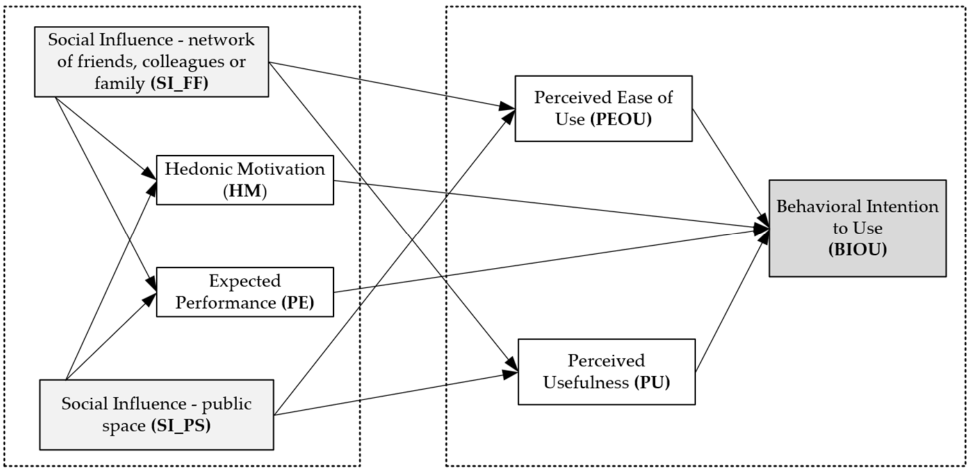

Figure 1. Conceptual model and research hypotheses.

One of the main features of the proposed conceptual model, which differentiates it from previous applications of the TAM model in the EESS technologies sector, is that of a differentiated approach to social influence on these dimensions: network of friends, colleagues, or family (SI_FF), and public space (SI_PS). This approach is justified, as shown previously, by a number of specificities of EESS solutions compared to other new technologies. In fact, some authors [5] consider that in the case of IT&C, the acceptance of new technologies is strongly influenced by the adoption at the level of the social network, and in the case of SET technologies, this correlation is less strong; it is considered that social influence should be exercised at public level, through media institutions. The stronger the social influence, the more inclined the individual is to engage in energy-saving actions [39]. A difference in the prospects of colleagues or friends can be a barrier to the adoption of such technologies [39]. On the other hand, social networks are a favorable environment for the personalized exercise of social influence, as it is a factor that emphasizes the role of social influence [40], while influence maximization (IM) becomes an important concept in both the analysis of social networks [41] and the optimization of marketing strategies to promote EESS technologies. Social influence is also a determinant that stimulates the network effect in adopting EESS. Research [9] showed that people with positive experiences using smart home technologies will recommend them to friends and family or promote them through social networks. In a study in Malaysia [19], it is shown that campaigns on environmental protection and the use of green technologies should be extended to social networks. The results of the proposed conceptual model are the behavior intention to use (BIOU). In conformity with the theory of planned behavior [42], at the individual level, behavioral intentions represent a result of attitude, subjective norms, and perceived behavioral control. BIOU is also a main construct of the UTAUT and UTAUT2 models, which condition use behavior. Another element of research originality is the consideration of four constructs of the model (perceived ease of use, perceived usefulness, hedonic motivation, and expected performance) as factors of mediation between the two dimensions of social influence and the behavioral intention to use EESS (BIOU). The argument for the substantiation of these hypotheses is presented in the following sections.

2.2. Social Influence and Perceived Ease of Use of EESS

Considering the higher level of complexity of EESS technologies in terms of functionality and use, the first direction in approaching the conceptual model is the impact of social influence on users' perceptions of the ease of use of EESS. This correlation was analyzed in other research to analyze the factors that influence the adoption of assimilated EESS technologies: smart meters [43], electrical vehicles [20], or smart connected objects [13]. Additionally, the correlation between perceived ease of use (PEOU) and behavioral intention to use (BIOU) is included in the initial TAM model [14], in UTAUT links [15], and in UTAUT2 [16], through construct effort expectancy. Therefore, we make the following hypotheses:

Hypothesis 1 (H1). *Social influence (SI)—specifically (a), the adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF), and (b), the promotion of the use of EESS in the public space (SI_PS)—will have positive effects on their perceived ease of use (PEOU).*

Hypothesis 2 (H2). *PEOU will mediate the relationship between (a) SI_FF and (b) SI_PS, and the behavioral intention to use EESS (BIOU).*

2.3. Social Influence and Perceived Usefulness of EESS

According to the original TAM model [14], perceived use (PU) represents, along with perceived ease of use (PEOU), the determinants of the intention to use the technology. The direct impact of social influence on perceived use (PU) is demonstrated in several research studies based on the technology acceptance model. Chou and Yutami [43] show the significant influence of social influence and subjective norms on perceived usefulness, which is seen as a critical determinant of the acceptance of smart meters by household consumers in a study conducted in Indonesia. Other authors [20] demonstrate the positive effect of social influence on the attitude toward use (ATU), which is a result obtained by the mediation of perceived usefulness (PU) in a study in the Chinese electric vehicle sector. In the smart meter sector, Gumz et al. [18] directly analyzes the impact of social influence on behavior intention to use (BIOU), showing the role of this determinant in shaping Brazilian public opinion on accepting these technologies. Lau et al. [44] argues that social influence has a greater impact on the behavioral intention to use than facilitating conditions, and that there is a mediating role of the facilitating conditions in the relationship between social influence and behavioral intention. Samadzad et al. [45] shows that subjective rules, defined as an indicator of social influence, are positively correlated with the behavioral intention to use technology, while other research [29] shows the positive relationship between social influence and the intention of Jordanian users to adopt smart city technologies. In another piece of TAM-based research, Große-Kreul [5] shows that the intention to adopt smart thermostats is positively and significantly influenced by performance expectations, hedonic motivation, and social influence. Therefore, we make the following hypotheses:

Hypothesis 3 (H3). *Social influence (SI), specifically (a), the adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF), and (b), the promotion of the use of EESS in public space (SI_PS), will have positive effects on their perceived usefulness (PU).*

Hypothesis 4 (H4). *PU will mediate the relationship between (a) SI_FF and (b) SI_PS, and the behavioral intention to use EESS (BIOU).*

2.4. Social Influence and Hedonic Motivation to Use EESS

A main direction of the analysis of the present research is the relationship between social influence and the hedonic motivation to use EESS. The inclusion of this correlation in the conceptual model is argued by the fact that EESS devices are generally programmed through software applications, and the degree of acceptance of these types of applications is conditioned for ease of use and hedonic motivation. Within the UTAUT2 model [16], hedonic motivation is defined as "the fun or pleasure derived from using a technology". Billanes and Enevoldsen [22] define hedonic motivation from the perspective of perceived enjoyment, specifically that the use of a certain technology is enjoyable. According to other authors [46], hedonic motivation is the strongest predictor of users' behavioral intentions. In a study in the education sector, Wijaya and Weinhandl [47] show that pleasant experience in operation positively influences the intention to use. In the field of EESS technologies, hedonic motivation is a relevant influencing factor, as it allows one to increase the degree of interaction with technology [5]. The role of social influence in stimulating hedonistic motivation is also addressed in several pieces of EESS research. Girod, Mayer, and Nagel [4] point out that, from both a marketing and a public policy perspective, among the factors that decisively influence the intention to adopt green technologies, organizations should focus on influencing hedonistic motivation. On the other hand, the same authors show that hedonic motivation is the least targeted determinant of established policy instruments. Other studies [48] show the correlation between social influence, the confidence in a certain technology, and the hedonic motivation. Gumz et al. [18] show the role of hedonic motivation as one of the main factors in accepting EESS technologies such as smart meters, while showing the significant positive effect of hedonic motivation on the behavioral intent to use. Therefore, we make the following hypotheses:

Hypothesis 5 (H5). *Social influence (SI), specifically (a), the adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF), and (b), the promotion of the use of EESS in the public space (SI_PS), will have positive effects on the hedonic motivation to use them (HM).*

Hypothesis 6 (H6). *HM will mediate the relationship between (a) SI_FF and (b) SI_PS, and the behavioral intention to use EESS (BIOU).*

2.5. Social Influence and Expected Performance of EESS

Given that EESS represent new technologies in continuous evolution, another relevant dimension of the analysis concerns the correlation between social influence and expected performance. Performance Expectancy (PE) is one of the main constructs of the UTAUT and UTAUT2 models, being also used in TAM-based research in the field of EESS-related assimilated technologies such as smart meters [5] or smart energy technologies [17]. However, other studies [18] did not indicate a significant influence of expected performance (PE) on acceptance in the target population, although the same study identified a strong correlation between SI and behavior intention to use (BIOU). This correlation is also demonstrated in the research of Billanes and Enevoldsen [6], carried out to analyze the influencing factors that influence the adoption of smart energy technologies in Denmark. Therefore, based on the analysis of the specialized literature, we formulate the following hypotheses:

Hypothesis 7 (H7). *Social influence (SI), specifically (a), the adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF), and (b), the promotion of the use of EESS in the public space (SI_PS), will have positive effects on their expected performance (PE).*

Hypothesis 8 (H8). *PE will mediate the relationship between (a) SI_FF and (b) SI_PS, and the behavioral intention to use EESS (BIOU).*

3. Materials and Methods

To validate the research hypotheses, in the first quarter of 2023, a survey was conducted on a sample of domestic electricity consumers in Romania. The tool used for data collection was the online questionnaire. More precisely, through the questionnaire, we aimed to analyze the behavior of domestic electricity consumers regarding the use of energy efficient smart solutions (EESS) such as smart light bulbs, smart sockets, etc. Before accessing the questionnaire, the consent of all respondents participating in the investigation was obtained regarding the participation in the survey, and they were also informed about the confidentiality of the answers.

The development of the questionnaire was carried out in correlation with the elements included in the conceptual model; for this purpose, six scales were taken from the specialized literature:

- Social influence (SI) [4,5,11,13,15,16,20,43]. Taking into account the main purpose of the research and the specificities of the EESS technologies in the case of this scale (SI—Social Influence) we opted for the use of two dimensions of analysis: SI_FF (Social influence—Network of friends, colleagues and family), which included 5 items, and SI_PS (Social influence—Public space), measured by 7 items. These items sought to assess the extent to which respondents would adopt EESS if family, friends, or colleagues encouraged them to do so, specifically the extent to which they would use EESS if they were recommended to by others on social networks.
- Hedonic motivation [4,5,15,16,18,48], assessed through 6 specific items such as ”Using EESS is pleasant/very fun”, ”I like to be aware of the latest technological developments”, and ”I like to try new apps and new devices”.
- Expected performance (PE) [5,15–17,43], measured by means of 6 items that aimed to evaluate the extent to which domestic electricity consumers in Romania consider that EESS are useful in everyday life and help to manage life more efficiently, as well as to what extent using EESS allows them to perform activities more efficiently, increase their chances of accomplishing important things, or make it easier for them to manage electronic equipment faster.
- Perceived ease of use (PEOU) [4,6,11,14–16], evaluated through 7 specific items which sought to assess, for example, how easy it is for respondents to use or learn to use the EESS or how clear their interaction with the EESS is.
- Perceived usefulness (PU) [6,14,19,20,43,49], conceptualized through 6 items. By means of these items, we aimed to analyze, for example, the extent to which domestic electricity consumers in Romania appreciate EESS as useful in the efficient management of electricity consumption, or the extent to which the respondents believe that the use of EESS allows for the reduction of electricity costs or consumption energy.
- Behavioral Intention to Use (BIOU) [4,5,11,15,16,18,20,29,43], measured using 8 items, among which were ”I intend to continue using EESS in the future”, ”I plan to use EESS in the future”, or ”When it comes to EESS, I would recommend my relatives and friends to accept it”.

The items of the above-mentioned scales are measured on a scale of 1–5 (strong agreement–strong disagreement), and are also adapted to the purposes of the research. In addition, a series of items considered to be more relevant in relation to the objectives pursued and the particularities of the technologies addressed have been added.

In terms of demographic criteria, the facilitating conditions identified in the UTAUT models were mainly taken into account [15], and UTAUT2 [16] materialized in the factors of gender, level of education, occupation, and level of income. Furthermore, other analysis criteria attributed to the facilitation conditions were introduced in the model, each having a specific role in relation to the specificities of the EESS technologies and the objectives of this research. Thus, first of all, the aim was to classify the respondents into different consumption profiles, taking into account the following facilitating conditions:

- The residential environment, taking into account the differences regarding the consumer behaviors of users in urban areas compared to rural areas; it was considered, on the one hand, that there is wider accessibility of EESS technologies in urban areas (ex. faster and more stable connections to the Internet, easier integration into hubs, higher e-readiness, etc.), and on the other hand, that there are a greater number of options for setting up smart home systems that integrate EESS in rural areas.
- The type of housing, a factor that correlates with the residence environment, taking into account the fact that, in general, the urban population lives in apartments, while the rural population generally lives in homes/villas. This factor influences both the variety of EESS solutions available depending on each type of home, as well as the need to streamline energy consumption, taking into account different energy consumptions depending on the type and size of the home.
- The form of ownership (family owned or rented), a factor that influences respondents' willingness to invest in home improvement through the integration of EESS technologies.
- The average monthly electricity consumption, which on the one hand, indicates the potential yield that could be obtained through the integration of EESS, and on the other hand, reflects the pressure that respondents feel in order to reduce energy costs. In Romania, for example, users with consumptions higher than 300 kWh/month (the consumption ceiling for subsidized energy prices in 2022) are more likely to adopt energy efficiency measures.
- The number of respondents who changed their supplier in the last year, an indicator that reflects one of the major trends in the sector in Romania—citizens' concern in the direction of optimizing electricity costs. For example, the year 2022 in Romania marked a significant increase in the market share of energy suppliers that offered lower prices.

Last but not least, in the category of facilitating conditions, two criteria that correlated with the possibility of subsidizing the purchase of EESS-like solutions were included, given that one of the objectives of the research is precisely that of providing proposals for improving public policies in the field of energy efficiency. Thus, the respondents were asked; one, whether they benefited from government subsidies for the price of electricity; and two, whether they benefited from subsidies for the purchase of EESS technologies.

Data were processed with the structural equation modeling technique (PLS-SEM) and the SmartPLS 4 application [50]. More specifically, PLS-SEM was used to specify and evaluate the measurement model and structural model, and to test the research hypotheses. The relationships between the variables included in the model were analyzed both through the lens of direct effects and indirect (mediated) effects. The specific peculiarities of the evaluation of the PLS-SEM model and the results obtained are described in Section 4, and indicate a significantly different impact of the two dimensions of social influence (SI_FF and SI_PS) on the other variables analyzed.

4. Results

4.1. Descriptive Statistics

The research was based on 302 valid questionnaires. Considering the fact that the data were processed using the structural equation modeling technique (PLS-SEM), the minimum sample size can be considered adequate according to the "10-times rule" which assumes that the sample size should be greater than 10 times the maximum number of inner or outer model links pointing at any latent variable in the model [51,52]. The structure of the sample is detailed in Table 1. Thus, 55.62% of the respondents register high incomes over 4000 lei per family member, among which 85.43% of them are graduates of a higher education institution. In terms of residence criteria, 55.30% of respondents live in apartments, and the rest in houses/villas, especially in urban areas (82.45%). In 88.76% of cases, the home is owned by the respondents. The average monthly electricity consumption (54.63% of total respondents) is in the range of 100–255 kWh. According to existing regulations in Romania, this consumption corresponds to an optimal price of electricity, and as for consumption exceeding the threshold of 255 kWh, tariff increases are generally applied.

Table 1. Sample structure.

Characteristics	N	%	Valid %	Cumulative %
Gender				
Female	174	57.616	57.616	57.616
Male	128	42.384	42.384	100.000
Total	302	100.000	100.000	
Level of study				
High school or post-secondary education	44	14.570	14.570	14.570
Undergraduate study	77	25.497	25.497	40.066
Master study	77	25.497	25.497	65.563
PhD student or equivalent level	104	34.437	34.437	100.000
Total	302	100.000	100.000	
Occupation				
Student/master student/Phd student	84	27.815	27.907	27.907
Employee	190	62.914	63.123	91.030
Entrepreneur	15	4.967	4.983	96.013
Freelancer	4	1.325	1.329	97.342
Retired	8	2.649	2.658	100.000
Total (no missing answers)	301	99.669	100.000	
Missing answers	1	0.3		
Total	302	100.0		
Income				
Under 1000 lei	10	3.311	3.311	3.311
1000–2000 lei	28	9.272	9.272	12.583
2000–4000 lei	96	31.788	31.788	44.371
Over 4000 lei	168	55.629	55.629	100.000
Total	302	100.000	100.000	

Table 1. *Cont.*

Characteristics	N	%	Valid %	Cumulative %
Type of housing				
Apartment in block	155	51.325	51.325	51.325
Apartment in house/villa	12	3.974	3.974	55.298
House/villa	135	44.702	44.702	100.000
Total	302	100.000	100.000	
Type of property				
Family property	268	88.742	88.742	88.742
Rented	34	11.258	11.258	100.000
Total	302	100.000	100.000	
Monthly energy consumption				
Under 100 kWh	33	10.927	10.927	10.927
100–255 kWh	165	54.636	54.636	65.563
255–300 kWh	59	19.536	19.536	85.099
Over 300 kWh	45	14.901	14.901	100.000
Total	302	100.000	100.000	
Change of energy supplier in the last year				
No	241	79.801	79.801	79.801
Yes	61	20.199	20.199	100.000
Total	302	100.000	100.000	
Residence environment				
Urban	249	82.450	82.450	82.450
Rural	53	17.550	17.550	100.000
Total	302	100.000	100.000	

N—number of cases.

The analysis of the sample structure also reveals a certain flexibility of the subjects in terms of decisions regarding the optimization of energy consumption; 20.20% of them changed their electricity supplier in the last year against the background of the development of the competitive market. The data collected confirms the existing situation in the market, indicating a significant increase in market shares for the market operators offering the lowest prices. For example, Hidroelectrica's turnover, one of the most important suppliers in Romania in this market segment, increased in the period 2020–2022 by approximately 140%, reaching approx. 1.86 billion euros [53]. Furthermore, 29.14% of the people surveyed have benefited in the last year from subsidizing the price of electricity and 13.25% from subsidies for the purchase of EESS technologies (Table 1). These last indicators reveal a relatively high interest of consumers in the direction of attracting nonrefundable funds for the efficiency of energy consumption.

The descriptive statistics associated with the variables of interest for the investigation are presented in Table 2. Taking into account social influence factors, the adoption of EESS at the level of the network of friends, colleagues, or family is felt with a relatively greater intensity (M = 3.210, SD = 0.980) than the promotion of the use of EESS in public spaces (M = 2.962, SD = 1.028, $t_{(302)} = 5.732$, $p < 0.001$).

Table 2. Descriptive statistics of research variables.

Variable	N	Min.	Max.	Mean	Std. Dev.
SI_FF	302	1.000	5.000	3.210	0.980
SI_PS	302	1.000	5.000	2.962	1.028
PEOU	302	1.000	5.000	4.102	0.856
PU	302	1.000	5.000	3.965	0.830
HM	302	1.000	5.000	3.602	0.864
PE	302	1.000	5.000	3.833	0.937
BIOU	302	1.000	5.000	3.953	0.960

N—number of cases.

4.2. Model Evaluation

As assumed in the conceptual model, the PLS-SEM model was specified to include two exogenous constructs (SI_FF and SI_PS) and five endogenous constructs (PEOU, PU, HM, PE, and BIOU). All constructs were modeled as reflective.

Following the appropriate steps [54–56], the reliability and validity of the measurement model were fully evaluated. First, the outer loadings (see Table 3) were above the recommended value of 0.708 [55]. Moreover, construct internal consistency reliability was evaluated in terms of composite reliability (rho_a and rho_c) and Cronbach's Alpha coefficients, and all values were found to be greater than the 0.7 threshold [55]. Therefore, considering all the reliability of the above criteria, the measurement model was supported. Furthermore, the average variance extracted (AVE) values (Table 3) for all reflective constructs were greater than 0.5, supporting the convergent validity of the PLS-SEM measurement model [55].

Table 3. Evaluation of the measurement model—reliability and validity.

Constructs	Indicators	Outer Loadings	Cronbach's Alpha	rho_a	rho_c	AVE
Adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF)	SI1	0.849	0.914	0.990	0.931	0.730
	SI2	0.883				
	SI3	0.887				
	SI4	0.780				
	SI5	0.867				
Promotion of the use of EESS in public space (SI_PS)	SI6	0.801	0.935	0.939	0.947	0.720
	SI7	0.870				
	SI8	0.884				
	SI9	0.838				
	SI10	0.903				
	SI11	0.828				
	SI12	0.812				
EESS perceived ease of use (PEOU)	PEOU1	0.890	0.966	0.967	0.972	0.831
	PEOU2	0.920				
	PEOU3	0.897				
	PEOU4	0.939				
	PEOU5	0.936				
	PEOU6	0.911				
	PEOU7	0.886				

Table 3. *Cont.*

Constructs	Indicators	Outer Loadings	Cronbach's Alpha	rho_a	rho_c	AVE
EESS perceived usefulness (PU)	PU1	0.865	0.930	0.932	0.945	0.743
	PU2	0.863				
	PU3	0.899				
	PU4	0.913				
	PU5	0.832				
	PU6	0.794				
Hedonic motivation to use EESS (HM)	HM1	0.826	0.916	0.918	0.934	0.703
	HM2	0.821				
	HM3	0.827				
	HM4	0.867				
	HM5	0.847				
	HM6	0.841				
EESS expected performance (PE)	PE1	0.897	0.956	0.956	0.965	0.820
	PE2	0.898				
	PE3	0.895				
	PE4	0.925				
	PE5	0.901				
	PE6	0.916				
Behavioral intention to use EESS (BIOU)	BIOU1	0.896	0.969	0.970	0.974	0.824
	BIOU2	0.877				
	BIOU3	0.928				
	BIOU4	0.933				
	BIOU5	0.929				
	BIOU6	0.919				
	BIOU7	0.888				
	BIOU8	0.890				

AVE—Average variance extracted. Source: authors with SmartPLS 4 [50].

In terms of discriminant validity [54–56], all the indicator cross loading, constructs, and heterotrait–monotrait criterion (HTMT) [57] were considered. None of the indicators had any loading higher on the other constructs than on its own, and all HTMT values were lower than 0.9 threshold and (with one exception) lower than 0.85 (Table 4), thus supporting the discriminant validity of the constructs.

Table 4. Discriminant validity—HTMT ratio.

Constructs	BIOU	HM	PE	PEOU	PU	SI_FF	SI_PS
BIOU							
HM	0.776						
PE	0.887	0.750					
PEOU	0.768	0.645	0.790				
PU	0.703	0.768	0.683	0.720			
SI_FF	0.524	0.477	0.523	0.427	0.391		
SI_PS	0.485	0.450	0.482	0.375	0.314	0.782	

Source: authors with SmartPLS 4 [50].

Once there was enough evidence for the reliability and validity of the outer model, the inner model was evaluated for predictive and explanatory power [54–56]. The first step in this process was to assess the multicollinearity between explanatory constructs based on the variance inflation factor (VIF). Except for the PE construct (VIF = 3.037), which may be considered an acceptable value, all VIF values fell in the ideal range—below 3 [58]. In terms of predictive power (Table 5), the R^2 values suggest that adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF) and promotion of the use of EESS in the public space (SI_PS) may explain 20.8% of the variance of EESS perceived ease of use (PEOU) $\left(R^2 = 0.208\right)$, 17.9% of EESS perceived usefulness (PU)) $\left(R^2 = 0.179\right)$, and 25.5% and 31.3% of the variance of hedonic motivation to use EESS (HM) and the EESS expected performance (PE), respectively $\left(R^2 = 0.255; R^2 = 0.313\right)$. Overall, all the above considered predictors are responsible for more than three quarters of the variance in behavioral intention to use EESS (BIOU) $\left(R^2 = 0.782\right)$. Moreover, analyzing the p-values in Table 5, it can be found that all R^2 are statistically significant.

Table 5. Model predictive power.

Constructs	R^2	p Value	Q^2
PEOU	0.208	0.000	0.196
PU	0.179	0.000	0.167
HM	0.255	0.000	0.242
PE	0.313	0.000	0.302
BIOU	0.782	0.000	0.310

R^2—Coefficient of determination; p value—the statistical significance; Q^2—The blindfolding-based cross-validated redundancy measure. Source: authors with SmartPLS 4 [50].

4.3. Hypotheses Evaluation

In terms of research hypotheses, the direct effects of social factors were examined. It was found that adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF) has a positive effect on EESS perceived ease of use (PEOU), perceived usefulness (PU), hedonic motivation to use EESS (HM), and EESS expected performance (PE). Therefore, H1a, H3a, H5a, and H7a were supported. In contrast, promotion of the use of EESS in the public space (SI_PS) may only determine an increased expected performance of EESS (PE), thus giving support only for the other hypotheses formulated in this sense; specifically, H1b, H3b, and H5b were not supported by the empirical results because the direct effects were not statistically significant.

Furthermore, we were also interested in the indirect effects of social factors on the behavioral intention to use EESS (BIOU). The bootstrapping procedure with 5000 subsamples revealed that the adoption of EESS at the level of the network of friends, colleagues, or family (SI_FF) also has an indirect effect on the behavioral intention to use EESS (BIOU), which is mediated by PEOU, HM, and PE; PU does not significantly mediate the relationship. Therefore, H2a, H6a, and H8a were supported, and H4a was not. Instead, promotion of the use of EESS in the public space (SI_PS) has an indirect effect on a BIOU mediated only by PE, thus supporting H8b. However, H2b, H4b, and H6b were not supported. All the direct and indirect effects of social factors, their associated metrics, and the decision on our research hypotheses are presented in Table 6.

Table 6. Research hypotheses.

Hypotheses	Relationships	Beta	ST. DEV.	T Statistic	BCCI	f^2	Supported/ Not Supported
H1a	SI_FF → PEOU	0.402 ***	0.068	5.948	0.284, 0.510	0.098 **	Supported
H1b	SI_PS → PEOU	0.071	0.077	0.923	−0.059, 0.195	0.003	Not supported
H2a	SI_FF → PEOU → BIOU	0.063 *	0.029	2.217	0.024, 0.119	-	Supported
H2b	SI_PS → PEOU → BIOU	0.011	0.014	0.796	−0.006, 0.041	-	Not supported
H3a	SI_FF → PU	0.430 ***	0.069	6.225	0.306, 0.535	0.109 **	Supported
H3b	SI_PS → PU	−0.010	0.079	0.132	−0.138, 0.121	0.000	Not supported
H4a	SI_FF → PU → BIOU	0.025	0.024	1.048	−0.013, 0.066	-	Not supported
H4b	SI_PS → PU → BIOU	−0.001	0.006	0.096	−0.014, 0.007	-	Not supported
H5a	SI_FF → HM	0.404 ***	0.072	5.623	0.274, 0.513	0.105 **	Supported
H5b	SI_PS → HM	0.129	0.082	1.572	−0.006, 0.265	0.011	Not supported
H6a	SI_FF → HM → BIOU	0.085 **	0.028	2.999	0.045, 0.139	-	Supported
H6b	SI_PS → HM → BIOU	0.027	0.020	1.360	0.002, 0.068	-	Supported
H7a	SI_FF → PE	0.461 ***	0.065	7.119	0.347, 0.560	0.149 **	Supported
H7b	SI_PS → PE	0.127 *	0.073	1.733	0.010, 0.254	0.011	Supported
H8a	SI_FF → PE → BIOU	0.253 ***	0.049	5.208	0.178, 0.338	-	Supported
H8b	SI_PS → PE → BIOU	0.070 *	0.041	1.690	0.009, 0.146	-	Supported

Beta—Standardized path coefficient; *—$p < 0.05$; **—$p < 0.01$; ***—$p < 0.001$; T statistic—t-test value; BCCI—Bias corrected confidence intervals; f^2—effect size. Source: authors with SmartPLS 4 [50].

5. Discussion

The research results indicate significant differences in perception regarding the impact of the two dimensions of social influence (SI_FF and SI_PS) on the other variables of the conceptual model. Basically, the influence of the promotion of the use of EESS in the public space (SI_PS) is relevant only as an expected performance improvement factor (PE), but without exerting a statistically significant influence on PEOU, PU, and HM. The results confirm certain previous approaches that either argue for the lower influence of social influence in the case of assimilated EESS technologies in relation to IT&C solutions [5], explain this situation by the still insufficient level of maturity of the analyzed technologies [37,38], or call into question the fact that established policy instruments are less focused on factors such as hedonic motivation [4]. In general, at least regarding Romania, the promotion in the public space of voluntary measures to reduce energy consumption using EESS solutions is still at an early stage; this is also due to the fact that the measures adopted at the European level through the policy documents REPowerEU Program [1] and 'Playing my part" [2] are relatively recent. Thus, the level of public visibility of policies undertaken at the European or national level is still low, which partly explains the lack of statistical significance of the correlations previously analyzed. In fact, only 13.25% of the respondents say they have benefited, in one form or another, from subsidies for the acquisition of assimilated EESS technologies in government programs, while 29.14% benefited from the subsidy of the electricity price, according to the legal provisions (Table 7). On the other hand, the positive correlation between the promotion of the use of EESS in the public space (SI_PS) and the expected performance (PE) can be argued less from the perspective of public policies and more from the perspective of marketing strategies of companies selling EESS solutions, strategies focused on promoting the performance of these technologies, including in terms of energy efficiency.

Table 7. Demographic data—subsidies for energy efficiency.

	N	%	Valid %	Cumulative %
Subsidies for energy consumption				
No	214	70.861	70.861	70.861
Yes	88	29.139	29.139	100.000
Total	302	100.000	100.000	
Subsidies for EESS				
No	262	86.755	86.755	86.755
Yes	40	13.245	13.245	100.000
Total	302	100.000	100.000	

N—number of cases.

The research results indicate a significant impact of social influence from the perspective network of friends, colleagues, or family (SI_FF) on PEOU, PU, HM and PE, confirming part of the study hypotheses. The results also confirm previous research, which demonstrate the role of social networks as a factor in accepting technology [19,40], the role of the network effect or influence maximization as a multiplier in this process [9,41], the correlation between the opinions of colleagues or friends, and the attitude towards the adoption of these technologies, [39]. If social influence is relevant from both perspectives analyzed (SI_FF and SI_PS) in the case of expected performance (PE), the network of friends, colleagues, or family plays a leading role in influencing the decision to adopt EESS technologies from the perspective of perceived ease of use, hedonic motivation, and perceived usefulness. The relevance of these three model constructs is even greater if we consider the software component of EESS technologies, the operation of which is most often controlled through mobile applications. In this context, the ergonomics of these applications, ease of use, specific functions (such as: remote access, automatic programming, dashboards, etc.), or enjoyable character are essential factors in accepting EESS. Moreover, these applications usually include certain collaborative facilities that allow the establishment of social networks in the field of EESS, accelerating the adoption of these technologies through the network effect.

The results of the research allow for the outline of directions to focus efforts and more intensively promote these technologies—both at the level of public authority and companies in industry—in the context of increasingly pressing needs to reduce energy consumption. First, in terms of communication in the public space, a more pragmatic and diversified approach to concrete solutions to change voluntary consumption behavior is needed in order to increase energy efficiency, including through the purchase of EESS solutions. The research results currently indicate a higher level of receptivity based on information from the public space in the case of the expected performance of these technologies, without emphasizing the issues related to the use and benefits obtained, which also influence the adoption of EESS solutions as shown in previous research. The study highlighted the direct positive impact of communication through social networks in stimulating the effect of the network and accelerating the spread of EESS. Public policies should, in this context, focus mainly on online communication actions and social media campaigns rather than on traditional communication channels that are shown to be less effective in the EESS situation. In the case of companies producing or marketing EESS, marketing policies should emphasize the pleasant nature of the EESS, as research has shown the significant impact of hedonistic motivation as a factor in mediating between the social influence (SI) and behavioral intention to use these technologies (BIOU).

In terms of theoretical contributions, this research brings a number of new elements. The use of the TAM model in the field of EESS is a less common research approach in the literature, although the pace of propagation of these technologies is very high, especially in the context of the energy challenges of the current period. For increased accuracy of the analysis of the correlations between the social influence (SI) and the other constructs of the conceptual model, two dimensions (SI_FF and SI_PS) are used, the analysis of which reveals, significant differences in perception, thus allowing a more efficient calibration of policy proposals resulting from the analysis. Correlations between social influence, on the one hand, and perceived ease of use (PEOU), perceived usefulness (PU), hedonic motivation (HM), and expected performance (PE), on the other hand, were also studied from two perspectives. First, the direct effect of social influence on these last four constructs was assessed, and second, their indirect role was analyzed as a factor in mediating the relationship between social influence and the behavioral intention to use EESS (BIOU). Last but not least, the research puts forward a number of proposals for the calibration of public policies in the field of energy efficiency by integrating measures to accelerate the growth rate of the EESS market and the use of these technologies at the home consumer level.

6. Conclusions

The research hypotheses are partially confirmed by the obtained results. The research indicates a strong and direct effect of social influence, exercised through networks of friends, colleagues, or family (SI_FF) on the perceived ease of use, perceived usefulness, hedonic motivation, and expected performance, as well as a significant indirect influence on behavioral intention to use EESS. On the other hand, considering the promotion of the use of EESS in the public space (SI_PS), the impact of social influence is only relevant from the perspective of expected performance. Based on the results obtained, a series of proposals were formulated to improve public and marketing policies in order to maximize the role of social influence in increasing the assimilation of EESS solutions.

The limitations of the research include, first of all, the relatively small number of studies that address the application of the original or extended TAM model at the level of energy efficiency technologies attributed to EESS. Also, the relatively early stage of development and propagation of these technologies means that the level of awareness among users is somewhat lower and is based more on documentation from various sources than on experience in use. Regarding how an important component of the analysis is the study of the impact of the promotion of EESS solutions in the public space, another limitation is the reduced visibility of these policies, as well as their degree of novelty, considering that the increased promotion of voluntary modification methods of consumer behavior at the level of household consumers is a relatively recent concern at the European and national level, justified by the current geopolitical context.

The potential effects of the aforementioned constraints on the research results are reflected, first of all, in the size and structure of the sample, structured in such a way as to ensure maximum relevance in conditions where the level of awareness regarding EESS is proportional to the level of education, resulting in a prevalence of subjects with higher education. Secondly, the high degree of newness of public policies in the field of EESS has generated less availability of external data, such as policy documents, indicators on the use of EESS, or information on the degree of penetration of these technologies, which would have allowed a higher accuracy in the process of interpreting the results. Future research directions can aim to analyze the behavioral intention to adopt EESS under the impact of social influence from two perspectives: from the cost aspect, given that EESS technologies and those mainly based on AI involve relatively high acquisition costs, as well as from the point of view of perceived risk, as a potential reason for consumers' reluctance to adopt EESS is precisely the security and privacy risks.

Author Contributions: Conceptualization, M.M.C. and Ș.C.P.; methodology, M.M.C., Ș.C.P. and A.A.O.; software, Ș.C.P. and A.A.O.; validation, M.M.C.; formal analysis, M.M.C., Ș.C.P. and A.A.O.; investigation, M.M.C. and Ș.C.P.; data curation, Ș.C.P. and A.A.O.; writing—original draft preparation, M.M.C., Ș.C.P., A.A.O., C.F.P. and C.-B.N., writing—review and editing, M.M.C., Ș.C.P., A.A.O., C.F.P. and C.-B.N.; visualization, M.M.C.; supervision, M.M.C.; project administration, M.M.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was approved by the Ethics Committee of the Management Faculty, The Bucharest University of Economic Studies.

Informed Consent Statement: The survey participants were informed that the completion of the questionnaire is their informed consent and had the opportunity to agree or not to participate in the survey by ticking the appropriate option in a closed ended question.

Data Availability Statement: The data are not publicly available due to confidentiality reasons.

Acknowledgments: This study was partially conducted through the doctoral and post-doctoral advanced research programs in the field of management, Bucharest University of Economic Studies.

Conflicts of Interest: The authors declare no conflict of interest.

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