HOUSEHOLD ELECTRICITY CONSUMPTION ANALYSIS UNDER THE USE OF SMART GRID APPLICATIONS-A DEMAND-SIDE APPROACH

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ABSTRACT

HOUSEHOLD ELECTRICITY CONSUMPTION ANALYSIS UNDER THE USE OF SMART GRID APPLICATIONS - A DEMAND-SIDE APPROACH

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Electricity networks that incorporate information and communication technology into the grid are known as smart grids. They call for a change from the centralized, fossil fuel-based power systems that are currently in place to ones that can support decentralized production and consumption using a wider range of energy sources. Smart grid technologies can solve some problems of today’s energy world. However, this utility of smart grids can only be realized when there is a change in users’ behavior. This dissertation aims to understand how electricity consumption behavior and smart grid applications usage are linked with a habitual behavior approach. Apart from social norms and self-efficacy, a Habitual Behavior Framework used to test the effects of mainly awareness, attitude, intention on behavior over 703 respondents in Ankara. An Explanatory Factor Analysis, Structural Equation Modeling and Logistic Regression Analysis results revealed that awareness and attitude have significant effect on electricity consumption behavior with smart appliances usage. Besides, Logistic Regression results show us the main target groups in society to engage in a program to adopt smart grid applications at the demand side.

Keywords: Household Electricity Consumption Behavior, Habitual Behavior Framework, Smart Grid Applications

ÖZ

AKILLI ŞEBEKE UYGULAMALARININ KULLANIMI KAPSAMINDA EVSEL TÜKETİCİ ELEKTRİK TÜKETİMİNİN ANALİZİ-TALEP TARAFI YAKLAŞIMI

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Bilgi ve iletişim teknolojisini şebekeye dahil eden elektrik şebekeleri, akıllı şebekeler olarak bilinir. Akıllı şebeke uygulamaları günümüz konvansiyonel elektrik şebekeleri olan merkezi, fosil yakıta dayalı güç sistemlerinden, daha geniş bir enerji kaynağı yelpazesi kullanarak merkezi olmayan üretimi ve tüketimi destekleyebilen sistemlere geçişi kolaylaştırmaktadır (Nye ve diğerleri, 2010). Akıllı şebeke teknolojileri, günümüzün enerji dünyasının bazı sorunlarını çözebilir. Ancak akıllı şebekelerin bu faydası ancak kullanıcı davranışlarında bir değişiklik olduğunda gerçekleşebilir. Bu tez, elektrik tüketim davranışı ile akıllı şebeke uygulamalarının kullanımının alışılmış davranış çerçevesi ile nasıl bağlantılı olduğunu anlamayı amaçlamaktadır. Sosyal normlar ve öz yeterliliği dışarıda tutarak, Ankara'da 703 katılımcı üzerinde, esas olarak farkındalık, tutum, ve niyetin davranış üzerindeki etkilerini test etmek için bir Alışılmış Davranış Çerçevesi kullanılmıştır. Açıklayıcı Faktör Analizi, Yapısal Eşitlik Modellemesi ve Lojistik Regresyon Analizi sonuçları, farkındalık ve tutumun akıllı şebeke uygulamaları kullanımı ile elektrik tüketim davranışı üzerinde anlamlı bir etkiye sahip olduğunu ortaya koymuştur. Ayrıca, Lojistik Regresyon sonuçları, talep tarafında başlatılacak bir akıllı şebeke

uyum programını benimsemede toplumdaki ana hedef gruplarının hangileri olabileceğini göstermektedir.

Anahtar Kelimeler: Elektrikte Evsel Tüketici Davranışı, Alışılmış Davranış Çerçevesi, Akıllı Şebeke Uygulamaları

To my dad Muzaffer and my son Kadir …

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CHAPTER 1

CONCEPT OF ELECTRICITY CONSUMPTION BEHAVIOR

1.1 Introduction

Our lives have become easier because of the rapid industrialization process and technological developments. The increase in efficiency and employment in production significantly increased individual income and mass consumption. However, these developments also caused severe problems such as climate change, air, water, earth pollution, drought, and rapid exhaustion of natural resources (Wackernagel et al. 2002). For this reason, especially from the 1970s, the research on the relationship between consumer responsibility and behavior changes with social, economic, and ecological issues began to increase (Dursun et al., 2018).

The belief in enabling consumers to change their behaviors to be more budget-saving and environmentally friendly lays at the basis of the national and international policies to encourage and support responsible consumption behaviors (d’Astous-Legendre, 2009). According to Wells et al. (2011) study, consumers know about the economic and ecological damage because of the increasing population and total consumption. They also mentioned that they were concerned with this situation, and they accepted their responsibility partially for this issue. However, the same consumers could not change their attitudes towards the behaviors supporting and protecting the home budget and nature (Moraes et al., 2012). This is because responsible behaviors require time, paying additional fees, and endeavoring the loss of their comfort (Kollmuss and Agyeman, 2002).

Energy saving and efficiency are important pillars for decreasing the consumption of heating, water, and electricity to minimize the environmental effect and the share of the budget spent during the consumption (Peattie, 2010). As household energy consumption corresponds to 30% of the global consumption and the total consumption continuously increases (IEA, 2017), the contribution of individual energy saving and preferring electronic devices that increase energy efficiency is important. The term ‘habitual energy consumption behavior’ (also referred to as "daily energy-saving behavior") refers to the reduction and adjustment of specific behaviors, or changes to specific habits, which can directly reduce the use of energy. Examples include turning off the lights, using the air conditioner less frequently, or making the proper thermostat adjustments for the air conditioner (Wang et al., 2018). Smart grid applications (or smart grid in short) increase production, transmission, distribution, and individual energy consumption efficiency while saving energy through increasing consumer awareness, leading to more environmentally responsible and budget-friendly consumption behaviors. These behaviors include decreasing electricity consumption in daily life, investment for efficiency in energy saving, and activities that prevent more energy consumption (Sütterlin et al., 2011).

This thesis aims to analyze the factors that affect electricity consumption behavior using smart grid applications under a habitual behavior framework. The research question in this study is to determine which elements drive the link between electricity consumption and smart appliance usage. The goals of this dissertation can be listed as: to assess how several factors such as awareness, attitude and intention effect the role of consumer, at this link; to examine the effect of smart grid applications on electricity consumption behavior of households and to see whether the Turkish society is ready to accept the smart appliances in electricity consumption.

In this study, electricity consumption is considered habitual behavior rather than planned. To support this, the literature is scanned in this context, and a habitual behavior model is taken as a base model to investigate the relations between electricity consumption and the drivers leading to a behavior. A habitual behavior may format the factors defining the electricity consumption behavior since this type of behavior is also related to internal factors of habitual behavior.

This dissertation is one of the first studies to examine the smart appliance usage in the demand side of electricity consumption under a habitual behavioral context. It intends to contribute to scientific knowledge by exploring the factors linking electricity consumption and smart grid application usage in demand side in Turkish electricity market, specifically uncovering how people make their electricity consumption choices under a habitual behavior context. Besides, it unravels the consumer group that is more ready to adopt the smart applications into their electricity consumption behaviors in this market where smart grid applications are being introduced in recent years and aims to contribute to the design of the policies to be implemented under smart grid context. The findings filling the gap in consumer adaptation are helpful to achieve the goals in the latest study called Turkey Smart Grid 2023 Vision and Strategy Roadmap and expected to be used during smart grid transformation on the household consumption side.

This study consists of three chapters. This chapter analyzes the consumer's view of electricity consumption and the factors influencing the inherited consumption behavior. First, the electricity consumption behavior concept is evaluated. Moreover, factors that affect electricity consumption behavior and the impact of consumer behavior on electricity consumption are analyzed in a detailed way. Besides, the awareness concept, with its sub-elements: attitudes, social norms, and self-efficacy, is elaborated under the habitual behavior framework. In addition, the significance and features of habits are analyzed from an electricity consumption view. The initial step necessary to change the consumption habits of electricity is evaluated.

The second chapter introduces smart grid applications (smart grids in short). For this aim, smart grids, smart grids for electricity systems, components of the smart grids, the benefits of the smart grids for energy consumers, smart grid concepts and implementations in the world, and impacts of the smart systems on consumption behavior take place in this chapter. The issues of how smart systems can help change electricity consumption behavior are discussed.

Finally, the third chapter lays out the theoretical approach, introduces the proposed framework used for the hypothesis, and presents the methodology applied to find an answer to the research question of what the drivers of the link between smart grid usage and electricity consumption behavior are investigated. The analysis results are presented, and some policy implications are proposed.

1.2 The Concept of Energy Consumption Behavior

Different factors are related to energy consumption. These factors could be external such as air temperature and wind speed, internal or individual, such as individual history, behaviors, and preferences, or the ones related to the buildings as home ownership and proper heating tools (Andersen et al., 2009).

Behavior is mainly described as a way of adaptation of one’s between the demands of oneself, i.e., a healthier environment, and the properties of what served to, and interaction of all these factors at the same time (Keirstead, 2006). Stephenson et al. (2010) see behavior as the composition of interacted aspects related to technology, action, and demand. Devine-Wright et al. (2008) state that behavior is affected by costs, awareness, and moral obligation. Energy consuming behavior in some studies is defined as a human action including mental processes that affect how energy is utilized to get targeted service using energy-based technologies such as dishwashers, making house isolation, changing heating tools (IEA-DSM, 2015).

Different research also remarks on the importance of cultural norms, routine habits, social relation networks, and fashion, such as the lightening of housing, the mutual interaction of the people, and the technology in the socio-technical systems (Karahan, 2014). In this broad sense, Figure 1.1 gives us an overview of the different factors that contribute to electricity consumption from a consumer point of view. It illustrates main categories with subcategories that are crucial to understand the contribution of each to the final consumption decision in electricity (Subbiah et a, 2016).

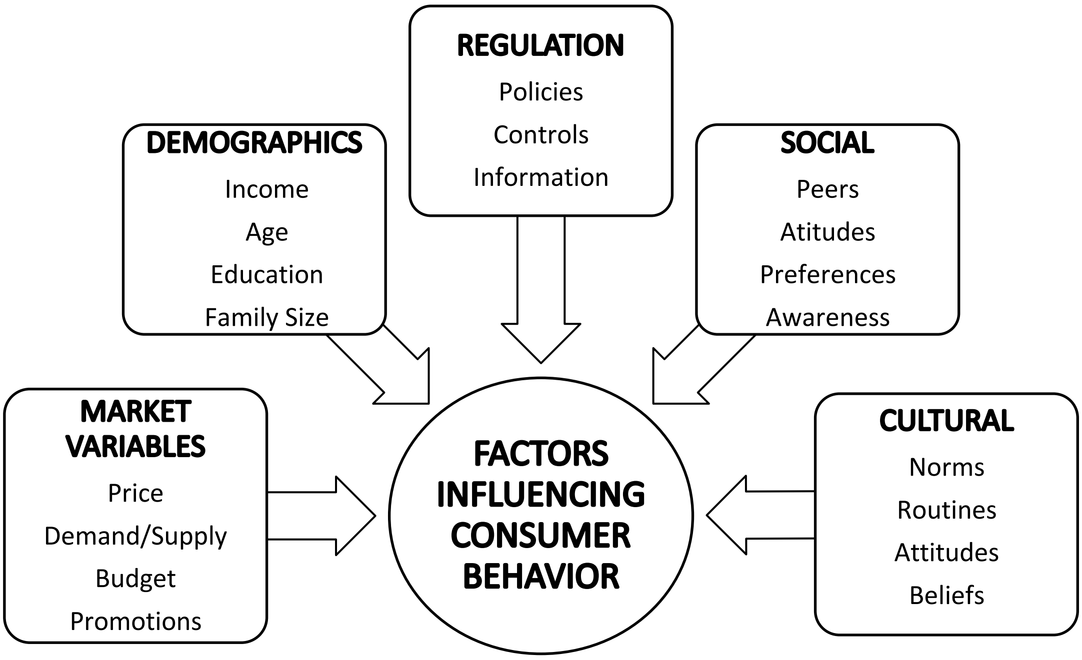

Figure 1.1 Factors Influencing Consumer Behavior (Subbiah et al, 2016)

Beyond any doubt, behavior is a multi-dimensional concept such that more internal, economic, technological, and psychological factors can be added and tested further. The habitual behavior framework tested in this study includes some of the subfactors in the figure above. These factors, such as attitudes, awareness, norms are detailed in the upcoming sections since these subfactors are main factors of our habitual behavior model.

1.3 Factors Affecting Energy Consumption Behavior

The climate-change era required many countries to reduce emissions, leading to more research on energy consumption. The studies from Europe and the US constitute the majority in this field. Although the research in countries such as Nigeria, China, and Kuwait take place in the international literature, they are few. The studies on behavioral aspects of household energy consumption in Turkey are also few and mainly focus on architectural design and building specifications. In the resources that evaluate the relationship between housing, energy consumption, and consumer behavior, some studies analyze consumer behavior, and the ones that focus on housing energy consumption (Karahan, 2014).

Fabi et al. (2012) divide the factors that affect consumer behavior into five categories as physical environmental factors (air temperature, moisture, wind speed, noise level, light level, and scent), contextual factors (building insulation that has indirect effects on humans, orientation, heating system, and thermostat), physical factors (age, gender, health situation, clothing, mobility level, and buying provisions), psychological factors (meeting the thermal, visual, and auditory comfort, health, and security requirements, awareness for the situations as finance and environment, cognitive resources such as information, habits, way of life, and perception), and social factors (relations between the consumers and the feature of the household). On the other hand, Wei et al. (2014) classifies these factors as environmental factors (climate, interior moisture level), housing-originated ones (building type, largeness, heating system, and fuel type), consumer-based ones (age of the consumer, gender, education level, size of the household, income, previous housing type, house ownership, health) and others (time, awareness, heating prices).

In their study, Gill et al. (2010) used a qualitative research method to explain the factors that impacted energy behavior in the United Kingdom. They categorized the factors as non-technical, human, and building-based ones. Similarly, Langevin et al. (2013) defined the factors as building type, bills, environmental situation (air temperature, moisture, and air quality), environmental satisfaction, consumer features, adaptation to the environment conditions, information, and behavior pattern in their study that evaluated energy behaviors of the households in the United States. In this context, they conducted interviews with 50 people having low incomes. Rijal et al. (2007) emphasized the impacts of the air temperature, season, hour, frequency of opening window, and design on the behavior in their study. When evaluating the research above, it seems that many physical and psychological factors as a way of life, preferences, behavior pattern, individual past, and features of the household, environment, building, and other factors, could affect the energy behaviors of consumers.

1.3.1 Consumer-based Factors

Linden et al. (2006) connected the differences in energy consumption in similar residences with consumer use. The features of households, such as lifestyle, choices, comfort perception, and individual experience, could determine consumer behavior patterns (Andersen et al., 2009). A study in Japan claimed that when consumers used heating systems, individual factors were influential for their behaviors rather than external impacts (Schweiker and Shukuya, 2009). In a study in Denmark, it was shown that heating of internal place behavior was affected by factors such as gender, homeownership, and perception as well as other ones (Andersen et al., 2009).

There was a relationship between the features of socio-economy, demography, and energy consumption (Sardianou, 2007; Steemers and Yun, 2009). Santamouris et al. (2007) showed that income was one of the most important decisive factors for the residences' size, age, kind, quality, and equipment. Therefore, it had a direct relationship with energy consumption. As the residents having old age prefer warmer internal places, there is a close relationship between age and energy consumption (Guerra-Santin and Itard, 2010). Similarly, the children choose warmer places (Raaij and Verhallen, 1983). According to a survey by Karjalainen (2007) in which 3094 persons participated, there was a connection between the consumer gender and internal place warmth, the women liked to be in warmer places, and the men changed temperature control often. On the other hand, Abrahamse et al. (2005) found no specific relation between age and gender in energy consumption.

Guerra-Santin (2011) claimed that the features of households, experience, motivation, values, behavior, and characteristics affected energy behavior. Culture, ethnicity, education level, and energy consumption were searched in many studies. It was observed that households maintained their energy habits from their previous residences in the new ones (Abrahamse et al., 2009). On the other hand, Sardianou (2008) mentioned that age, the size of the household, annual income, residence size, and home ownership were influential on energy consumption. And Burney (1995) stated that income was the most influential factor for electricity consumption.

Despite there was a specific relation found between the demographic variables, such as the size of household, income, and energy consumption, there was no similar relation between these variables and energy saving found. Individuals having different environmental concerns have different energy-saving measures. Older people, singles, and low-income people behave unwillingly to implement energy-saving measures. Habits, lack of information, and comfort perception create bans for behaviors (Huebner et al., 2013). In the study of Vringer and Blok (2007), the impacts of values, motivation, and weather change perceptions of different Dutch families for energy consumption were evaluated. Although there were no differences in energy consumption between households with different value patterns, it was determined that the households unwilling to save energy consumed 4% more energy.

It was stated that energy behavior was not different in many households, and it intertwined with hobbies, homework, and childcare. According to the surveys in Holland with 145 households, five different energy behavior patterns were determined. And in the result of the study, it was seen that the household's lifestyle affected energy behaviors (Raaij and Verhallen, 1983).

Steemers and Yun (2004) state that the frequency of ventilation devices caused to 47% variance in the electricity used to cool down. On the other hand, Gill et al. (2009) mentioned that the high number of electricity devices was very influential in electricity consumption. User behaviors such as leaving the lighting elements on, using electricity devices excessively, and leaving devices on increased electricity consumption. The kinds of behavior such as the internal temperature, levels of lightening, loaded or semi-loaded usage of washing machine and dishwasher, shower habits, willingness or unwillingness are related to energy and electricity consumption.

As seen above, the factors such as building specifications, household features, climate and weather conditions, and time influence energy behavior. While external features such as building structure and climate conditions affect energy consumption, it changes mostly according to household behaviors. Even when many features are constant, there are different energy consumption patterns because of the features and habits of the consumers. The users living in cold climate conditions and/or buildings with insufficient insulation prefer higher temperatures and heating systems that significantly cause higher energy consumption. The ones that live in large residences and have more rooms tend to heat more spaces and consume more electricity (Karahan, 2014).

1.4 The Impact of Consumer Behavior on Energy Consumption

Consumer-based factors alter energy consumption, but what is the degree of it? One of the methods for measuring consumer effect on energy is comparing the energy consumption of two similar residences. There are different studies on this issue beginning in the 1970s. For example, in the Socolow (1978) study, the energy consumption difference could be 71% between two residents using the same house. This situation indicates the diversity of the user consumption pattern. And according to Guerra Santin (2010), it was seen that 12% of the differences in energy consumption stemmed from diversity in energy behaviors. It was also stated that when there was an increase in the frequency of using energy-saving lightbulbs, its relationship with energy consumption became more specific. Gill et al. (2010) stated in their study for searching the effect of energy behavior on energy consumption that there were 51%, 37%, and 11% variations for heating, electricity, and water consumption, respectively. Chen et al. (2013) mentioned that the 28,8% variations in energy consumption for heating and cooling in China were due to the socio-economy and behavioral differences. And Burney (1995) stated in his study, including 93 countries, that income was the most important factor for electricity consumption.

To sum up, the consumer's behaviors play a key role in energy consumption. With this outcome stated up to now, there becomes a question: what are the individual elements of energy consumption behavior? The next parts analyze this issue.

1.4.1 Awareness of Energy Consumption

According to Kollmus and Agyeman (2002), awareness of energy consumption has two pillars: knowing the issue and taking affective behaviors towards these issues through emotional participation. In other words, awareness shows itself as having information and approaching energy consumption in an informed and sensitive way while taking required actions for efficient social, economic, and environmental results.

Awareness of energy consumption is required for personal and pro-environmental attitudes. Policies and implementations could have negative implications focused on increasing energy awareness and its positive sides. For instance, preferring renewable energy sources such as hydropower or wind power to coal may be crucial to fighting against global warming, which is one of the most important features of climate change. However, this choice could also bring new problems, such as the migration of residents from their towns due to dam building (Arias et al., 2014). However, the positive sides of creating and/or increasing awareness outnumber the possible negative sides. First, awareness in this area is appropriate for a more sustainable global lifestyle. Second, awareness directly affects personal incentives. Ziadat (2010) claims that the degree of awareness of individuals helps people to develop the required behaviors and attitudes. People who are conscious of the budget they consume for energy tend to behave more economically, creating personal incentives for themselves. Higher awareness of energy issues also means more positive attitudes toward the environment (Saricam and Sahin, 2015).

Third, there is a connection between sound behavior in energy and individual awareness (Deci and Ryan, 1985). Awareness is necessary for the “internalization of a particular behavior” to become an essential trigger for building a behavior (Schultz and Ryan, 2015). Therefore, there is a close relationship between sound energy behaviors and awareness of energy consumption issues.

Finally, awareness is crucial in formation of pro-environmental behavior (Filho et al., 2010). Different research mentions the contribution of awareness for pro-environmental behavior (Brounen et al., 2013). According to research by Zsoka et al. (2013), college students having high awareness of energy issues wanted to pay more for environmentally friendly products. The same study also stated that college students were more aware of the relationship between environmental subjects and consumption than high school students and had higher pro-environmental behaviors. In the research of Brounen et al. (2013), the householders aware of energy consumption were using less gas than others.

Nevertheless, different studies, such as Csutora (2012), claimed no direct relation between awareness and pro-environmental behaviors. Other studies expressed the importance of personal experience for awareness and pro-environmental behavior. Due to this approach, direct experience has a significant effect on these behaviors (Korhonen and Lappalainen, 2004). Thus, awareness that was an outcome of personal experience could play a key role in pro-environmental behavior (Chawla, 1998). In this framework, the individuals who faced environmental problems or were involved in these issues would have a higher awareness level. Three individual elements are linked to awareness in our framework: attitudes, social norms, and self-efficacy.

1.4.2 Attitudes

According to Schultz et al. (2004), attitude means the extent to which a person favors or disfavors an action based on the comparison of numerous rewards and costs, such as financial benefits, work, or time. Regarding energy consumption, it states the favorability degree that an individual holds for energy issues. In other words, a household that has a positive attitude toward energy issues supports energy saving and wants to endeavor to spend their own time on this. On the other hand, an individual having a negative attitude does not want to make such an effort. Therefore, energy saving is a certain behavior kind (Çakır Yıldırım, 2017).

The studies have mentioned that attitudes have been generally referred to for evaluating pro-environmental behaviors (Wells et al., 2016). According to these studies, there is a relationship between pro-environmental intentions and behaviors (values, attitudes, and beliefs) with positive mentality and attitudes (Abrahamse and Steg, 2011). There is also a connection between energy consumption and saving. For solving energy consumption problems, the use of technology is not sufficient only. Rather, attitudes and behaviors play key roles in the issue at the same time (Kollmuss and Agyeman, 2002). Nair et al. (2010) stated that positive pro-environmental behavior cannot decrease energy consumption directly. Some researchers argued that it could not also give the expected results with the awareness of renewable energy and climate change. And continuous changes in attitudes and behaviors toward energy saving will be effective when the costs (money, time, effort) minimize instead of aiming the social benefit (Abrahamse and Steg, 2011). On the other hand, Wells et al. (2016) claimed that attitudes closely related to a definite environmental behavior will be effective on the behaviors either at home or in workplaces.

Attitudes are evidenced to be more related to pro-environmental behavior. Therefore, the consumer should know the actions cause environmental damage. In our context, the consumer should know that electricity consumption may harm the environment, and smart grid application usage may reduce this harm.

1.4.3 Social Norms

The social norms approach deals with values and changing behaviors based on normative information. This approach could be used in impacting different behaviors as pro-environmental behavior. Social norms could effectively decrease household energy consumption through energy-saving behavior (Harries et al., 2013).

According to Nolan et al. (2008), social norms influence 10% of household energy savings. Allcott (2011) also showed a 2% saving in this consumption through social norms. Nevertheless, it is not always possible to make a difference between the social norms and other factors for determining the real impact on energy saving (Harries et al., 2013).

Information obtained from the behaviors and anticipations of other users could provide proper approaches for the impact of social norms on smart grid decisions. For this purpose, the simulation developed in Li's thesis (2016) showed a clear increase of 53% in the supporting group after social norms passed networks. In daily life, people make decisions based on the features of smart grids in terms of cost, infrastructure, and technology. However, the impact of the social norm campaigns could increase participating in the proper reference groups. The individuals could also inform their relatives and friends to participate in the social networks related to the issue.

According to Jackson (2005), values are considered higher-level social constructs than beliefs or attitudes. Some writers claim that people have different values, from 'egoistic' to 'altruistic,' from 'conservative' to 'open-minded,' from 'bio-centric' to 'anthropocentric' (Barr, 2007). In the context of environmental behavior, the value-belief-norm model of Stern (2000) includes high level values related to beliefs about the relations between humans and nature. Bio-centric and altruistic values are in line with the ecological point of view. This approach positively influences environmental issues because it has a moral obligation that reflects itself as pro-environmental behavior. On the other hand, egoistic values, as seen in different fields, have negative aspects that prevent from having required human responsibility for environmental issues.

Hargreaves (2008) mentioned that these values were built up from a societal perspective rather than an individual one. However, endeavors try to change the values maintained depending on information planning and moral persuasion or training for personal consumption (Wilson and Dowlatabadi, 2007) instead of directing the society depending on the normative essence for more 'altruistic and reflexive environmentalism' (Jackson 2009).

Harland et al. (1999) claimed that if individuals consider that their behaviors were perceived positively by others, they tend more to behave in that way. Thus, subjective norms become social norms handled as usual or legitimate in a social context. Therefore, social norms could be important factors for pro-environmental behaviors (Evans, 2007). In other words, individuals tend to participate in decreasing energy consumption practices if they take place in a group that considers these behaviors normal. If turning off the lights is normal at work, then people tend to behave this way. A person's capability for considering these kinds of social norms is important for their perception and acceptance in the group as social ones.

Fischer (2008) stated that normative feedback, that is comparing energy consumption of one household with another one, as contrary to informative feedback, that is supplying information about energy consumption for households, could be more beneficial and effective as the former can trigger a social norm and thus a change in behavior. Nevertheless, there are different experimental findings for this issue. Darby (2010) mentioned that normative feedback promoted saving in energy consumption. Some others, such as Nolan et al. (2008), claimed that the effect was 'under-detected.' And the rest suggested that the research using normative feedback might influence consumption (Fischer, 2008).

On the other hand, there is a common acceptance that social norms are evaluated as suitable behavior forms in a class (Jackson, 2005). Adopting an individual's behavior to the norm could positively or negatively affect their energy use. Thus, Fischer (2008) stated that the households that consumed low energy might increase their energy use when comparative feedback mentioned that their usage was under the norm. Therefore, social norms could be effective in different ways as *pro*, *anti*, and *neutral* for environmental issues. Besides, norms are closely related to the degree of social consciousness (Davodi, 2014). Lorenzoni et al. (2007) evaluated that there was an important ban for endorsing pro-environmental behaviors in the UK due to a common understanding of 'abnormality and undesirability' for low consumption that results in green living.

1.4.4 Self-efficacy

Self-efficacy has two pillars: outcome expectancy, the conviction that one's actions have consequences and efficacy expectation, the conviction that one can achieve a particular behavior (Bandura, 1977). Bandura (1986) mentioned that a person's ability to execute specific behavior identifies their self-efficacy for this behavior.

It is stated that when two persons want to learn how to ski, it is mostly probable that the one who is aware of their ability will achieve it (Ajzen, 1991). Abrahamse and Steg (2011) showed that consumers tend to have more energy-saving behavior if they become aware of its negative environmental effects. Tobler et al. (2012) stated that there was a connection between self-efficacy and knowledge. According to this approach, when individuals have information about climate change and its consequences, they could be more active in climate conservation. So, it can be inferred that there is a link between self-efficacy and awareness.

Decisions and behaviors are heavily influenced by internal elements, such as one's own inspirations or acts, which are determined by self-efficacy, values, and attitude. Furthermore, a low level of self-efficacy means that an individual's choices and activities are mostly affected by external factors that are out of control of the person (Vining and Ebreo, 2002). For energy issues, it means that external factors will be influential in having a specific energy behavior or changing it rather than internal, individual factors such as self-efficacy and values.

1.5 The Significance of Habits for Energy Consumption

Different studies elaborate on the significance of habits for energy consumption. The studies of the Brussels Energy Challenge present evidence that habits were important for domestic energy consumption. Jackson (2005) defined three conditions: a low degree of involvement, low perceived complexity, and a high degree of constraint for having automaticity in behaviors such as turning off the lights or appliances from cognitive practices to achieve balance in the decision-making process.

Daily energy-based behaviors do not necessitate much intended effort as seen in other cases, such as the study of adolescents' food consumption (Kremers et al., (2007). This is confirmed by different studies that evaluate domestic energy consumption, such that habits can be barriers for environmentally friendly behavior to exist and cause someone to act contrary to their intentions without even realizing it (Martiskaïnen, 2008).

On the other hand, the scholars approach the energy from the point of mobility: 'highly ritualized forms of behavior that are hardly reflected upon in everyday life' (Schäfer and Bamberg, 2008). This mentions that there is still an empirical gap that relates the significance of habits with domestic energy consumption.

Some issues might stem from the paralyzed feature of habits that leads people to undervalue the significance of habits as a problem. At this point, self-report can play a role in evaluating the strengths of habits (Danner et al., 2008). Then, it is important to present a response to this issue for the ones that seem inappropriate to inquire about the strength in someone's habit when an important aspect of habit is its unconscious nature (Klockner et al., 2003). Regarding this matter, two elements are crucial. First, the fundamental characteristic of habits is their automatic nature but not their unconscious nature. Additionally, lack of awareness is just one of the features of automaticity for a process to be evaluated as a habit (Maréchal, 2009). Second, as Chatrand (2005) mentioned, it will be useful to establish an explicit differentiation between the diverse phases where awareness can work: the environmental clues that can impact the behavior and the product of this behavior. Dijksterhuis and Smith (2005) stated that consumers are generally aware of the outcome and sometimes aware of the clues, but most of the time, unaware of the behavior in question. As a result, it can be inferred that the consumers are aware of their practices in a broader perspective rather than behavioral details.

While consumers don't deal with many automatic and implicit processes, they can report the existence of some of them. It could be defined as comprehensive awareness. Therefore, the individuals are aware of the habits even though they do not completely know about the factors behind or drivers of them during practicing the habitual behavior. The broad awareness has a diverse aspect of habits than complete automatic behaviors as reflexes (Marechal, 2009). As mentioned in the study of Dijksterhuis et al. (2005), consumers could choose many products as a fleeting moment of awareness' without any memory of acting this way. However, after their practice, they could also comprehend that they were not considering these choices when they made them (Verplanken and Orbell, 2003).

Moreover, informing people about their habits could be the first stage for getting knowledge back from practical to discursive awareness. This will be important for changing habits (Bartiaux, 2008). This is crucial because repetition gradually trains cognitive processors in procedural memory, which is how habits are formed (Neal et al., 2006). Getting information from practical to discursive memory might be regarded as a back step as the discursive phase, as cognitively evaluating information in memory, is the initial phase of habit forming that comes to be the procedural phase (Jager, 2003).

1.5.1 Initial Step for Changing Energy Consumption Habits

Though the habits could be firm for determining how to deal with the intentions during behaviors, their contextually specific automaticity features can present different ways for change. The automatic feature of habits partially mentions their preponderance for more purposeful thinking as coming to mind lately, and the dependency of habits on circumstantial clues presents a significant indicator of vulnerability (Verplanken and Wood, 2006).

Stability in context is required for the progress of habits with repetition (Danner et al., 2008). This causes the suggestion of many habit researchers that the changing conditions related to habit forming could be easy to change a habit (Verplanken and Wood, 2006). From this point of view, different research mentioned that there is a right proportion between the sensitivity of daily habits changing with the stages of changing conditions such as relocation and the birth of a baby (Schäfer and Bamberg, 2008). On the other hand, these usual changes do not have an automatic or direct feature; rather, they present channels for chance. From this point, they have been studied for their interaction with an integral measure. This is the situation that Verplanken and Wood (2006) define as ‘downstream-plus-context-change interventions. Different studies elaborated on the efficiency of connecting providable measures to delicate cases or situation changes such as temporary freeway closing (Verplanken et al., 2008).

Physical location is a significant environmental clue for disseminating habits for domestic energy consumption. Incentives for developing energy effectiveness could be key when backing information was provided, especially for the new residents. Therefore, changing a location could facilitate changing domestic energy habits (Maréchal, 2009).

1.5.2 Features of Habits for Energy Consumption

The influence of habits should be considered in developing efficiency measures for domestic energy consumption. In addition to habitual factors, different technical, and societal causes play important role in energy consumption. In line with this, houses built without technological standards and energy-inefficient buildings matter for high energy consumption (Martiskaïnen, 2007). However, habits become important here, that this help to explain the differences in energy consumption among households that live in similar situations (Gram-Hanssen, 2008). In this context, stand-by consumption is a proper sample for the relationship between habits and technological developments. Designing measures is significant for changing domestic energy consumption habits. Interferences at the micro level are important as the ones at the macro level as “an exogenous increase in energy efficiency may not lead to lower energy consumption” because of the stable energy consumption habits (Brännlund et al., 2007).

For explaining the success of different implementations, habits have a key role. Implementation of feedback and social commitment measures on decreasing energy consumption was studied in different research, as in Darby (2006). When the habits point of view is elaborated, it is seen that the efficiency of these two measures (feedback and social influences) relates to two important factors of habit enforcement: skewed data and indefinite long-term benefits linked to the optional behavior as making in comparison with habits. Feedback is used for informing and motivating via raising visibility (Fischer, 2007); meantime, commitment plans develop self-satisfaction brought about by living up to one's values and thus raises the price of inaction (Matthies et al., 2006).

According to Martiskaïnen (2007), the features of efficient measures for decreasing energy consumption should be:

- Clear and simple
- Related to the customer.
- Having a commitment and being goal oriented.
- Visible and
- Stable and constant.

These measures depend on the features of habits. Feedback also could be added to these features. When looking at the subject in a general way, it is seen that universal sizing does not suit every customer and efficient changes should be adopted to the features of the targeted group as norms, motives, and consuming figures (Maréchal, 2009).

Besides these features, habits also change due to mobility. More mobile groups as military staff and students have different energy consumption habits than those living in their residences for a long time (McMakin et al., 2002). Therefore, effective implementations should be regarded according to the features of living conditions of the target groups. Veblen evaluated this more than a century ago, mentioning that different people acquire different habits with varying degrees of ease and give up habits with differing degrees of reluctance. From this point, choosing a combination of action plans could be more beneficial than implementing one action plan (Abrahamse et al., 2005).

To understand energy consumption behaviors, this chapter elaborated on internal factors (attitudes, social norms, values, self-efficacy, and habits). On the other hand, personal features such as age and income also affect energy behaviors. By affecting these features an individual can behave as a pro-environmental consumer implementing energy-saving practices. The smart grid concept emerges as a proper implementation tool that influences such energy behaviors on the demand side, which will be evaluated in the next chapter.

CHAPTER 2

EFFECTS OF SMART GRIDS ON THE BEHAVIOR OF ELECTRICITY CONSUMERS

Access to electricity in a wide range of fields has been very significant for the foundations and developments of current technology. Through the availability of electricity, mankind can introduce new technological devices and vehicles, from computers to spacecraft. In this context, the smart grid is not only an outcome of these technological developments, but it is also a required apparat for energy consumption behavior aiming to reduce bills, increase the consumer's well-being, and save energy.

Smart grid applications are new power network devices based on information and communication technologies. They help generate, distribute, and consume electricity through a more convenient (in terms of economy, saving, security, effectiveness, and sustainability) way. On the other hand, a smart grid system also includes automatic repairing, checking, remote measuring, automatic adjustment and especially responding against the cyber-attacks, providing distributed generation, and storing. In other words, these devices have the features of effectiveness, consumer oriented, pro-environment, and durability (İlisulu et al., 2020).

Smart grids, as a new technological instrument, might impact on changing energy consumption behaviors. As seen in many situations, this system has enablers and barriers from the social acceptance perspective. In the enablers side, more definite, pro-environmental factors and energy independency take place. In the barriers part, vague information about this system, the concerns about the health and security can be seen. This study analyses the contribution of the smart grids for its users.

2.1 Introduction to Smart Grids

Guy (2006) defines smart grid as a socio-technical network characterized by the active management of both information and energy flows, to control practices of distributed generation, storage, consumption, and flexible demand. Following this socio-technical perspective, such infrastructure systems should be seen as combinations of certain technical elements and of elements and characteristics that are needed to make the technology active. Smart grid is also a kind of energy management system that has efficient information and communication technologies. This system is influential in the whole structure from generating to consuming energy. These devices can provide real time monitoring and control mechanisms in all the energy system that includes generation, transmission, and distribution for the behalf of the consumer side. Developed algorithmic structures in these devices enable detecting the problems in the grids more rapidly with higher accuracy. Moreover, with the self-betterment in these devices, manual maintenance operations having malfunction and interrupt are minimized. For controlling and operation, these devices provide a more formable structure through consisting of renewable energy sources(Karaman, 2020). Nevertheless, use of energy storing systems with smart grids improves this feature. Following table shows the differences between the traditional and smart grid systems.

Table 2.1 Conventional Electricity Grid vs Smart Grid (Kıral, 2014)

Characteristics	**Conventional Grid**	**Smart Grid**
Operation of Grid	Electronic and mechanical	Digital
Communication	One Direction	Two Directions
Production	Centered	Distributed
Sensors Implemented	Limited	Advanced
Maintenance	Misfunction and/or disruption based, manual	Automatic detection of disruption, self-healing
Feedback	Limited	Self-auditing system
Consumer Interaction	Limited	Advanced

2.2 The Effects of Smart Grid on the Electricity Network

Smart grids affect electricity system by means such as:

- Enabling direct interaction between the supplier, consumer, and producer.
- Users having the control on the time and amount of the electricity consumed.
- Providing a secure and effective system.
- Reduction in the system costs.
- Providing supply security as well as a continuous and qualified service.

Besides these impacts, smart grids also have different implementations such as:

- Distributed Generation: This implementation enables the integration of domestic generation to generators with high power in the smart grid system.
- Distributed Storage: This implementation provides a surplus of electrical energy in the storage points in the distributed system. Furthermore, if necessary, this implementation puts this surplus into use.
- Demand Side Management: This implementation helps efficient management of the consumer-producer balance and electricity pricing. These implementations also include points for embedded generation with storing possibilities in the grid (Akçin et al., 2013).

Distributed generation in the network has different advantages in an interruption such that these points provide electricity for the users. In different countries including those in Europe and America, the old-fashioned grid systems have been improving through these points. However, some issues may occur in the process of integrating these points to the grids. These are:

- Two-way electricity flow can cause difficulty for reactive power control.
- Changeable active and reactive power can result in undesirable voltage fluctuations.

- The effects of short circuit currents might worsen depending on how the grid's transformation connections are connected, and the criterion for selecting relays can alter over time.
- The current generated by a short circuit may have an impact on the current grid elements' thermal endurance capacities.
- The amount of harmonic and flicker creation might not be within the permitted range.
- System stability cannot be within the value limit in scenarios like switching and quick activation (Tanrıöven, 2011).

Monitoring the grid, reading through automatic meters, and utilizing energy distribution and management implementations start with combining the smart grid implementations and power systems.

Moreover, electricity quality, energy efficiency and energy security instruments can be provided by making use of the structure of these combined systems and the analysis of the results of the continuous information from the smart grid. Therefore, different problems for the grids as loss and leakage percent and disconnection delay, can be reduced within the standard boundaries and increase of supply quality can be achieved (Demirkol, 2019).

2.3 The Constituents of Smart Grids

The constituents of smart grids include improved control techniques, integrated communication, smart meters, smart stations, smart distribution, and smart generation.

2.3.1 Smart Generation

Smart generation is described as the network-based integration providing momentary information flow from the generation points in the system. Different information from the grid such as energy generation optimization and automatic arrangement for frequency, power, and voltage can be achieved by the feedback provided from the points. It also sets up causal relationship in particular situations and can be used as a tool for administration and planning. Smart generation facilitates sensor-based data factors as real time simulation, modelling, and analysis. When necessary, the key people in the system can access these data properly in the design, engineering, planning, and generation phases.

2.3.2 Smart Stations

Smart stations serve to control the factors in the system, such as power factor performance, interrupter, and control of both critical and noncritical operations.

2.3.3 Smart Distribution

Smart distribution serves as a stabilizer and optimizer for self-improvement. The system can detect malfunctions via automatic and analyzing structures. It can also provide estimations about the weather (Eldem, 2017).

2.3.4 Smart Meters

Smart meters provide real-time information for payment data through two-way communication using devices like general packet radio service, and power line communication. Smart meters can convey data about electricity cut, power quality, and consumption. More measurement and control mean easier energy consumption management such that something measured can be managed more effectively. Smart meters take place at the heart of smart grid by providing data about energy consumption tendencies and the balance between supply and demand and conveying this information to the distribution companies.

2.3.5 Integrated Communication

The systems for data collection, protection, and control present an integration among the smart devices and consumers within a communication system. The players of the grid will make us of the communication gains by a generator-consumer matching software in the next step. Quality of service-based systems are generally used in smart grid implementations.

2.3.6 Advanced Control Methods

Advanced control methods identify the algorithms and devices that define and estimate the grid via evaluating. Advanced control methods are inhibitory tools to decrease negative effects of power cuts with the help of automatically correcting precautions. Smart grids consist of software and hardware elements. About the percentage of cooling and heating in the household energy consumption, 70%, it is an unquestionable fact that smart devices are required because of their features as being dynamically adopted, programmed, and their contribution to the household energy consuming behaviors. On the other hand, internet-based systems and data infrastructure can be samples for hardware (Eldem, 2017).

2.4 The Advantages of Smart Grids for Consumers of Energy

Using smart grids do not only provide direct benefits as decreasing of costs for the energy consumers, but this also helps develop pro-environmental and energy conservation behaviors of the consumers. These benefits are:

- Consumers can have lower electricity consumption costs and make more saving via having access to consumption data in a detailed way.
- Tariffication will develop and there will be reductions in the voices because of the competition of the energy suppliers through hourly consumption data.

- Changing supplier process and shifting to more profitable tariffs will become easier for the consumers.
- The users enable reduction in the energy costs by consuming electricity in cheaper times.
- Because of being a player in the energy market, the consumers can increase their gains by charge transfers in peak times stemming from the agreements.
- Reduction in the operational costs of distributors and supply countries results in the discounts for different tariffs.
- Efficiency and advances in different fields as interruption management, technical and commercial quality, meter operations, and services having value added will affect customer satisfaction positively.
- User participation will lead to energy saving and thus, effectiveness in the implementations will be provided.
- The users will choose more suitable tariffs in terms of energy costs by benefiting from consumption data.
- Because of the pro-environmental and energy conservation practices through this smart system, the goals of the Kyoto Protocol can be realized more easily.
- Peak moment usages will reduce, and this will result in inhibiting energy investments having high costs.
- Advanced effectiveness of smart grid system and increased competition in the energy market will provide implementation of new technology electrical devices for a smart house. Therefore, the related investments will be facilitated and become cheaper (Deloitte, 2015).

As seen in this part, the advantages of smart grids are mainly about decreasing costs of energy consumed (this contributes to the income of the consumers at the same time), increasing efficiency, and pro-environmental favors. In this line, the next part will be about the approaches and implementations of smart grid systems by different countries.

2.5 Smart Grid Implementations in the World

Much research has aimed to progress the smart system in many countries. Particularly, the United States (US) and the European Union (EU) and are pioneering in this field. Different implementations in various countries take place.

2.5.1 Europe

EU (European Commission, 2016) established the features of smart grids as:

Flexibility: While smart grids meet the consumers' demand, they should be able to adopt to the changes properly.

Accessibility: The consumers should get connection in the system.

Reliability: Smart grids should have supply security, advanced quality, and handle with unexpected situations.

Economy: This system should present an efficient energy management and field renewal for the users.

Similarly, it was also mentioned that this system should have the characteristics below: (Hamilton et al., 2010):

Effectiveness: This system must be able to have the distribution and transmission losses at the minimum level. At the same time, this system should provide effective power generation and price control.

Security: This structure should not be harmful both for the public and grid workers. It should also regard for the different health issues of the consumers in a sensitive way.

Swift recovery: This system should have swift recovery mechanisms for different developments as natural disasters and cyber-attacks.

Pro-environmental: Advanced effectiveness in this system should result in decreasing CO_2 emission via consisting of renewable sources in the structure more.

EU established a future vision about grid system around features listed above and set European Union Smart Grids Technology Platforms (EUSGTP). Using cleaner energy resources, increasing effectiveness in the sector, developing new procedures, products, and services, and enhancing competition power of EU globally appear in this vision. It is mentioned that smart grids are to have a key role for the Union in terms of economy and environmental issues in this vision. Based on 20-20-20 target of EU (the energy produced through renewable resources accounts for 20% of total energy produced, the reduction in CO_2 emissions is 20% and the increase in energy effectiveness is 20%), the candidate countries including the member states of EU started to set up necessary understructure activities for the smart grid system to accomplish and realize this target. Spain, England, Norway, Malta, France, Holland, Italy, and Sweden are the countries which had obligatory legislation for operational plot programs and smart meters. Even though there are some countries as Czech Republic, Slovenia and Germany which did not have a legislative obligation, various distribution companies began to shift from traditional meters to the smart ones. There were approximately 5.5 billion investments in Euros for about 300 smart grid projects in Europe in the beginning of 2010's. By 2013, nearly 10% households had smart meters and by 2020, In all of Europe, it was targeted that the number of active smart meters would be up to 240 million (Kırmızıoğlu, 2013).

2.5.1.1 Telegestore Project in Italy (2000-2005)

Telegestore Project was implemented between 2000 and 2005 in Italy. Smart meter integration into the smart system, the ability of measuring sensitively, data management, and communication specifications were some samples of various instruments of this project. This was the first practice for a smart grid in the world.

There were different expenses including advancements of IT systems, enhancing of grid structure, and montaging and production of concentrators and smart meters and the amount of these costs were 2.1 billion Euros. Despite of high costs, there were different benefits of this project as probability of remote control, accuracy, and sensitiveness in the billing, establishing consumption amount measurement in a better way, favoring from different opportunities, reduction in the technical and nontechnical losses, covering the investment costs in 5 years, decrease in carbon emission (Rogai, 2007).

In the context of the project, the number of smart meters that replaced traditional ones was 27 million. Besides, there were 350 thousand concentrators that were used. Implementation of meters that were multiphase and able to transfer electrical power obtained from renewable energy resources to the network and provide a two-way communication were realized after 2006. In this project, approximately 700 thousand consumers participated. Communication technologies such as concentrator-based GSM (global system for mobile communications), LV (low voltage), PSTN (public switched telephone network) and GPRS (general packet radio service) were also implemented.

Telegestore project provided changing of energy demand and power automatically and various tariffs in different periods (daily, weekly, monthly and seasonal). Additionally, this project accomplished authorization, remote energy opening and cutting, mitigating loss and leak, active-reactive energy measurement, data management for each subscriber, balancing each transformator, creating a power profile and storing capacity, producing real-time consumption data, and communicating energy consumption values to the users. (Rogai, 2007).

2.5.1.2 Enemalta Project of Malta (2008-2013)

All meters in water and electricity network were replaced with smart ones in five years' time by Enemalta Project. Thus, with this project, Malta became the first country with smart grid in the world. The underground waters are very crucial for Malta as the country does not have any lake or river. On the other hand, petrol import also plays a key role for desalination system of Malta. This system covers all energy production and half of the water supply of Malta. Therefore, Malta uses high energy amounts. And electricity and water systems are handled with together. Malta supplied a smart system for the people to decide about how and when they consume electricity and water and started production of the energy from pro-environmental, clean, and natural resources rather than petrol and its products by this project. Through integrating energy and water systems, smart grid project supplied the inhibition of the water leaks and energy losses. This project also provided using resources more effectively by the smart strategies of grid ventures of electricity distribution companies. 250 thousand smart meters in this project began to provide information automatically for the management about electricity usage by real time measurement. They also supplied different opportunities for various tariffs for the consumers and effective consumption methods by rewarding users when they used less amount of water and energy.

2.5.1.3 Smart Grid Projects DENA I and II in Germany

Integration of renewable energy resources with electricity grid was the essential target of Smart Grid Project DENA I. It was aimed that increasing the usage of energy from renewable resources for electricity from 10% to 12.5% in 2004 and to 20% by 2020 with this project. The montage of smart meters was also a target of the project. German authorities aimed to decrease carbon emissions by 13 million tons to 846 million tons between 2008 and 2012. After finishing DENA I, the authorities began DENA II Smart Grid Project. This project was aiming to achieve three targets. These were: raising the ratio of electricity from renewable resources to 39% (particularly from wind and solar), increasing the flexibility of suppliers and developing the infrastructure of the grid. The weak points were defined and the required precautions such as adding new lines, reactive power control as well as active controls and undertaking regulations. On the other hand, ensuring reliability and stability control of the system and designating of the significant grid issues were targeted (Demirkol, 2019).

2.5.2 The United States

With the Energy Independence Law, the smart grid legislation has begun in 2007. The law determined how to develop the national transmission and distribution system. The essential aims were application of digital information technologies for advancing the quality, security, and efficiency of the network, optimization of resources and activities in a dynamic way; and integration of the instruments and applications required for demand reaction and energy efficiency (Deloitte, 2015).

The share of the smart meters implemented by the companies responsible for electricity distribution was 11%. And there were endeavors for reaching out number of 60 million for smart meters by 2020. Through the smart vision of US, there were plannings for achieving 80% usage of renewable resources for the electricity supply till 2035. This vision also includes enhancing smart grid usage in the country, raising the number of electricity vehicles, and developed measurement infrastructure (Demirkol, 2019).

Research was initiated for advancing the road map of smart grid. The modernization in electricity network was also one of the aims of this road map in Kentucky, one of the states in US. Therefore, Smart Grid Assessment Model of Kentucky– KSGAM was set up. The branches in the model were Organization and Structure, Strategy and Management, System Architecture, Technology, and Operation, Business and Value Management, Physical and Cyber Management, Supply and Demand Management, and Customer, Environmental and Social management. The other aspects necessary to discuss to improve smart grid such as customer willingness, regulatory and policy adjustments, technological restrictions, and financial and commercial handicaps were also evaluated in this research (Liao et al., 2014).

2.5.3 China

Hydrocarbon resources based thermal power plants have been supplying most of the electricity in China and this also has resulted in severe air pollution. Because of this, the country has been facing with a danger of crucial environmental disaster if requir safety measures are not realized. Therefore, more efficient, clear, and alternative energy sources should be implemented, and Chinese authorities made different regulations to benefit more from renewable resources. They put a target ratio of renewable resources for energy consumption that would reach out 15% by 2020. To accomplish the target, smart grid system was laid on the table and research were begun for implementing smart grid system. Thus, the Conference on Ultra High Voltage Transmission held in 2009 was a turning point for taking required steps for smart grids.

State Grid Corporation of China, the most influential actor in the sector, began a detailed plan for realization a sound smart grid system by 2020. Therefore, there were three periods, 2009-2010, 2011-2015, and 2016-2020, for implementing this detailed plan (Aktaş, 2020).

2.6 Effects of Smart Grids on Consumption Behavior

Hierarchical structure was one of the main pillars of the traditional electricity mechanism. A smaller number of generation plants was supplying energy for many consumers (households and companies) in the conventional system. A centralized distribution control plants depending on either hydrocarbon or nuclear sources was responsible for the security of the supply. However, new, small-sized, and efficient generation elements and energy from renewable sources began to change the electricity grid structure with the help of smart network. One of the most significant features of a smart network is simultaneous management and control for every stage. For example, a rapid rise in the generation of a photovoltaic unit, that is integrated into a distribution network with a low voltage, can send in a signal when there is a lower load as feedback to the principal high voltage transmission network using smart grid communication channels. This mechanism depends upon an innovative grid system with an advanced information technology, suitable investment, a guaranteed cyber security, and management of consumption, i.e., New York grid system, a proper smart structure that meets the requirements of the users in upstream and downstream (Department of Public Service, New York State, 2014).

There are various reasons to introduce a smart grid as a liberal energy market and pro-environmental energy approach that focuses on energy effectiveness, supplying energy from the renewable resources and reduction of CO_2 emissions. In addition to these facts, smart grid system also enables active involvement of the consumers, the demand-side, in the mechanism that is not seen in the conventional system. Then, a new term emerges in the context of smart grid. The energy users are identified as ‘prosumers’. In other words, the users do not only consume, but also, they are able to produce the energy and store it (Kanchev et al., 2011).

One of the important issues is the new energy consumption behavior, and whether the consumers will adapt themselves in this system. Smart grid system introduces the application a new comprehensive behavior as well as of the new technologies. Development and application of the smart grid system necessitate integration of various instruments as altering the behaviors, attitudes, practices, and habits of the users which relate to personal factors and willingness in the active participation in this system. For the success of a smart network, the consumer support is inevitable (Verbong et al., 2013). By giving feedback on their consumption using a mobile app named Social Power, people are involved in changing their behaviors in the use of home energy, demonstrating the effectiveness of a collaborative or competitive approach. This app was used in two different environments and there were no discernible changes between the two gamified environments when the software was used in each to meet a predetermined 10% energy saving goal (Wemyss et al., 2018).

On the other hand, there are different barriers for the users for adopting this system. The main barriers are customer acceptance, confidentiality, fees, cyber security, and regulations (Kaldellis, 2005).

There has been different research for the acceptability of the smart grid system. These studies enable us to understand the perception of the users for this system and the reasons that caused them to change their behaviors. While different studies emphasize on positive approaches of the users for smart grid system, they also reflect their concerns for various tariffs. Moreover, this mechanism has different issues from installing to management. Thus, these can also influence the users' behaviors that breed the concerns for this system. As a result, some consumers may not want to use smart grids (Broman Toft et al., 2014).

Consumer privacy plays a critical role for the society to accept and adopt smart grids. Accessibility to the personal data of the smart users by the energy providers is a great concern for these consumers. Furthermore, this smart electrification operation results in the gathering personal data by energy services in a greatest way (Rusitschka et al., 2010). There is a dilemma when using the smart grids. While the personal data (i.e., sleeping times and length, watching TV time) that affects the energy consumption behavior are required for management and control of the energy conservation, as mentioned before, the providers can also have accessed these data. The system obtains personal information of the consumers during their individual activities. This may cause people to have concerns for their private data to be gathered and used illegally (McKenna et al., 2012). This is valid for the companies that are actors of the grid from upstream to downstream. Various business operations and activities can be followed by smart grid system. As an outcome, the impact of the smart grids for the privacy and secrecy of the people lay behind the concerns of the individuals (Rial and Dazenis, 2011).

Contrarily, the costs of installation of smart grid when somehow reflected to consumers in the bills result in concerns of users. This creates another obstacle for the acceptance of smart networks. Despite covering the costs in the long-term, smart system also requires significant installation, distribution, and investment costs as seen in implementing of other new technological developments. And the quantitative analysis of the costs for the implementation of smart grids basically covered through institutions. Some research mentions the importance of the decisions of the authorities in forming the effective tariff strategies including the highest participation of the users. Effective pricing applications can be proper for reducing electricity costs related to the smart grid for the users. In this framework, the users can prefer the most suitable hours for energy consumption instead of the critical time periods. Thus, this will be effective on the energy consumption behaviors due to the dynamic pricing structure. Besides the monetary benefits, this can provide reduced duration of energy outage and increased share of energy from renewable resources (Schwister and Fiedler, 2014).

One of the factors that negatively affect the customers about smart grids is cyber security. As there is digital technology in smart grids, they can face with cyber-attacks. The attacks can be in different ways as controlling the smart system or obtaining data from the smart tools. Nevertheless, smart system has responding instruments to these threads and can be equipped with required hardware and software to protect the grid such as sophisticating the communication structure against possible attacks (Park et al., 2014).

There are various studies in several countries targeting to evaluate the connection between consumption behaviors and smart grids. Tritthart and Mert (2009) made research to analyze whether the users wanted to change their behaviors and they were prepared to admit the functioning of the system by the network operator. In this framework, a survey was conducted with 2907 participants in five countries, Slovenia, Austria, Britain, Germany, Italy. They particularly focused on approaches of the users for managing the loads of smart grids that are shiftable and getting data on the length of shifting these loads.

Another study was carried out for deciding electricity consumption behaviors and attitudes of the users about the smart meters in Britain Oseni et al. (2013). The questions were for evaluating the behaviors of the individuals over 18. These were about gender, income level, education, behaviors for recording of the measured consumption data, the factors that were influential for changing the electricity consumption behavior, attitudes towards automatically remote controlling of the electrical devices, and determining the electricity consumption behaviors. Statistical frequency analysis was used to elaborate the answers. According to the results, even though there was an increase for the acceptance of the smart system compared with the research in 2006, 2008, and 2010, the secrecy issue maintained to be the most concerning one. Although more than half of the people admitted recording of consuming data by the smart system in detail, the participants were also concerned about the accessibility to these data by the third parties. This study also showed an important potential for changing the optional electricity charge from the peak using times by smart system. However, the users were mainly concerned about the probability of not using these devices when they need and their privacy. According to the answers, electricity price was the most important factor for changing their behaviors.

Although there is a general awareness for the climate change in worldwide, nevertheless, the contribution of the electricity consumption and its impact on climate change are disregarded. Only 42% of the people have this awareness while 75% of them mention that they think about the optimization of their electricity consumption. 28% has an approach for electricity management programs, however, 58% do not have an idea about that these programs provided by the energy suppliers. And only 9% of these persons engaged in one of these programs. This low-level engagement also states a high passivity for majority of the participants having a high awareness for the issue subject (Ellaban and Abu-Rub, 2016).

There were three main factors that affected the users to participate in these programs. These are: Low energy bill (88%), lower environmental impact (66%) and more comfort level (better control over the heating and cooling) (51%). Moreover, there were also three negative factors for the users that prevented them to involve in these programs. These are: an increase in electricity bill (46%), provider making a profit from personal electricity saving (41%) and accessibility to individual electricity consumption data (directly related with the privacy of the individual consumption) (32%). When we the ratios are evaluated, it is seen that the positive side has more weight over the negative side. And in line with this, the user has a tendency for getting more information about the energy management programs and they also consider that these programs can provide alternative solutions for energy usage. They are also prone to participate in a program in which energy providers do not any influence for the consumption of home tools (Bigerna et al., 2016).

Different studies have been made for analyzing the readiness of the electricity users for the smart system. Due to research conducted in February 2010, 68% of the Americans stated that they did not know the smart grid concept. While 57% of the American adults was aware of their electricity usage, 67% of this ratio mentioned that they would reduce their usage if they got information about the subject and 75% wanted to monitor and control their electricity consumption (Ponce et al., 2016). Due to a study about the awareness of American users in May 2011, while 41% of the participants mentioned that they were aware of the energy usage, 59% of these stated that they were not aware of the subject. In the framework of their association with smart grids, 69.9% of them mentioned that they did not any information, 26.1% stated that they had partial information, and 4.1% declared that they had much information (Ellaban and Abu-Rub, 2016).

They responded about the benefits of the smart grids as: saving money (81.3%), more efficient energy use (78.2%), decrease in electricity use (73.2%), creation of new jobs (67.4%), protection of the environment better (63.9%), increase in security of the U.S. (62.6%), increase of the use of domestic energy (58.3%), decrease in the number of power outages (61.7%), and development of communication when outages occur (52.0%). They responded for the negative sides as: different features of smart meters and secrecy issue by 79% and 65% respectively (Zpyrme, 2011). According to a study in December 2011, nearly half of the American users (51%) did not have an idea about these grids and 21% mentioned that while they had some information about smart grids, this was not enough to know the system as a whole(Smart grid, 2012). Research in Canada showed that people had some fundamental information about the smart grids (21% basic and 6% complete understanding) (IndEco Strategic Consulting Inc., 2013).

Moreover, Li (2016) made research about the awareness of the smart grids using a scale of *very often, often, occasionally,* and *no information* and found the ratios as 21,8%, 18,4%, 38%, and 21,8% respectively. When this study is evaluated with the one conducted in the U.S. in 2011 which is stated above, it is seen that the awareness of the people about smart grid system raised importantly in a few years. The enablers for smart grid, and the barriers for them are listed in the following table.

Table 2.2 Classes, Facilitators, and Obstacles for End-User in Smart Grids (Mengolini et al., 2013)

Class	**Facilitators**	**Obstacles**
Comfort	Comfort (Gain)	Comfort (Loss)
Control	More independence in energy usage	Loss of control on electrical devices
	More chance to actively be included in the electricity market	
	More control of appliances e.g., through using mobile devices	
Environment	Benefits in several environmental aspects	
Finance	Economic bonuses, incentives	Increase in investment costs
	Decrease in electricity bill	Increase in electricity bill (due to decreased cost of consumption)
Knowledge	More clear and periodic billing	Unclear information about the Smart Grid program
	Detailed information about electricity usage, costs, incentives	Lack of competency such as in dealing with new technologies
		Lack of awareness in Smart Grid and possible gains
Security	Increased energy supply and reliability	Concerns about security and privacy
Social Acceptance Process	The effect of role models	The effect of free riders
	User reference	Job losses
	Feelings, feedback in Community	
	Competition	
	Fun	

2.7 Conclusion

Theoretical background of this study was evaluated in the first part of this chapter. Habitual behaviors were analyzed first. In this context, it was seen that the features of households as experience, motivation, values, behavior, and characteristics affected their energy consumption behaviors. There was also a close relation with awareness and behaviors. These can be categorized as internal factors. Moreover, besides the other personal features as, especially the role of the income cannot be disregarded. It is perhaps the most influential factor for energy consumption behavior. On the other hand, awareness for the pro-environmental issues is also effective for this type of behavior.

With the developments of the new technologies and digitalization in electricity industry, smart grids began to play more roles in our lives. While they have positive effects on welfare of the consumers, they can also have negative influences mainly as accessibility of personal data of the consumers by energy providers and even by the third parties. However, it was observed that when people have more information about the smart grids, their acceptance level also raises.

As seen in the habitual behavior discussion, income is the most important factor to choose the smart grids. Independence, having management and control on the personal electricity consumption also play important role for acceptance of the smart grids. Therefore, if the decision makers demand to increase energy conservation and efficiency, and affect the consumption behaviors of the energy users, they should provide people with sound information about the smart grids and create awareness.

CHAPTER 3

BEHAVIORAL APPROACH

3.1 Introduction

In this chapter, the drivers that determine the link between the consumers' electricity consumption behavior and smart appliance usage are investigated by taking one of the models used in the literature as basis, habitual behavior model as because almost all electricity consumption behavior (%95) of a household is a form of habitual behavior (Wagenaar, 1992; Von't Riet et al., 2011).

In Turkey, the smart grid applications are not embedded in the network broadly. We can say that Turkey is in the very beginning phase of the adoption of the smart grid both in the upstream and in the downstream, namely for production, transmission, distribution or in the demand-side, consumption. There is little number of behavioral studies made for Turkish market up to now. We believe that testing smart grid effect on consumption behavior through a habitual behavior model framework will be useful for literature and policy makers, besides consumers.

This chapter is designed as follows: first, a literature review in terms of habitual behavior model is given and the proposed model is introduced. Then, within the methodology described, the hypotheses are tested in accordance with the Structural Equation Modeling (SEM) and results are shared. A logistic regression analysis is followed. Then some policy implications are listed.

3.2 Theoretical Background and Literature

A form of automatic and routine behavior is habitual behavior. People continue this behavior because it is simple, convenient, or satisfying. Habitual behavior in most cases begins automatically in response to a stimulus or a change in the environment. In other words, habits are behavioral responses to an environmental stimulus that make it easier to achieve specific goals or end states (Verplanken and Aarts, 1999). It is more effective to act out of habit than to continuously ask oneself what the best course of action is. Therefore, behavior's inherent benefits surpass any potential drawbacks.

The choices made in daily electricity use are probably seen as having less significant consequences than other choices. In such circumstances, people are more likely to rely on habits, claims (Tversky, 1969). It goes without saying that the low cognitive effort required by decision-making tasks connected to daily electricity usage is also a result of their low complexity (Maréchal, 2010).

There are complementary findings in literature about the nature of the habits and electricity usage. The three criteria outlined for the balance of the decision-making process to shift away from cognitive effort and towards automaticity are met by electricity consumption, as a habitual behavior: low levels of participation, low levels of perceived complexity, and high levels of constraint (Jackson, 2005; Verplanken, 1999). To put it another way, habits are actions that are undertaken in predictable environments, don't demand a lot of cognitive effort, successfully accomplish a specific goal, and happen repeatedly (Karlijn L. van den Broek et al., 2019)

The limitations of today's society, the feeling of time pressure, an excessive amount of information, and other factors tend to support the adoption of daily routines that provide the user a sense of increased comfort (Lindbladh and Lyttkens, 2002) which also accounts daily electricity consumption.

Given that daily electricity use is functional, frequently takes place in predictable environments, i.e., homes and workplaces, can be carried out automatically, and occurs frequently, many energy behaviors are likely to be habitual in nature (Jackson, 2005; Maréchal, 2010).

In addition to above, Macey and Brown, 1983 states that most energy behavior can be predicted by experience if these behaviors are frequent ones. However, when the behavior is an infrequent one, it can be predicted by intentions. Strong habits characterized with a high degree of automaticity might prevent the implementation of new intentions (Maréchal, 2010; Verplanken and Faes, 1999). Therefore, habits are probably going to have a significant impact on how people behave in their use of energy (Karlijn L. van den Broek et al., 2019).

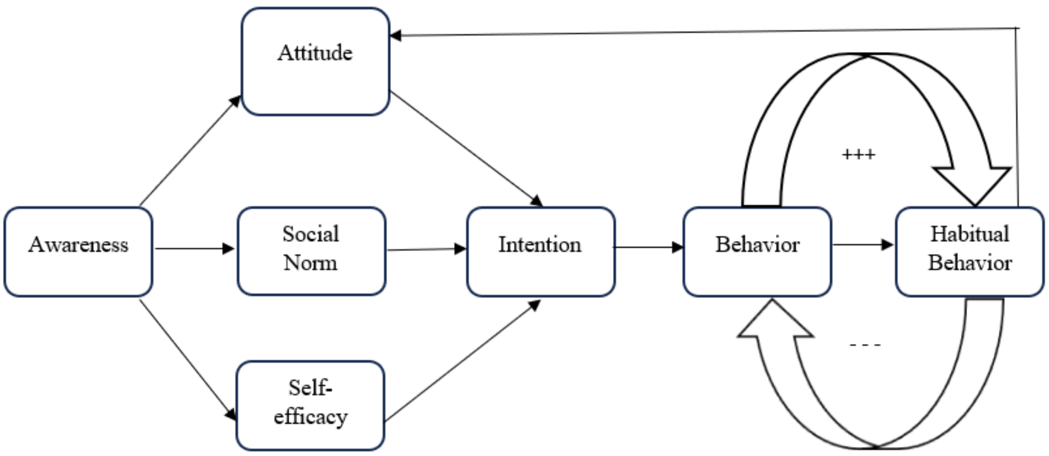

Figure 3.1. Habitual Behavior Model (Jager, 1992)

In Figure 3.1 Jager (1992) illustrates the driving forces determine the basic setting for habitual behavior. At the individual consumer level, awareness is the triggering point according to model.

Awareness is the activator that the household is conscious of the change in the environment. The household evaluates the new situation in accordance with his attitudes, social norms and in terms of his self-efficacy. All behavioral aspects lead to an intention to behave.

Literature confirms that awareness has a significant impact in influencing home energy use (Jager, 1992, Jager, 2003, Li et al., 2021; Hassan et al., 2009; Paço and Lavrador, 2017; Pietrapertosa et al., 2021; Loise et al., 1981; Endres, 1997; Hirazawa and Yakata, 2005). Without the necessary information, customers or users are unaware of when they use electricity, how much they consume, and how much the amount used will ultimately cost, which part could have an more impact on their electricity bills. As a result, if customers lack energy awareness, it will be exceedingly difficult for them to change consumption behavior, e.g., reduce consumption, or choose more energy-efficient ways of consumption (Khan et al., 2019). Several studies on direct linkage of awareness and energy (utility) consumption emphasize the significance of raising consumer participation and improving energy knowledge to enable environmentally responsible consumption practices. Awareness has been considered as a decisive parameter in modeling environmental policies and production decisions (Yu et al., 2017; Lian et al., 2018). Additionally, awareness and utility use are directly related, and it is recommended that governments encourage environmental awareness to cut expenditures (Conrad, 2005; Daube and Ulph, 2016).

Research suggests that attitude has significant role in energy consuming behaviors and habits of households (Belaid et al., 2020; Mills et al., 2012; Baharoon et al., 2015; Martins et al., 2020). Attitudes refer to the degree to which a person has a favorable or an unfavorable evaluation of a given behavior. For instance, households may refrain from lowering ambient temperatures at home in the wintertime, because they feel that it will compromise comfortable living (Abrahamse, W, 2007). Therefore, attitudes are one of the determinators of intention in consumer behavior such that positive attitude is an accurate measure of intention (Ajzen and Fishbein, 1980). Attitude is positively affected by the perceived usefulness of the impact of behavior on environment in terms of energy consuming behavior where the consumer builds a positive attitude towards that behavior (Hua et al., 2019)

Intention can be defined as ideological tendency and action motivation in short (Jager, 1992, Jager, 2003, Li et al., 2017). Behavioral intentions are an indication of the extent to which people are willing to perform the behavior in question. In turn, intentions are assumed to be determined by attitudes, subjective norms, and perceived behavioral control. According to literature, despite there is a intention-behavior gap in action, intention is positively related to energy saving behaviors. It has significant effect especially when the consumers are aware of the emission-reduction perspective of the behavior (Lin et al., 2022; Le-Anh et al., 2022, Tan et al., 2017). Consumers' intention for adopting smart grid technology and solutions is positively correlated with their assessment of the outcomes of such an adoption of smart technologies (Perri et al., 2020).

Self-efficacy refers to level of belief and confidence in one's action. As a result, the higher the self-efficacy is, the more likely he is to perform the action (Jager, 1992, Jager et al., 2013, Guo et al., 2017). In order self-efficacy to exist, the beliefs need to be exposed to behavior-promoting activities. In addition, the experiences of one's directly influence through the processing of past information. There should be collective efficacy rather than an individual one to see a pro-environmental behavior in action such that self-efficacy itself is insignificant to this type of behavior (Jugert et al., 2016; Foster et al., 2022; Han et al., 2017; Liu et al., 2021).

Social norms, which are based on subjective values, refer to the perceived social pressure to perform or not to perform a behavior. It encompasses individual and collective perceptions of the extent to which important others would endorse (or disapprove of) a given behavior and individual motivations to comply with this social pressure (Abrahamse, W, 2007). Social norms are described as a combination of values, customs, traditions, guidelines, ideals, rules and so forth (Sherif M., 1966) with different dimensions as subjective norms, descriptive norms, personal norms, and cultural norms. Literature suggests that social norms are indirectly related to habitual behavior in energy consumption context such that norms are not guiding behavior unless they are activated. The activation process is often unconscious and needs a triggering information to build a norm against the energy related behavior (Biel et al., 2006). The mentioned information is provided by awareness such that social norms are not directly examined in our study. In research, self-efficacy and social norms are indirectly included in extended models with different variables as the two either show low explanatory power over the independent variable or appear insignificant.

The topic of this thesis concerns with an empirical study regarding investigation of whether a relation between smart grid applications usage and household electricity consumption exists in a context of habitual behavior. In this context, we try to show how consumer awareness, attitude and intention help us understand this behavior formation. Self-efficacy and social norms are excluded in the proposed model and not investigated through the survey.

The present study adopts the habitual behavioral model by excluding the norms and self-efficacy and adding perceived well-being (PWB) as the pros of the behavior loop in action, based on the literature above. When there is positive feedback for the behavior, which is an increase in the perceived well-being in this study, it turns out to be a habit. The proposed model accepts awareness as the triggering mechanism which is demonstrated below in Figure 3.2.

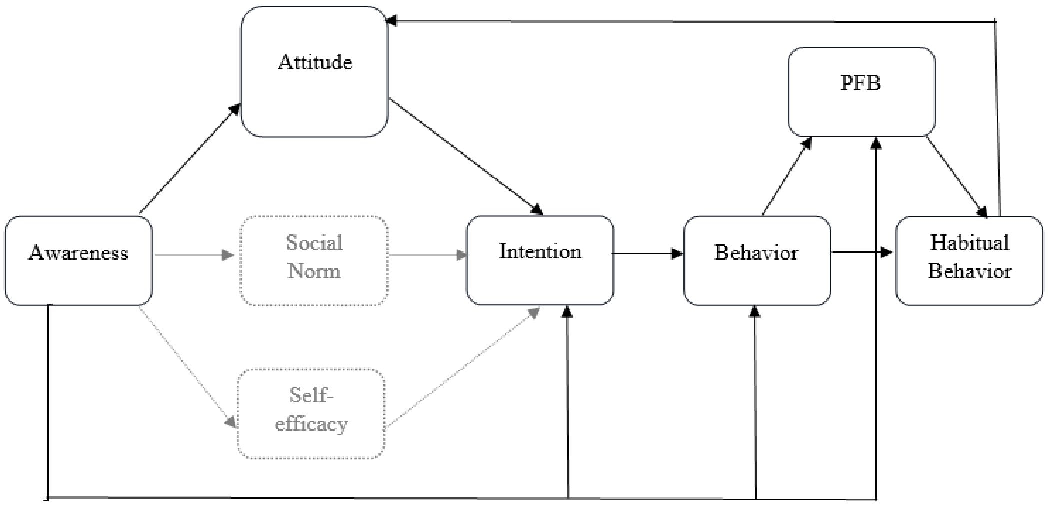

Figure 3.2. Proposed Model of Habitual Behavior

3.2.1 Methodology

The methodology of this study consists of following parts: research question and hypothesis, questionnaire, sampling and analysis and results.

3.2.1.1 Research Question and Hypothesis

The purpose of this thesis is to find out the drivers of the link between smart appliance usage and consumption behavior in electricity. We want to examine the effect of smart grid applications on electricity consumption behavior of households, and assess how awareness, attitude and intention affect the role of consumer, at this link based on the theoretical background mentioned above in this chapter. Our research question is to determine which factors drive the link between smart appliance usage and electricity consumption behavior.

According to the literature and discussions above, awareness as the most effective factor to start a behavior is tested against other factors in our proposed model. Besides the relations between the attitude, intention, behavior and behavior with positive feedback (PFB) are tested. Our hypotheses are listed as follows:

H_1: There is significant effect of awareness on attitude.

H_2: There is significant effect of awareness on intention.

H_3: There is significant effect of awareness on behavior.

H_4: There is significant effect of awareness on PFB.

H_5: There is significant effect of attitude on intention.

H_6: There is significant effect of attitude on behavior.

H_7: There is significant effect of intention on behavior.

H_8: There is significant effect of behavior on PFB.

The hypotheses, H_1, H_5, H_6, H_7, H_8 are based on the traditional habitual behavior framework. The rest, H_2, H_3, and H_4 are added to the original model to test the significance of awareness on different variables.

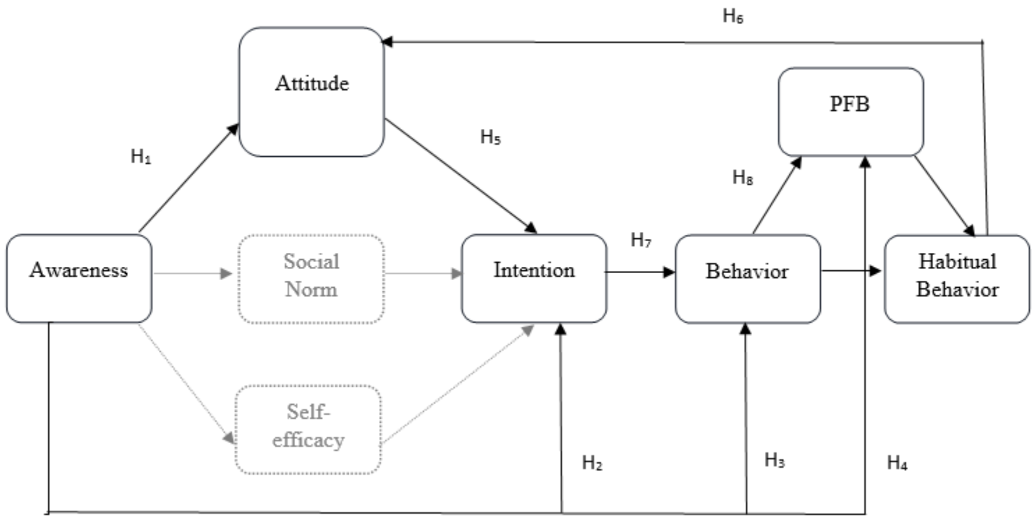

Figure 3.3. Hypotheses Tested in the Study

3.2.1.2 The Questionnaire

For this study, a six-part questionnaire was used, and the data are collected by using this questionnaire. The first part consists of demographic information, basically about the participants' personal information and background. The other parts are of the questions about Awareness, Attitude, Intention, Behavior, and behavior with positive feedback, shorted as PFB.

Table 3.1 Measurements of Construction

Constructs
Awareness (Jager, 1992, 2000, 2003; Wagenaar, 1992) - Do you know what type of electricity meter are you using? - Do you know which items are included in the electricity bill? (You can choose more than one option.) *Scale: Yes (or chooses an option) or No* - Do you check your electricity bill, if so, how often? *Scale: Yes, sometimes; Yes, regularly; No* - Do you know which invoice items are included in electricity bills?

Table 3.1 Continued

Scale: Yes (or chooses an option) or No - Do you know which electrical appliances consume more electricity in your home, if so can you indicate? (You can choose more than one option.) *Scale: Yes (or chooses an option) or No* - The smart grid is a system that ensures easy and fast communication between the producer and the consumer. Have you heard of the smart grid that allows you to control your electricity budget? *Scale: Yes or No* - Could you please indicate if you have heard of them, have you used them? *Scale: Yes, I have heard, I use; Yes I have heard, I do not use; or No I haven't heard* - Do you use smartphone apps? *Scale: Yes or No*
Attitude (Abrahamse and Steg, 2011; Wells et al., 2016; Schults, 2004, Jager, 1992, 2000, 2003) *Scale: Strongly disagree (0) to strongly agree (4)* - Using smart grid reduces electricity consumption, do you agree? - I am not sufficiently informed by my electricity supplier. - If my supplier offers a discount on my bill, I use a smart meter. - If there was a smart app that alerted me in case of above-average consumption, I would use it. - If there was a smartphone app that alerted me when a cheaper supplier was found, I would use it - I do my best to reduce the electricity bill (turning off unnecessary lights, running devices at certain hours, etc.) - When there is a supplier that will lower my electricity bill, I immediately change my supplier.
Intention (Verplanken and Wood, 2006; Jager, 1992, 2000; Wagenaar, 1992) *Scale: extremely unacceptable (1), acceptable (2), extremely acceptable (3), no idea (0)* - Could you indicate the possibility of using a smart meter that shows the amount of energy consumed if it is put into your service? - Would you use a mobile application that calculates your electricity consumption and suggests new suppliers accordingly, if offered to your service? - Would you use an application that allows you to switch to cheaper suppliers with one click if it is offered to your service? - Would you use a home screen that measures your instantaneous electricity consumption if it is put to your service? - Would you use a social media network where you can follow the electricity supplier campaigns and news if it is offered to your service?

Table 3.1 Continued

- Could you indicate the possibility of recommending it to your friends, family and/or circles? : A smart meter showing the amount of energy used. - Could you indicate the possibility of recommending it to your friends, family and/or circles? : A mobile application that calculates your electricity consumption and suggests new suppliers accordingly - Could you indicate the possibility of recommending it to your friends, family and/or circles?: A mobile application that calculates your electricity consumption and suggests new suppliers accordingly - Could you indicate the possibility of recommending it to your friends, family and/or circles? An application that allows you to switch to cheaper suppliers with one click. - Could you indicate the possibility of recommending it to your friends, family and/or circles? A home working screen that measures your instant electricity consumption - Could you indicate the possibility of recommending it to your friends, family and/or circles?: A social media network where you can follow the campaign and news
Behavior (Jager, 1992, 2000, 2003; Verplanken, 1999) *Scale: Yes or No* - I am using a power bulb. - I try to turn off unnecessary lights. - I am using a smart meter. - I run the appliances at certain hours (such as running the washing machine after 22:00) - I apply alternative methods such as solar or wind energy. - I care about building insulation. - I raise awareness of people living at home about saving. - I run the dishwashers and laundry fully loaded. - I'm not doing anything to save electricity
Positive Feedback Behavior (PFB) - What is your electricity bill on average per month? Please Specify in TL. - What was your last electricity bill? Please Specify in TL. *Scale: Strongly disagree (0) to strongly agree (2)* - Do you think that your bill amount will decrease when you use the smart grid applications mentioned above?

3.2.1.3 Sampling

The population of the research is the electricity consumers in the province of Ankara. The sample of the research consists of 703 electricity consumers. Care was taken to select these 703 people by paying attention to the balanced distribution of variables such as gender, income, education level and age. In the research, a questionnaire based on interview technique was applied to participants with various demographic characteristics. The size of the sample, after the missing data and outliers are handled, is enough to conduct the analysis covered in this study (Kline, 2016).

3.2.1.3.1 The Demographic Characteristics of Sample

In this part consists of demographic information, basically about the participants' parental and educational background. 51.4 % of participants are male and 48.6 % are female.

Among the participants, the proportion of 18-34 age participants is higher than the other age groups. While 33.9 % of the participants are between the ages 18-24, 41.1 % are between the ages 25-34, 11 % are between the ages 35-44 and 7.1 % are between 45-54 and 7 % are over 55.

The percentage of people married is 63.4, while 36.6 of the participants are single. 8.1% of the participants are self-employed and 10.6% of them are salaried workers or managers. The portion of unemployed people in the sample is 14.4%. the students account for 10.2% of the participants while the percentage of retired people is 5.

31.8 % of the participants have a bachelor's degree, 24.9 % have a high school degree, 23.9 % have associate degree, 8.3 % have middle school degree, 6.8 % have primary school degree and 3.2 % have master's degree.

Table 3.2 Demographic Characteristics of Sample

		n	**%**
Gender	Female	342	48.6
	Male	361	51.4
Age	18-24	238	33.9
	25-34	289	41.1
	35-44	77	11.0
	45-54	50	7.1
	Over 55	49	7.0
Marital Status	Married	446	63.4
	Single	257	36.6
Educational Status	Non-graduate	20	2.8
	Primary School	48	6.8
	Middle School	58	8.3
	High School or Equivalent	170	24.2
	College	168	23.9
	University	217	30.9
	Graduate	22	3.1
Occupation	Self-Employed Merchant	44	6.3
	Self-Employed Professional	13	1.8
	Salaried Worker	62	8.8
	Salaried Manager	13	1.8
	Civil servant(Employee)	233	33.1
	Civil servant(Manager)	30	4.3
	Housewife	100	14.2
	Retired	35	5.0
	Student	72	10.2
	Unemployed	101	14.4
Monthly Income(Adjusted for inflation)	Under 6,500 TL	178	25.3
	6,500-13,000 TL	83	11.8
	13,001-26,000 TL	107	15.2
	26,001-39,000 TL	69	9.8
	39,001-52,000 TL	134	19.1
	52,001-65,000 TL	81	11.5
	Over 65,000 TL	51	7.3
Number of People in the Household	Under 3	73	10.4
	3	115	16.4
	4	370	52.6
	5	93	13.2
	6 or over	52	7.4

7.3 % of the participants have monthly income over 65K in TL, 11.5 % have a monthly income between 52K and 65K in TL. The percentage of the workers who get between 39K and 52K in TL account for the highest portion.

3.2.2 Analysis and Results

Pilot research was done prior to the main survey with 86 individuals. The results of the pilot study were promising such that the Cronbach's Alpha for each variable was fluctuating between 0, 85 at minimum and 0,87 at maximum. The phrasing of the questions was changed and double-checked in the light of the preliminary results and feedback. As a result, the survey's final form, which is shown in Appendix A, was prepared to start gathering data.

3.2.2.1 SEM Analysis

Before the data collected from participants in the survey are computer coded, the answers with missing data and the outliers are removed from the sample. SPSS 25 and SPSS AMOS 26 tools are used to process the collected data. The analysis of data made within the scope of research questions. To achieve this, the frequency distributions of the results obtained from the questions in each section are calculated. Frequency tables show the distributions and percentages of the answers given to the questions. Afterwards, Independent Samples t-Test and Analysis of Variance (ANOVA) were used to measure the effect of demographic data on the variables, explanatory factor analysis was applied to check validations before SEM analysis was conducted to test the relationship between the variables in the habitual behavior framework proposed in this study (Please refer to Appendix B for validation checks).

Structural equation modeling (SEM) is a powerful, multivariate technique found increasingly in scientific investigations to test and evaluate multivariate causal relationships. SEM is different from other modeling approaches as they test the direct and indirect effects on pre-assumed causal relationships. SEM is a nearly 100-year-old statistical method that has progressed over three generations. The first generation of SEMs developed the logic of causal modeling using path analysis (Wright 1918, 1920, 1921). SEM was then morphed by the social sciences to include factor analysis. By its second generation, SEM expanded its capacity. The third generation of SEM began in 2000 with Judea Pearl's development of the 'structural causal model', followed by Lee's (2007) integration of Bayesian modeling (Pearl, 2003).

To indicate how well the proposed model theory fits the data, there are fundamental measures. In this study, three of these measures will be examined and the accuracy of the model will be tested. One of these measures is The Comparative Fit Index (CFI). The Comparative Fit Index (CFI) is most used and compares the existing model with a null model. When evaluating fit statistics, CFI values ≥ 0.90 are considered adequate. In a model also low residual values are important. Low residual values represent the amount of variance not accounted for the model. These are calculated as indices such as the Root Mean Square Error of Approximation (RMSEA), which is the square root of mean differences between the estimate and the true value. Although the cutoff point of the RMSEA has changed over the years, more recently, a cut-off value close to 0.06 or a stringent upper limit of 0.07 seems to be the consensus amongst authorities in this area. The third statistic that minimizes the impact of sample size on the Model Chi-Square is relative/normed chi-square ($\chi 2/df$). Although there is no consensus regarding an acceptable ratio for this statistic, recommendations range from as high as 5.0 to as low as 2.0 (Hooper et al., 2008).

After getting the data input, a pre-analysis including descriptive statistics, validation tests and explanatory factor analysis conducted to understand whether the SEM is appropriate methodology such that there are a large sample size, normal-distributive data, and reliability and validity. Then, to test the main hypothesis and research question with the primary data in line with the habitual behavioral model, SEM is conducted as it estimates the multiple and interrelated dependence. The variables are awareness, intention, attitude, behavior, and behavior with positive feedback (PFB). The effects of awareness, intention, and attitude, on behavior and on PFB are examined according to the proposed model. Besides, the effect of attitude on intention is tested. In this model, CFI value < 0.9 and RMSEA value > 0.06. So, according to SEM criteria, the modal does not fit with the data.

Table 3.3 SEM Fit Indexes with Results of Proposed Model

Model	NPAR	CMIN	DF	P	CMIN/DF	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI	RMSEA
Default model	112	3397.9	517	0	6.572	0.636	0.605	0.673	0.643	0.671	0.089
Saturated model	629	0	0			1		1		1	
Independence model	68	9324.7	561	0	16.622	0	0	0	0	0	0.149

Table 3.4 The Estimates for Paths-Proposed Model

	Path		Estimate	S.E.	C.R.	P
Awareness	<-->	Attitude	0.013	0.005	2.702	0.007
Awareness	<-->	Intention	0.005	0.005	1.027	0.304
Behavior	<-->	Intention	0.000	0.000	-0.157	0.876
Behavior	<-->	Attitude	0.000	0.000	0.512	0.608
Intention	<-->	Attitude	-0.004	0.007	-0.606	0.544
Behavior	<-->	Awareness	0.000	0.000	0.432	0.666

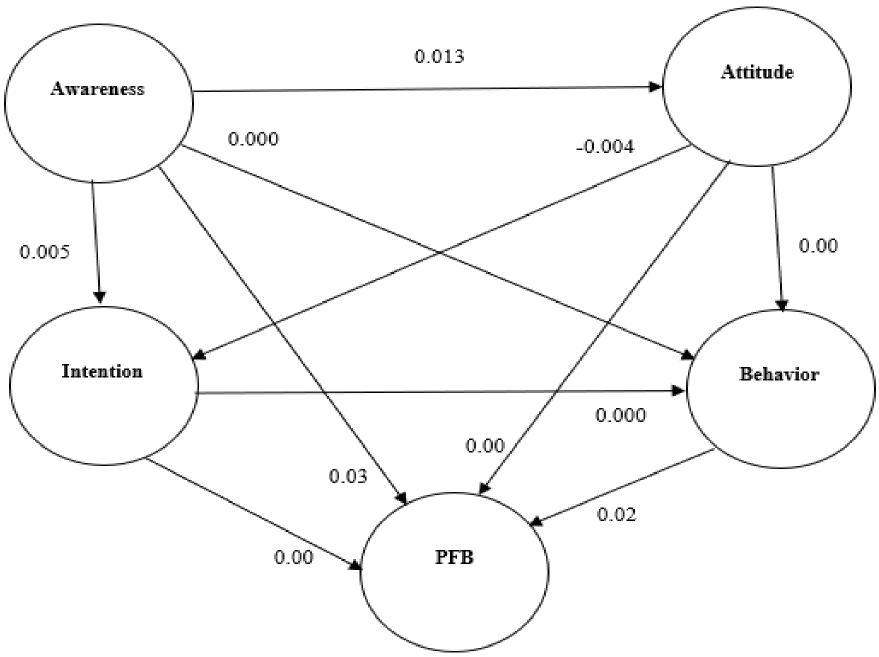

Figure 3.4. SEM Results for the Proposed Model with Standard Estimates

According to the results, there is significant effect of awareness on attitude for %10 significance level and the hypotheses H_1 is accepted. However, the rest of the hypotheses are rejected.

After these results from the proposed model, the SEM analysis conducted over the proposed model with limited variables. If the proposed model is called as the first case, then in the second case, the effects of awareness on attitude, the effect of attitude on intention, the effect of intention on behavior and the effect of behavior on PFB is examined. Also in this model, CFI value < 0.9 and RMSEA value > 0.06. So, the modal does not fit with the data.

The model is transformed again in the third case. Since the behavior data is nominal, it was removed from the analysis. The modal effects of awareness on attitude, the effect of attitude on intention, the effect of intention on PFB was investigated. Also in this model, CFI value < 0.9 and RMSEA value > 0.06. So, the modal did not fit with the data.

Table 3.5 SEM Fit Indexes with Results of Proposed Model-4

Model	NPAR	CMIN	DF	P	CMIN/ DF	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI	RMSEA
Default model	30	339.279	48	0	7.068	0.792	0.714	0.816	0.744	0.814	0.093
Saturated model	78	0	0			1		1		1	
Independence model	12	1630.2	66	0	24.7	0	0	0	0	0	0.184

In the fourth case, instead of items of intension and attitude, sub-dimensions of them were included to the analysis. The effects of awareness on attitude, intention and PFB, the effect of attitude on intention, the effect of intention on PFB was examined. Also in this model, CFI value < 0.9 and RMSEA value > 0.06. Also, this modal did not fit with the data but in this modal CFI value is closer to 0.9. Besides there was an effect of awareness on intention, attitude, and PFB.

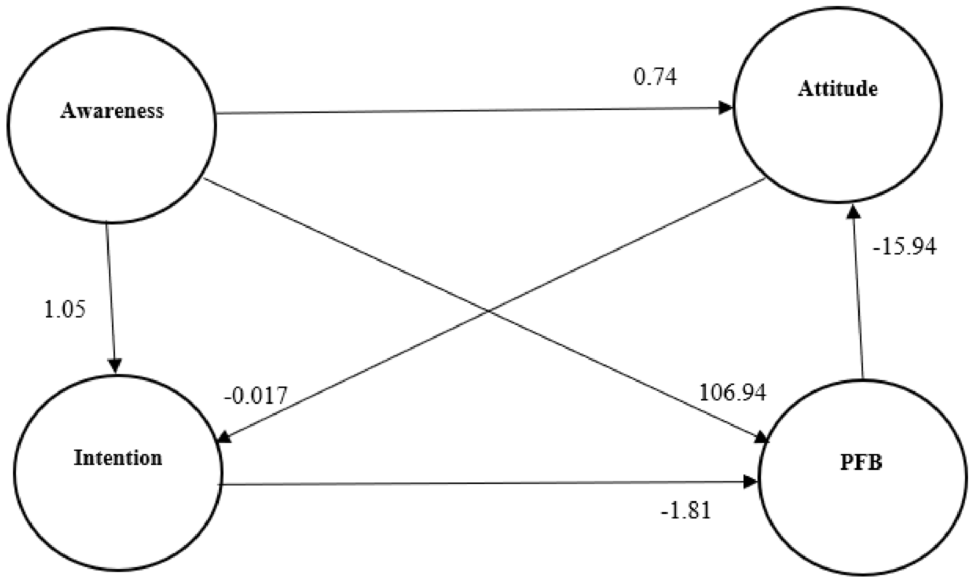

Figure 3.5. SEM Results for the Limited Version of Proposed Model with Standard Estimates

Table 3.6 The Estimates for Paths-Limited Proposed Model-4

Path			Estimate	S.E.	C.R.	P
Intention	<-->	Awareness	1.051	0.280	3.748	**0.001***
Attitude	<-->	Intention	-0.017	0.038	-0.431	0.666
Attitude	<-->	Awareness	0.742	0.265	2.801	**0.005***
Behavior	<-->	Awareness	1.069	35.544	3.009	**0.003***
Behavior	<-->	Attitude	-15.939	16.598	-0.960	0.337
Behavior	<-->	Intention	-1.810	4.647	-0.389	0.697

According to results above, the hypothesis H_1 is accepted. There is significant effect of awareness on attitude. It can be concluded that awareness is influential on attitude towards electricity consumption under smart appliances usage in the context of habitual behavior. People can change their attitudes shaping their electricity consumption habits when they are more aware of smart grid. Awareness explains 14.36% of total variance on attitude ($R2$: 0.144, $\beta = 0.379$, $p<0.05$).

At the same time, the hypothesis H_2 is accepted. There is significant effect of awareness on intention. It can be concluded that awareness is influential on intention towards electricity consumption under smart appliances usage in the context of habitual behavior. People can change their intentions shaping their electricity consumption habits when they are more aware of smart grid. Awareness explains 7.45% of total variance on intention (R2: 0.074, $\beta = 0.273$, $p<0.05$).

Additionally, the hypothesis H_3 is accepted. There is significant effect of awareness on behavior. It can be concluded that awareness is influential on behavior towards electricity consumption under smart appliances usage in the context of habitual behavior. People can change their behaviors shaping their electricity consumption habits when they are more aware of smart grid. Awareness explains 6.35% of total variance on behavior (R2: 0.063, $\beta = 0.252$, $p<0.05$).

Besides, the results of SEM analysis show that the hypothesis H_4 is rejected. There is no significant effect of awareness on PFB. It can be concluded that awareness is not influential on PFB towards electricity consumption under smart appliances usage in the context of habitual behavior.

The hypothesis H_5 is rejected. There is no significant effect of attitude on intention. It can be concluded that attitude is not influential on intention towards electricity consumption under smart appliances usage in the context of habitual behavior.

The hypothesis H_6 is rejected. There is no significant effect of attitude on behavior. It can be concluded that attitude is not influential on behavior towards electricity consumption under smart appliances usage in the context of habitual behavior.

The hypothesis H_7 is rejected. There is no significant effect of intention on behavior. It can be concluded that intention is not influential on behavior towards electricity consumption under smart appliances usage in the context of habitual behavior.

The hypothesis H_8 is rejected. There is no significant effect of behavior on PFB. It can be concluded that behavior is not influential on PFB towards electricity consumption under smart appliances usage in the context of habitual behavior.

To conclude, despite it is accepted that awareness has significant effect on attitude, the line of awareness-attitude-intention-behavior-PFB is not completely realized

(H_1-H_5-H_7-H_8 hypotheses respectively) for electricity consumption analysis under smart grid appliance usage through a habitual behavior framework. Therefore, the habitual loop is broken for electricity consumption when the smart grid applications are in use. Besides, the SEM results are intelligible and intuitive, although the model does not fit the data. It can be inferred that use of smart grid appliances changes electricity consumption behavior over awareness since awareness has effect on attitudes, intention, and behavior.

3.2.2.2 Logistic Regression Analysis

Although the indicators in SEM analysis were not exactly what is recommended in literature, the results were expected. A Logistic Regression analysis is conducted to support SEM results statistically since there are categorical variables in this research. Tools used are SPSS 25, and SPSS AMOS 26. Logistic regression analysis was applied in demographics and to behavior items of the survey separately.

3.2.2.2.1 The Methodology

The data was examined with a 95% reliability level using the SPSS 26.0 tool for analysis. Frequency (n) and percentage (%) for categorical (qualitative) variables, mean (X), standard deviation (ss), minimum and maximum statistics for numerical (quantitative) variables are given. Calculating the skewness and kurtosis values is one method to check whether the scores generated from the scales belong to the normal distribution. The kurtosis and skewness values obtained from the scale scores are considered sufficient for normal distribution (Groeneveld and Meeden, 1984; Moors, 1986; Hopkins and Weeks, 1990; De Carlo, 1997). Accordingly, it was accepted that the calculated scores of attitude, intention, and awareness showed a normal distribution (the Skewness/Kurtosis coefficients were within the limits). Parametric methods were used in the analysis. In the study, independent groups t test, Chi-square test, Logistic Regression test, ROC analysis was used.

Independent groups t is a test technique used to compare two independent groups in terms of a numerical (quantitative) variable. Chi-square is the test technique used to determine the correlation between categorical variables. ROC Analysis is a test technique used to predict the result variable of the numerical measurement determined, developed, and examined. Sensitivity (the rate of detecting positivity), specificity (the rate of detecting negativity), positive predictive (the positive value of the measurement is actually positive), the negative predictive (the negative value of the measurement is actually negative) probabilities were calculated. In most socio-economic studies conducted to reveal cause-effect correlations, some of the variables examined consist of two-level data as positive-negative, successful-unsuccessful, yes-no, satisfied-not satisfied. If this type of dependent variable consists of two-level or multi-level categorical data, Logistic Regression Analysis has an important place in examining the cause-effect correlation between the dependent variable and the independent variable(s) (Agresti, 1996). In logistic regression analysis, one of the purposes of which is classification and the other is to investigate the correlations between dependent and independent variables, the dependent variable creates categorical data and takes discrete values. There is no obligation for all or some of the independent variables to be continuous or categorical variables (Işığıçok, 2003). Logistic regression analysis is an alternative method to discriminant analysis and crosstabs when some assumptions of regression analysis such as normality and common covariance cannot be met.

In addition to being applicable when the dependent variable is a discrete variable with two levels, such as 0 and 1, or more than two levels, its mathematical flexibility and easy interpretability increase the interest in this method (Tatlıdil, 2002; Lemeshow & Hosmer, 2000). Logistic regression analysis is a regression method that helps to perform classification and assignment. There is no prerequisite for the assumption of normal distribution, the assumption of continuity. The effects of explanatory variables on the dependent variable are obtained as probabilities, and the risk factors are determined as probabilities (Özdamar, 2002; Lemeshow and Hosmer, 2000). -2log likelihood is a model fit index. The basic measure of how well the maximum likelihood estimation indicates a fit is similar to the sum of squares in multiple regression ‘likelihood value’. Logistic regression measures take the estimated model fit by –taking -2 log of the likelihood value. The smallest value that -2 log of the likelihood can take is 0 and corresponds to a perfect fit. When -2 log of the likelihood =0, likelihood=1. Cox & Snell R2 and Nagelkerke R2 values indicate the amount of variance explained by the logistic model and 1.00 indicates perfect model fit. Cox & Snell R2 never reaches 1 and therefore is not very easy to interpret. By this way the Nagelkerke R2 value is calculated. The Nagelkerke R2 coefficient is a modified form of the Cox & Snell coefficient to allow the range to range from 0 to 1. ODDS Ratio (OR) shows the correlation between the probability (yes) of an outcome variable and the probability that it will not (no). In logistic regression models, the ODDS ratio is used when talking about the correlations between the categorical variable groups and the reference group.

3.2.2.2.2 Demographical Analysis

Before the analysis of logistic regression model, it is important to run over analysis over demographics to better understand the sample characteristics. Here, the demographical findings are listed. Detailed analysis with tables can be found in Appendix C.

To start, it is seen that there is significant difference between age groups in Awareness. ($p<0.05$). The group with the highest awareness is the age group of 35-44, the income group with the lowest awareness is 55+.

There is significant difference between age groups in Intention ($p<0.05$). There is significant difference between the age group 25-34 and the age groups 18-24 and 55+. The mean of the age group 25-34 is higher than other groups.

There is significant difference between age groups in Attitude ($p<0.05$). There is significant difference between the age group 18-24 and the other age groups. The mean of the age group 18-24 is lower than other groups.

There is significant difference between the number of people in the household groups only in Awareness. ($p<0.05$) There are significant differences between the group 1-2 and 4. The group with the highest awareness is the group of 4 people, the group with the lowest awareness is the group of 1-2.

There is significant difference between single and married participants only in Awareness and Intention ($p<0.05$) Awareness of the married participants is higher than the singles.

There is significant difference between income groups in Awareness. ($p<0.05$) There are significant differences between almost all groups except for the group with the highest income.

There is significant difference between income groups in Intention ($p<0.05$). Besides, there is significant difference between income groups in Attitude ($p<0.05$). Additionally, there is significant difference between income groups in the thought of there will be a decrease in the bills of the participants if they use smart grid applications ($p<0.05$).

3.2.2.2.3 Analysis of Logistic Regression Models

Logistic regression is run over 8 behavior variables and 1 PFB variable such that:

Behavior1: I use energy saving bulb.

Behavior2: I try to turn off unnecessary lights.

Behavior3: I use a smart meter.

Behavior4: I run devices at certain hours.

Behavior5: I employ alternative methods such as solar or wind energy.

Behavior6: I give importance to building insulation.

Behavior7: I raise the awareness of household people on saving.

Behavior8: I run the washing machines and dishwashers fully loaded.

PFB1: Thinking that the electricity bill will decrease with smart grid applications.

For Behavior3, using smart meters, there is a statistical relationship between the gender, monthly income, education level and smart meter usage of the respondents ($p<0.05$). The rate of smart meter usage is higher among women (9.6%), primary school graduates (11.8%), and those with low monthly income (12.4%).

For Behavior4, running devices at certain hours, there is a statistical relationship between the age of the respondents and the status of operating the devices at certain hours ($p<0.05$). The rate of operating devices at certain hours is higher in those aged 18-24 (52.5%).

For Behavior7, raising the awareness of those living in the house about saving, there is a statistical relationship between the income of the respondents and ($p<0.05$). Those with an income of 26001-39000 TL (49.3%) have a higher awareness of saving in the household.

To see the effect of attitude, awareness, and intention variables on behavioral characteristics, a model consisting of dependent variables related to 8 sub-features of behavior and PFB were tested. The model through which the effect of attitude, awareness and intention variables are analyzed on the use of a saving bulb is statistically significant ($X2=23.437$; $p<0.05$). The effect of the attitude variable is statistically significant and positive ($B=0.447$; $t=4.557$; $p<0.05$). The models established for variables including the effect of Awareness ($t=0.170$; $p>0.05$) and Intention ($t=0.615$; $p>0.05$) variables was not significant ($p>0.05$). Taking care to turn off unnecessary lights, which are dependent variables ($X2=0.780;p>0.05$), using smart meters ($X2=0.140;p>0.05$), operating devices at certain hours ($X2=0.859;p>0.05$) , using alternative methods ($X2=0.349;p>0.05$), giving importance to building insulation ($X2=0.537;p>0.05$), raising awareness of people living at home about saving ($X2=1.587;p>0.05$), running the laundry and dishwashers fully loaded ($X2=2.623;p>0.05$), thinking that the electricity bill will decrease with smart grid applications (X2=3.767;p>0.05) are statistically insignificant (p>0.05). According to the results of the Hosmer-Lemeshow test, the data is statistically compatible with the model (p>0.05), showing the goodness of fit.

It can be inferred that attitude has significant effect on using energy saving bulbs. To make people use energy saving bulbs, their attitude should change towards it or any appliances that direct them to use saving bulbs, like smart grid appliances.

Table 3.7 The Effect of Attitude, Awareness, Intention Variables on Behavioral Characteristics

	Attitude		**Awareness**		**Intention**		**Model**		**Hosmer-Lemeshow**		**Cox& Snell R^2**	**Nagelkerke R^2**
	t	**p**	**t**	**p**	**t**	**p**	**X^2**	**p**	**X^2**	**p**		
Behavior1	4.56	**0.000***	0.170	**0.866**	0.615	**0.539**	23.437	**0.000***	4.714	**0.788***	0.033	0.050
Behavior2	0.75	**0.455**	0.214	**0.830**	0.475	**0.634**	0.780	**0.854**	13.987	**0.082**	0.001	0.002
Behavior3	0.18	**0.854**	0.224	**0.851**	0.187	**0.824**	0.140	**0.987**	1.384	**0.994**	0.000	0.000
Behavior4	0.83	**0.407**	0.346	**0.729**	0.307	**0.759**	0.859	**0.835**	10.724	**0.218**	0.001	0.002
Behavior5	0.58	**0.560**	0.134	**0.893**	0.032	**0.981**	0.349	**0.951**	11.625	**0.169**	0.000	0.001
Behavior6	0.49	**0.625**	0.477	**0.633**	0.335	**0.738**	0.537	**0.911**	10.477	**0.233**	0.001	0.001
Behavior7	1.03	**0.302**	0.786	**0.432**	0.261	**0.795**	1.587	**0.662**	3.636	**0.888**	0.002	0.003
Behavior8	0.00	**0.999**	0.130	**0.895**	1.628	**0.103**	2.623	**0.453**	5.808	**0.669**	0.004	0.006
PFB 1	0.01	**0.990**	1.880	**0.060**	0.631	**0.528**	3.767	**0.288**	4.504	**0.809**	0.005	0.012

According to the results of the ROC Analysis performed for the model above, which was found to be significant in the logistic regression model, the probability values determined can significantly predict the outcome variable (p<0.05). Accuracy rate is 63.6% in participants classified according to Cut-off Value. In other words, the model correctly estimates the answers 63.6% of the time.

Table 3.8 ROC Analysis Results of Estimated Probabilities According to the Model Results

ROC Analysis	Model
Real Positive	86
Real Negative	361
False Positive	182
False Negative	74

Table 3.8 (Continued)

ROC Field	0.627
p	**0.000***
Cut-off Value	>0.2447
Sensitivity	0.538
Specificity	0.665
PP+	0.320
NP-	0.830
Accuracy	**0.636***

To see the effect of attitude, awareness, intention, and demographic characteristics variables on 8 sub-features of behavior and 1 PFB, a model consisting of dependent variables (continuous variables and demographic characteristics model) related to 8 sub-features of behavior and its utility-related feature have been tested. The models on which the effects of the following variables are statistically significant; using energy saving light bulbs (X2=41.844;p<0.05), operating devices at certain hours (X2=41.430;p<0.05), thinking that the electricity bill will decrease with smart grid applications (X2=34.034;p<0.05), while taking care to turn off unnecessary lights (X2=18.815;p>0.05), using smart meters (X2=23.288;p>0.05), using alternative methods (X2=8.649;p>0.05), giving importance to building insulation (X2=23.240;p>0.05), raising awareness of people living in the household about saving (X2=23,226;p>0.05), running washing and dishwashers fully loaded (X2=18.830;p>0.05) models are statistically insignificant (p>0.05). According to the Hosmer-Lemeshow test results, the data is statistically compatible with the model (p>0.05), showing goodness of fit for Behavior1, Behavior4 and PFB1. Reference category ‘last’ was taken for categorical variables in impact tests.

Table 3.9: Model Statistics of Attitude, Awareness, Intention, Demographic Characteristics Variables for Behavior Characteristics

Variable	**Model**		**Hosmer- Lemeshow**		**Cox&Snell R^2**	**Nagelkerke R^2**
	X^2	**p**	**X^2**	**p**		
Behavior1	41.844	**0.009***	6.506	**0.591***	0.058	0.088
Behavior2	18.815	**0.712**	6.865	**0.551**	0.026	0.042
Behavior3	23.288	**0.444**	12.330	**0.137**	0.033	0.079
Behavior4	41.430	**0.011***	3.366	**0.909***	0.057	0.076
Behavior5	8.649	**0.997**	6.235	**0.621**	0.012	0.027

Table 3.9 (Continued)

Behavior6	23.240	**0.447**	9.191	**0.326**	0.033	0.044
Behavior7	23.226	**0.448**	12.814	**0.118**	0.032	0.044
Behavior8	18.830	**0.711**	8.255	**0.409**	0.026	0.044
PFB1	34.034	**0.018***	5.071	**0.750***	0.047	0.110

To analyze in detail, the logistic regression is run to see the effects of variables and demographics on each of the 8 behavior and 1 behavior with positive feedback-PFB items in the model separately. There have been statistically meaningful findings for Behavior1 (the use of energy saving bulbs), Behavior4 (running devices at certain hours), Behavior6 (giving importance to building insulation) and PFB1 (thinking that the electricity bill will decrease with smart grid applications).

The effect of the Attitude variable on the use of saving bulbs, that is Behavior1, is statistically significant and positive (increasing the use of saving bulbs) (B=0.461;t=4.383;p<0.05). The effect of Awareness (t=-0.039;p>0.05), Intention (t=0.034;p>0.05), Gender (t=0.501;p>0.05), age (t=1.279;p>0.05), Marital status (t=0.164;p>0.05), Educational Status (t=1.315;p>0.05), Monthly income (t=3.3032;p>0.05), Number of people living at home (t=2.675; p>0.05) was not significant (p>0.05). The ODDS ratio is 1.585 meaning that attitude and using a saving bulb is positively related since the ratio is over 1. The remaining part over 1 is 0.585, attitude alone increases the probability of using saving bulb by 58.5%.

Table 3.10 The Effect of Attitude, Awareness, Intention, Demographic Characteristics Variables on Using Energy Saving Bulbs

	Effect			ODDS Rate	
	B	**t**	**p**	**OR**	**%95 GA**
Attitude	0.461	4.383	**0.000***	1.585	1.948-1.29
Awareness	-0.039	0.327	**0.743**	0.962	1.215-0.761
Intention	0.034	0.344	**0.732**	1.034	1.254-0.853

The effect of awareness (B=0.274; Wald=7.497; p<0.05), age (Wald=13.583;p<0.05), educational status (Wald=11.563;p<0.05) variables on the status of operating devices at certain hours, that is Behavior4, is positive and statistically significant. Besides, the rate of not operating the devices at certain hours is higher in those aged 35-44 (61.1%) and those aged 45-54 (76.4%). The first two young groups cannot arrange hours. The rate of operating devices at certain hours is 3.553 times higher for primary school graduates and below, 3.765 times for secondary school graduates, 2.496 times higher for high school graduates and equivalent. The ODDS ratio is 1.315 meaning that awareness and operating devices at certain hours is positively related since the ratio is over 1. The remaining part over 1 is 0.315, attitude alone increases the probability of using saving bulb by 31.5%. same applies for other variables that are positively related to Behavior4.

According to the results of the ROC Analysis performed, which was found to be significant in the logistic regression model, the probability values determined can significantly predict the outcome variable ($p<0.05$). ROC analysis shows that 424 estimate out of 703 are true. The accuracy rate in the participants classified according to the cut-off value was 60.3%.

Table 3.11 The Effect of Attitude, Awareness, Intention, Demographic Characteristics Variables on Operating Devices at Certain Hours

	Effect			**ODDS Rate**	
	B	**t**	**p**	**OR**	**95% GA**
Attitude	-0.029	0.348	**0.728**	0.972	1.143-0.826
Awareness	0.274	2.738	**0.006***	1.315	1.599-1.081
Intention	0.021	0.257	**0.798**	1.021	1.2-0.869
Gender(1)	-0.320	1.647	**0.100**	0.726	1.063-0.496
Age		3.686	**0.009***		
Age(1)	-0.084	0.200	**0.842**	0.919	2.104-0.401
Age(2)	-0.176	0.430	**0.667**	0.839	1.869-0.376
Age(3)	-0.944	2.005	**0.045***	0.389	0.979-0.155
Age(4)	-1.442	2.843	**0.004***	0.236	0.639-0.087
Marital Status(1)	-0.007	0.032	**0.970**	0.993	1.42-0.695
Educational Status		3.400	**0.021***		
Educational Status(1)	1.268	2.556	**0.011***	3.553	9.394-1.344
Educational Status(2)	1.326	3.240	**0.001***	3.765	8.397-1.689
Educational Status(3)	0.915	2.585	**0.010***	2.496	4.993-1.248
Educational Status(4)	0.408	1.429	**0.153**	1.504	2.631-0.859

The effects of educational status2, graduates of secondary school ($B=0.890;p<0.05$), and income1, income level up to 13000 TL, ($B=-1.265;p<0.05$) variables on giving importance to building isolation, that is Behavior6, is statistically significant. The ODDS ratio for those graduated from secondary school is 2.434 meaning that they care about isolation 2.434 times higher. Same way, being in the lowest income group decreases the probability of caring about the building isolation by 71.8%.

Table 3.12 The Effect of Attitude, Awareness, Intention, Demographic Characteristics Variables on Giving Importance to Building Isolation

	Effect			ODDS Rate	
	B	**t**	**p**	**OR**	**95% GA**
Educational Status		2.500	**0.181**		
Educational Status(1)	0.773	1.552	**0.121**	2.167	5.752-0.816
Educational Status(2)	0.890	2.171	**0.030***	2.434	5.433-1.09
Educational Status(3)	0.344	0.976	**0.329**	1.411	2.816-0.707
Educational Status(4)	0.456	1.631	**0.103**	1.578	2.732-0.912
Monthly Income		3.484	**0.059**		
Monthly Income(1)	-1.265	2.668	**0.008***	0.282	0.715-0.111
Monthly Income(2)	-0.848	1.654	**0.098**	0.428	1.169-0.157
Monthly Income(3)	-1.160	2.450	**0.014**	0.313	0.793-0.124
Monthly Income(4)	-0.172	0.404	**0.686**	0.842	1.943-0.365
Monthly Income(5)	-0.390	1.019	**0.308**	0.677	1.434-0.32
Monthly Income(6)	-0.464	1.201	**0.230**	0.629	1.341-0.295

The effect of monthly income ($t=3.869$; $p<0.05$) on thinking that the electricity bill will decrease with smart grid applications, that is PFB1, is significant, but this is not observed in the subgroups. Attitude ($t=0.455$; $p>0.05$), Awareness ($t=1.142$; $p>0.05$), Intention ($t=1.259$; $p>0.05$), Gender ($t=1.118$; $p>0.05$), marital status ($t=0.767$; $p>0.05$), and the number of people in the house ($t=1.642$; $p>0.05$) are not significant. According to the results of the ROC Analysis performed, which was found to be significant in the logistic regression model, the probability values determined can significantly predict the outcome variable ($p<0.05$). ROC analysis shows that 448 estimate out of 703 are true. The accuracy rate in the participants classified according to the cut-off value was 63.8%.

Table 3.13 The Effect of Attitude, Awareness, Intention, Demographic Characteristics on Thinking that Electricity Bill Will Reduce with Smart Grid Applications

	Effect			ODDS Rate	
	B	**t**	**p**	**OR**	**95% GA**
Monthly Income		3.869	**0.020***		
Monthly Income(1)	-0.692	0.806	**0.420**	0.500	2.696-0.093
Table 3.13 (Continued)					
Monthly Income(2)	-0.787	0.852	**0.394**	0.455	2.781-0.074
Monthly Income(3)	-1.285	1.478	**0.139**	0.277	1.521-0.05

Table 3.13 (Continued)

Monthly Income(4)	1.284	0.991	**0.322**	3.610	45.667-0.285
Monthly Income(5)	0.891	0.897	**0.370**	2.437	17.062-0.348
Monthly Income(6)	-0.279	0.310	**0.757**	0.757	4.41-0.13

To sum up, there is a significant difference only in the item ‘I'm using a saving bulb’. among the behavior items. There is a significant difference between those who use and do not use a saving bulb in their attitudes. ($p<0.05$) Also, there is a significant difference between the participants who run and do not run the appliances at certain times in their intentions. ($p<0.05$) Since p value of intention very close to 0.05 in the item ‘I run the dishwashers and washing machines fully loaded.’ It can be concluded that there is a significant difference between those who run the dishwashers and washing machines fully loaded and partially loaded. Results show that awareness has no effect on behavior items. Attitude and intention have small effects on behavior items.

3.2.2.2.4 Interactions

To check for the interactions between variables based on all 9 behavior models, there created interaction variables with demographics and awareness, attitude, and intention. There have been statistically significant findings only with the interaction variables which are extensions of educational status among demographics.

Educational Status models consisting of dependent variables related to 8 sub-features of behavior and its positive feedback-related feature have been tested. Models examining the effects of variables on the state of using energy saving bulbs ($X2=33.746;p<0.05$), thinking that the electricity bill will decrease with smart grid applications ($X2=25.366;p<0.05$) are statistically significant. The models established for taking care to turn off unnecessary lights ($X2=8.975;p>0.05$), using smart meters ($X2=4.880;p>0.05$), operating devices at certain hours ($X2=5.098;p>0.05$), employing alternative methods ($X2=4.194;p>0.05$), giving importance to building insulation ($X2=3.043;p>0.05$), raising awareness of people living at home about saving (X2=5.859;p>0.05), using the dishwashers and washing machines at full-load (X2=11.767;p>0.05) are statistically insignificant (p>0.05). According to the Hosmer-Lemeshow test results (except for Behavior 3 and utility1 models), the data is statistically compatible with the model (p>0.05). Reference category 'last' was taken for categorical variables in impact tests.

Table 3.14 Model Statistics of Attitude, Awareness, Intention, Educational Status Interaction Variables for Behavior Characteristics

Variable	Model		Hosmer- Lemeshow		Cox&Snell R^2	Nagelkerke R^2
	X^2	p	X^2	p		
Behavior1	33.746	**0.001***	8.161	**0.227**	0.047	0.071
Behavior2	8.975	**0.705**	5.623	**0.467**	0.013	0.020
Behavior3	4.880	**0.962**	15.156	**0.019**	0.007	0.017
Behavior4	5.098	**0.955**	2.331	**0.887**	0.007	0.010
Behavior5	4.194	**0.980**	5.124	**0.528**	0.006	0.013
Behavior6	3.043	**0.995**	3.420	**0.755**	0.004	0.006
Behavior7	5.859	**0.923**	7.390	**0.286**	0.008	0.011
Behavior8	11.767	**0.465**	3.673	**0.721**	0.017	0.028
PFB1	25.366	**0.013***	30.911	**0.000**	0.035	0.082

The effect of educational status*Attitude interaction variable (t=4.601; p<0.05) on the use of energy saving bulbs is significant. The rate of using energy saving bulbs is 2.196 times higher for secondary school graduates who has high level of attitudes, 1.700 times higher for high school graduates and 1.613 times higher for college graduates. The effects of Awareness*Educational Status (t=2.390; p>0.05), Intention *Educational Status (t=2.587; p>0.05) variables are not significant. According to the results of the ROC Analysis performed for model 1 (use of energy saving bulbs), which was found to be significant in the logistic regression interaction model, the probability values determined can significantly predict the outcome variable (p<0.05). The accuracy rate in the participants classified according to the cut-off value was 47.8%. In other words, the model correctly estimates the answers 47.8% of the time.

Table 3.15 The Effect of Attitude, Awareness, Intention, and Educational Status on Using Energy Saving Light Bulb

	Effect			ODDS Rate	
	B	**t**	**p**	**OR**	**95% GA**
Educational Status * Attitude		4.601	**0.000***		
Educational Status(1) Attitude	0.590	1.834	**0.067**	1.805	3.391-0.96
Educational Status(2) Attitude	0.787	2.279	**0.023***	2.196	4.319-1.116
Educational Status(3) Attitude	0.531	2.669	**0.008***	1.700	2.51-1.151
Educational Status(4) Attitude	0.478	2.427	**0.015***	1.613	2.373-1.096

The effect of Educational Status* Awareness interaction variable ($t=3,328$; $p<0.05$) on thinking that the electricity bill will be low with Smart Grid applications is significant. The rate of thinking that the electricity bill will decrease with Smart Grid applications is 2.754 times higher for high school and equivalent school graduates, whose awareness level is high, and 1.643 times higher for college graduates. Besides, the effect of Educational Status(3)*Intention interaction variable ($t=2.17$; $p<0.05$) on thinking that the electricity bill will be low with Smart Grid applications is significant. That is, the graduates of high school of an equivalent college have more tendency to think use of smart grid applications will decrease electricity bills. At the same time, the effect of Educational Status(1)*Attitude interaction variable ($t=2.132$; $p<0.05$) on thinking that the electricity bill will be low with smart grid applications is significant. That is, the graduates of primary school or lower have positive attitude to smart grid applications reducing their bills. The effects of Attitude* Educational Status ($t=2.858$; $p>0.05$), Intention* Educational Status ($t=2.806$; $p>0.05$) variables are not significant. According to the results of the ROC Analysis performed for the interaction model 9, which was found to be significant in the logistic regression interaction model, the probability values determined can significantly predict the outcome variable ($p<0.05$). The accuracy rate in the participants classified according to the cut-off value was 65.6%. In other words, the model correctly estimates the answers 65.6% of the time.

Table 3.16 The Effect of Attitude, Awareness, Intention, Educational Status Interaction Variables Thinking that Electricity Bill Will Reduce with Smart Grid Applications

	Effect			ODDS Rate	
	B	**t**	**p**	**OR**	**95% GA**
Educational Status * Attitude		2.858	**0.086**		
Educational Status(1) Attitude	0.939	2.132	**0.033***	2.558	6.064-1.079
Educational Status(2) Attitude	-0.776	1.797	**0.072**	0.460	1.073-0.197
Educational Status(3) * Attitude	0.031	0.109	**0.913**	1.031	1.794-0.593
Educational Status(4) Attitude	-0.192	0.718	**0.473**	0.825	1.394-0.489
Educational Status * Awareness		3.328	**0.026***		-
Educational Status(1) Awareness	0.281	0.664	**0.507**	1.325	3.039-0.578
Educational Status(2) Awareness	1.013	2.244	**0.025***	2.754	6.675-1.137
Educational Status(3) Awareness	0.496	2.172	**0.030***	1.643	2.571-1.05
Educational Status (4) Awareness	-0.563	1.793	**0.073**	0.570	1.054-0.308
Educational Status * Intention		2.806	**0.096**		-
Educational Status (1) Intention(s)	-0.989	1.741	**0.082**	0.372	1.132-0.122
Educational Status (2) Intention(s)	-0.025	0.050	**0.960**	0.975	2.595-0.366
Educational Status (3) Intention(s)	-0.683	2.170	**0.030***	0.505	0.936-0.273
Educational Status (4) Intention(s)	0.126	0.449	**0.653**	1.134	1.962-0.655

3.3 Conclusion

SEM results state that awareness has effect on attitude, intention, and behavior. The factor driving the link between the electricity consumption behavior and smart appliance usage is awareness according to SEM results.

Th results of logistic regression analysis mostly support that attitude is another driver of smart appliance usage towards electricity consumption.

These two statistical methodologies are totally different such that, SEM does not include demographic variables and logistic regression is based on categorical variables. So, it is expected that the two analysis give different results.

Logistic regression analysis provided to see the effect of attitude towards smart grid applications in terms of electricity consumption. Besides, the target groups in the community who can be early movers for policies to implement smart grid applications became obvious with the help of logistic regression analysis.

To support the analysis in this chapter, the data collected from the sample has been revised such that the answers with ‘I have no idea’ are excluded and the SEM and logistic regression are run over the new sample. The details can be seen in the Appendix B.

CHAPTER 4

OVERALL CONCLUSION

4.1 Contributions

This dissertation contributes to our understanding of consumers' electricity consumption behavior in several ways. First, electricity consumption behavior is more habitual than planned behavior. It includes a low level of cognitive effort and automaticity in action, requires low self-efficacy, and is not much affected by social norms and values unless the behavior is made obvious to the public.

Second, awareness drives the link between smart appliance usage and electricity consumption behavior. To break the habitual loop in electricity consumption and direct people to use smart grid applications, policymakers should increase awareness on the demand side.

Third, attitude can be another driving factor for the public to adopt smart grid applications in electricity consumption behaviors.

Fourth, the study reveals the possible target groups in society to apply smart grid applications as a pilot group. The features of the respondents help us find the right consumers to raise awareness about the benefits of smart appliances on the demand side, break the existing consumption habits in electricity and become early adopters of the applications mentioned above in society so that the followers can act safely and easily.

4.2 Policy Implications

The findings of this dissertation bring valuable implications for future practices in designing the electricity consumption behavior of households in society in the context of smart grid applications.

The analysis shows that married people are more ready to increase awareness and build intention toward smart appliances affecting electricity consumption. The target group in raising awareness could be the ones with four or more people in the family. If there were an applied program for smart grid adoption with goals in household electricity consumption, it had better cover all income groups since all have significant relationships. The public intention could be changed through the age group 25-34. They can be early movers.

The target behaviors while designing a smart apps usage adoption program should be:

- use of energy-saving lamps
- operating devices at certain hours and
- showing the electricity bill decreases with smart appliance usage.

The target audience at first during this program should be:

- Age groups of 18-24 and 35+
- Families with 4+ people
- All Income levels except for the last one, the highest income level in the sample.
- Educational level 2&3 is secondary school graduates and high school or equivalent school graduates.

For the above suggestions to succeed, implications aiming to change a habitual behavior should consider breaking the habitual loop. To break a habitual loop, a persuasive program designed in line with below suggestions can be promising (Jager, 1992):

- Replacing methods i.e., rewards and punishments, can be used in intervening tools to treat the habit itself.
- By altering the cue or circumstance, the habit activation can be stopped.
- After activation, habitual behaviors may be impeded by situational, psychological, or social barriers that force a change to deliberate action.
- Because behavioral retraining may not be necessary, one option is to restrict or redirect the harmful effects of ingrained behaviors by making equipment automatic or ‘fool-proof’ (Heijs, 2006).

To apply the above principles to the routine behavior for electricity consumption of households:

- the rewards that encourage the repetitive behavior can be removed if they exist, and incentives for the desired behavior can be placed into the billing and/or tariffs.
- consumers can be educated about their routine behavior and raise awareness about smart grid applications served on the demand side and how they help them in terms of well-being, developing a more sustainable and reliable grid, developing a pro-environmental consumption behavior, and becoming a prosumer for the grid.
- enabling them to communicate with both the upstream and the downstream players and become able to regulate or avoid undesirable results and offer alternatives beneficial to themselves (Cres, 2006).

On the other hand, to gather results from a smart grid adaptation program that directly targets the demand side in electricity, the preferences of early movers, who are the households that are risk-takers and willing to be the first to adopt the ‘new’ in the market, should be analyzed in detail and the adoption scheme must be put in progress accordingly. The willingness to use smart appliances can only be encouraged by prioritizing end-users’ actions. Thus, the program should incorporate less recognizable operations while adhering to early movers' user choices. In addition to end-user practices, the usage behaviors and the ownership of appliances must be evaluated sensitively to reach the adoption potential (Lopes et al., 2016).

Smart grids may be effective in the form of a smart meter, a smart app in mobile phones, or home displays showing snapshots of the consumption and the costs simultaneously., all of which can be accepted as this ‘new’ in the demand side.

4.3 Future Research

A comprehensive framework that considers the pertinent factors that affect electricity consumption behavior is required to evaluate the relative impact of the various drivers. A more recent model, the Comprehensive Action Determination Model (CADM), which attempts to integrate the theory of planned behavior (TPB), the norm activation model (NAM), and the Ipsative theory to produce a multi-factor model, can be extended in terms of electricity consumption behavior so that the policymakers better understand the consumer preferences and design result-oriented programs accordingly. Besides, the evolving technology and its bringings can be included in future studies, such as artificial intelligence and machine learning technics to understand consumers better, respond to and learn more about consumer preferences, plug-and-play technologies, self-healing grids, and total grid automation.

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APPENDICES

A. Survey Form Sample

Bu çalışmanın temel amacı, katılımcıların akıllı şebeke uygulamaları ve elektrik kullanımları ile ilgili bilgi toplamak, akıllı şebeke uygulamalarının elektrik tüketimine etkisini ve bu etkiye nelerin sebep olduğunu anlamaya çalışmak, bu konuda bilimsel çalışma yapmaktır. Ankete yanıt veren kişilerin 18 yaşından büyük, toplumun farklı gelir gruplarından ve eğitim seviyelerinden gelen kişiler olmaları gerekmektedir. Çalışmada, hiçbir kişisel veri istenmemekte ve verilen cevaplar tamamen gizli tutumaktadır. Çalışmadan elde edilecek sonuçlar sadece bilimsel amaçlı olarak kullanılacaktır.

Çalışmaya katılım gönüllülük esasına dayanmakta olup çalışmaya devam etmek istenmemesi halinde istenilen aşamada ankete yanıt vermek sonlandırılabilir. Çalışmada yaklaşık 7 dakikalık bir anket formunda yer alan sorulara cevap verilmesi talep edilmektedir. Herhangi bir konuda ulaşmak isterseniz [redacted] e-posta adresini kullanabilirsiniz. Değerli katkılarınız için teşekkürler.

Rabia Ulusoy Y. Doktora Öğrencisi

☐	Anket çalışmasına gönüllü olarak katılmayı kabul ediyorum. Verdiğim cevapların bilimsel amaçlı olarak kullanılmasına izin veriyorum. Anketin zorunlu olmadığını, istediğim an yanıtlamayı bırakabileceğimi biliyorum.

BÖLÜM 1: DEMOGRAFİ

D1. Cinsiyet

Kadın	1
Erkek	2

D2. Yaş

18-24	1
25-34	2
35-44	3

45-54	4
55 ve üzeri	5

D3. Medeni Durum

Evli	1
Bekar	2

D4. Eğitim Durumu

İLKOKUL	1
ORTAOKUL	2
LİSE VEYA DENGİ	3
YÜKSEKOKUL	4
ÜNİVERSİTE	5
LİSANSÜSTÜ	6
HİÇBİRİ	7

D5. Meslek

Kendi işini yapan esnaf	1
Kendi işini yapan şirket sahibi	2
Kendi işini yapan profesyonel meslek sahibi (avukat, mühendis mali müşavir vs.)	3
Ücretli maaşlı çalışan işçi	4
Ücretli maaşlı çalışan yönetici	5
Devlet memuru(Çalışan)	6
Devlet Memuru(Yönetici)	7
Ev hanımı	8
Emekli	9
Öğrenci	10
İşsiz	11
Diğer……..	12

D6. Aylık Gelir (TL)

1000 TL ve altı	1
1000-2000 TL	2
2001-4000 TL	3
4001-6000 TL	4
6001-8000 TL	5
8001-10000 TL	6
10000 TL ve üstü	7

D7. Hanedeki Kişi Sayısı

3 ten az	1
3	2
4	3
5	4
6 ve üzeri	5

BÖLÜM 2: FARKINDALIK

S.1. Kullandığınız elektrik sayacının türünü biliyor musunuz? Eğer biliyorsanız türü nedir?

Analog sayaç	1
Elektronik sayaç	2
Ön ödemeli sayaç	3
Bilmiyorum….	4

S2. Elektrik faturasında hangi kalemlerin yer aldığını biliyor musunuz?

Elektrik tüketim değeri	1
Elektrik birim fiyatı	2
Elektrik tüketim tutarı	3
Dağıtım bedeli	4
Elektrik enerji fonu	5
TRT payı	6
Elektrik tüketim vergisi (ETV veya BTV)	7
KDV	8
Diğer……………………….	9
Hiçbiri/Bilmiyorum	10

S3. Elektrik faturanızı kontrol eder misiniz, ne sıklıkla kontrol edersiniz?

Her ay kontrol ederim	1
Bazen kontrol ederim	2
Hiç etmem	3

S4. Evinizde hangi elektrikli aletlerin daha fazla elektrik tükettiğini biliyor musunuz? Biliyorsanız belirtir misiniz?

Klima	1
Buzdolabı	2
Çamaşır makinesi	3
Bulaşık makinesi	4
Televizyon	5
Ütü	6
Saç kurutma makinası	7
Elektrikli soba	8
Elektrikli süpürge	9
Diğer……………	10
Bilmiyorum/fikrim yok	11

S5. Elektrik bütçenizi kontrol etmenizi sağlayan Akıllı Şebeke'yi daha önce duydunuz mu?

Evet duydum	1
Hayır hiç duymadım	2

S.6. Akıllı şebeke üretici ve tüketici arasındaki iletişimin kolay ve hızlı olmasını sağlayan bir sistemdir. Aşağıdaki akıllı şebeke uygulamalarını duyup duymadığınızı, duyduysanız kullanıp kullanmadığınızı belirtir misiniz?

Akıllı Şebeke Uygulamaları	**Duymadım**	**Duydum ama kullanmıyorum**	**Duydum ve kullanıyorum**
Donanımsal şebeke sistemlerinden olan akıllı sayaçlar	A	A	A
Donanımsal şebeke sistemlerinden olan ev içi bilgi ekranı	B	B	B
Yazılımsal şebeke sisteminden olan veri altyapısı sistemi (Web siteleri)	C	C	C
Yazılımsal şebeke sisteminden olan veri altyapısı sistemi (Sosyal Medya Ağı)	D	D	D
Yazılımsal şebeke sisteminden olan internet tabanlı uygulamalar (Örnek: EnerjiSa mobil uygulama)	E	E	E

S7. Akıllı telefon uygulamalarını kullanıyor musunuz?

Evet kullanıyorum	1
Hayır kullanmıyorum	2

BÖLÜM 3: NİYET

S8. Aşağıdaki hizmetleri kullanma olasılığınızı belirtir misiniz? (Kullanma Niyeti)

	Kesinlikle kullanmam	**Emin değilim / belki kullanırım**	**Kesinlikle kullanırım**	**Fikrim yok / bilmiyorum**
Kullanılan enerji miktarını gösteren akıllı sayaç	0	1	2	3
Elektrik tüketiminizi hesaplayan ve buna göre size yeni tedarikçiler öneren bir mobil uygulama	0	1	2	3
Tek tıklama ile daha ucuz tedarikçileri değiştirmenizi sağlayan bir uygulama	0	1	2	3
Anlık elektrik tüketiminizi ölçen evde çalışan bir ekran	0	1	2	3
Kampanya ve haberleri takip edebileceğiniz bir sosyal medya ağı	0	1	2	3

S9. Aşağıdaki hizmetleri arkadaş, aile ve/ya çevrenize tavsiye etme olasılığınızı belirtir misiniz? (Tavsiye Etme Niyeti)

	Kesinlikle tavsiye etmem	**Emin değilim / belki edebilirim**	**Kesinlikle tavsiye ederim**	**Fikrim yok / bilmiyorum**

Kullanılan enerji miktarını gösteren akıllı sayaç	0	1	2	3
Elektrik tüketiminizi hesaplayan ve buna göre size yeni tedarikçiler öneren bir mobil uygulama	0	1	2	3
Tek tıklama ile daha ucuz tedarikçileri değiştirmenizi sağlayan bir uygulama	0	1	2	3
Anlık elektrik tüketiminizi ölçen evde çalışan bir ekran	0	1	2	3
Kampanya ve haberleri takip edebileceğiniz bir sosyal medya ağı	0	1	2	3

BÖLÜM 4: TUTUM

S10. Aşağıdaki ifadelere ne derece katıldığınızı 0 ile 4 arasında değerlendirebilir misiniz? 0 kesinlikle katılmıyorum 4 kesinlikle katılıyorum anlamına gelmektedir.

	Kesinlikle katıl-mıyorum	**Katıl-mıyorum**	**Ne katılıyorum ne katıl-mıyorum**	**Katılıyorum**	**Kesinlikle katılıyorum**
Elektrik tüketimini azaltmak çevreyi korumanın umut verici bir yoludur	0	1	2	3	4
Akıllı şebeke kullanmak elektrik tüketimini azaltmaktadır	0	1	2	3	4
Elektrik tedarikçim tarafından yeterince bilgilendirilmiyorum	0	1	2	3	4
Tedarikçim faturamda bir indirim önerirse akıllı sayaç kullanırım.	0	1	2	3	4
Ortalamamın üzerinde bir tüketim durumunda beni uyaran bir akıllı telefon uygulaması olsa kullanırdım	0	1	2	3	4
Daha ucuz bir tedarikçi bulunduğunda beni uyaran bir akıllı telefon uygulaması olsa kullanırdım	0	1	2	3	4
Elektrik faturasını azaltmak için elimden geleni yapıyorum (gereksiz ışıkları söndürmek, belirli	0	1	2	3	4

saatlerde cihaz çalıştırmak vs.)					
Elektrik faturamı aşağıya çekecek bir tedarikçi olduğunda hemen tedarikçimi değiştiririm	0	1	2	3	4

BÖLÜM 5: DAVRANIŞ

S11. Elektrik tasarrufu sağlamak için elimden geleni yapıyorum aşağıdakilerden hangilerini yaptığınızı belirtir misiniz?

Tasarruf ampulü kullanıyorum	1
Gereksiz ışıkları kapatmaya özen gösteriyorum	2
Akıllı sayaç kullanıyorum	3
Belirli saatlerde cihazları çalıştırıyorum (çamaşır bulaşık makinesinin saat 22:00 den sonra çalıştırılması gibi)	4
Güneş yada rüzgar enerjisi gibi alternatif yöntemler uyguluyorum	5
Bina yalıtımına önem veriyorum	6
Evde yaşayanları tasarruf konusunda bilinçlendiriyorum	7
Çamaşır, bulaşık makinelerini tam dolu çalıştırıyorum	8
Diğer……………………..	9
Hiçbiri	10

BÖLÜM 6: FAYDA (OLUMLU BESLENEN DAVRANIŞ)

S12. Elektrik faturanız aylık ortalama ne kadardır? Son elektrik faturanız ne kadardı? TL olarak belirtiniz.

Aylık ortalama fatura tutarı	Son elektrik fatura tutarı

S13. Yukarıda belirtilen akıllı şebeke uygulamalarını kullandığınızda fatura tutarınızda azalma olacağını düşünüyor musunuz?

Evet	0
Hayır	1
Emin Değilim	2

B. SEM Validation Checks for Sample

Awareness:

About awareness 12 questions were asked to participants. In the first question, the participants were asked about the type of electricity meter they used. 39.1% of the participants use electronic, 25.5% analog and 19.5% prepaid meters. 15.9% of the participants do not know the type of meter they use.

Table 3.3 : Types of meters used by participants

	Frequency	Percent	Valid Percent	Cumulative Percent
Analog Meter	179	25,5	25,5	25,5
Electronic Meter	275	39,1	39,1	64,6
Prepaid Meter	137	19,5	19,5	84,1
I don't know	112	15,9	15,9	100,0
Total	703	100,0	100,0	

Participants were asked whether they knew which items were included in the electricity bill. Most of the item in the electricity bill were known by the participants. 86.49 % of the participants know the item ETT, 85.78 % know the items EBF and DB, 81.93 % know the item ETV, 79.66 % know the item TRT and 78.24 % know the item ETD. Only 4.27 % of the participants do not know the items were included in the electricity bill.

Table 3.4: Awareness of the items in the electricity bill

	f	%
EBF	603	85,78
ETD	550	78,24
ETT	608	86,49
ETV	576	81,93
DB	603	85,78
TRT	560	79,66
I don't know	30	4,27

While 42.7 % of the participants control their electricity bill sometimes 39.8 % control every month. 17.5 % of the participants never control their electricity bills.

Table 3.5: At what intervals participants control their electricity bills

	Frequency	Percent	Valid Percent	Cumulative Percent
Never	123	17,5	17,5	17,5
Sometimes	300	42,7	42,7	60,2
Every month	280	39,8	39,8	100,0
Total	703	100,0	100,0	

Participants were asked which electrical appliances consume more electricity in their homes. While 94.59 % of the participants answered this question as fridge, 74.25 % answered as iron, 59.60 % television, 56.9 % washing machine, 44.8 % electric stove, 37.70 % dishwasher and vacuum cleaner, 34.99 % hair dryer and 20.77 % air conditioner. 5.41 % of the participants do not know which electrical appliances consume more electricity in their homes.

Table 3.6: Electrical appliances which consume more electricity

Electrical Appliances	**f**	**%**
Fridge	665	94,59
Iron	522	74,25
Television	419	59,60
Washing Machine	400	56,90
Electric Stove	312	44,38
Dishwasher	265	37,70
Vacuum Cleaner	265	37,70
Hair Dryer	246	34,99
Air Conditioner	146	20,77
I don't know.	38	5,41

The participants were asked whether they had heard of the smart grid, which allows them to control their electricity budgets, and how much knowledge about it. 46.9 % of the participants didn’t hear the smart grid. 40.1 % of the participants heard the smart grid but they do not have any knowledge about it. Only 12.9 % of the participants heard the smart grid and they have a knowledge about it. Participants who heard about the smart grid were asked where they heard about the smart grid. While all participants stated that they heard the smart grid from TV and radio, 98.12% stated that they heard the smart grid from family and friends, 93.3% from social media, 58.45% from their own websites of energy companies and 47.8% from internet news sites.

Table 3.7: Awareness of Smart Grid

	Frequency	Percent	Valid Percent	Cumulative Percent
No, I didn't hear.	330	46.9	46.9	46.9
Yes I heard but I don't know about it.	282	40.1	40.1	87.1
Yes I heard, I know about it.	91	12.9	12.9	100.0
Total	703	100.0	100.0	

To evaluate awareness score:

1. In the question "What type of electricity meter are you using?", those who did not know were accepted as 0 and those who stated electricity meters were accepted as 1. Because the awareness of those who know is higher. But there's no difference between knowing electricity meter is analog or smart.
2. In the question "Do you know which items are on the electricity bill?" points were given according to how many items the participants knew. There were participants who knew at most 7 items. The score was divided into 7 to evaluate the data on a scale of 0-1.
3. In the question "How often do you check your electricity bill?", the answers given were evaluated as 0-1-2. Finally, the score was divided into 2 to evaluate the data on a scale of 0-1.
4. In the question "If you know which electrical appliances consume more electricity in your home, can you tell me?", the participant who answered more on this question was given more points. The score was divided into 6, the highest score. (For it to be between 0-1)
5. In question "Have you heard of the smart grid that allows you to control your electricity budget? How much knowledge do you have if you have heard?",

the answers given were evaluated as 0-1-2 and divided into two. (For values to be between 0-1)

Awareness score was calculated by summing these 5 scores. It was a homogeneous evaluation as the scores of the answers in all questions were reduced to 0-1. Since it was not possible to evaluate the awareness score based on questions separately, it was realized in this way. The mean and standard deviation of awareness score is 3.39 ± 0.74. While the scores of awareness of electricity meter and the items in the electricity bill are highest, the score of awareness of smart grid is lowest.

Table 3.8: The mean and standard deviation of awareness scores

	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Awareness of electricity meter	0	1	0,84	0,37
Awareness of the items in the electricity bill	0	1	0,84	0,22
At what intervals participants control their electricity bills	0	1	0,61	0,36
Awareness of electrical appliances which consume more electricity	0	1	0,76	0,26
Awareness of Smart Grid	0	1	0,33	0,35
Awareness	1	5	3,39	0,74

Intention:

About intention, participants were asked 10 4-point Likert-type (0-I definitely don't use, 1- No idea / I don't know, 2- I'm not sure / maybe I will use it, 3-I definitely use it) questions. Intention score was evaluated by calculating the mean of these 10 questions. The mean of the intension score is 2.36 ± 0.44. The mean of the items is generally above 2. This means that most of the participants stated that they could use the suggestions in the items. The item with the highest mean is “Could you indicate the possibility of recommending it to your friends, family and/or circle? An application that allows you to switch to cheaper suppliers with one click.”. The item with the lowest mean is “Would you use a home screen that measures your instantaneous electricity consumption if it is put at your disposal?”

Table 3.9: The mean and standard deviation of intention scores

Items	Mean	Std. Dev.
Could you indicate the possibility of using a smart grid that shows the amount of energy consumed if it is offered to your service?	2,43	0,80
Do you use a mobile application that calculates your electricity consumption and suggests new suppliers accordingly, if offered to your service?	2,37	0,74
Would you use an application that allows you to switch to cheaper suppliers with one click if it is offered to your service?	2,45	0,79
Would you use a home screen that measures your instantaneous electricity consumption if it is put at your disposal?	1,94	0,95
Would you use a social media network where you could follow the campaigns and news if it was offered to your service?	2,34	0,76
Could you indicate the possibility of recommending it to your friends, family and/or circle? : Smart grid showing the amount of energy used	2,48	0,66
Could you indicate the possibility of recommending it to your friends, family and/or circle? :A mobile application that calculates your electricity consumption and suggests new suppliers accordingly	2,46	0,65
Could you indicate the possibility of recommending it to your friends, family and/or circle? :An application that allows you to switch to cheaper suppliers with one click	2,51	0,62
Could you indicate the possibility of recommending it to your friends, family and/or circle? :A home working screen that measures your instant electricity consumption	2,09	0,73
Could you indicate the possibility of recommending it to your friends, family and/or circle? :A social media network where you can follow the campaign and news	2,56	0,72
Intention	2,36	0,44

Explanatory factor analysis was applied to 10 items here. The use of factor analysis has improved especially in the last thirty years, with the increase in the number of variables in multivariate analyzes. Factor analysis was developed by Spearman in the early 20th century and became more widespread with the use of computers. The main purpose of factor analysis is to collect less number of factors and reduce the number of variables by collecting the ones that are correlated with each other into a category. In this way, latent variables that cannot be measured directly are tried to be measured. In short, factor analysis is a data reduction technique. Researchers have resorted to this technique especially when there are many problems and the data is large and difficult to analyze.

In factor analysis, Bartlett Test of Sphericity and Kaiser-Meyer-Olkin (KMO) sample suitability test are used to evaluate the suitability of the data. The Barlett Test of Sphericity tests whether our correlation matrix is equal to the unit matrix. For factor analysis, this test should be significant, that is, the significance coefficient should be $p<0.05$. In addition, sufficient sample size is tested with Kaiser-Meyer-Olkin (KMO). If the value we obtained as a result of the Kaiser-Meyer-Olkin (KMO) test is greater than 0.5 (0.7-0.8 good, 0.5-0.7 moderate, at least 0.5) sample size will be sufficient for analysis. In the study, $p<0.05$ in the Barnett Test of Sphericity and KMO value were found to be 0.699. These values show that the data are suitable for factor analysis.

Table 3.10: KMO and Bartlett's Test for Intention

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,699
Bartlett's Test of Sphericity	Approx. Chi-Square	2932,259
	df	36
	p	,000

Varimax rotation technique was used in factor analysis. The 5th item was excluded from the analysis for its equal distribution among the factors. As a result of factor analysis, it is seen that there are 3 factors with eigenvalues greater than 1. With these 3 factors found, it explains 72,677% of the total change in the data set, which is a high rate in factor analysis. After applying rotation to the data, homogeneous distribution of the variability between these 3 factors was ensured.

Table 3.11: Total Variance Explained-Intention

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Comp.	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,247	36,078	36,078	3,247	36,078	36,078	2,528	28,094	28,094
2	1,853	20,589	56,666	1,853	20,589	56,666	2,511	27,896	55,990
3	1,441	16,010	72,677	1,441	16,010	72,677	1,502	16,687	72,677
4	0,795	8,832	81,509						
5	0,522	5,795	87,304						
6	0,473	5,251	92,556						
7	0,350	3,885	96,441						
8	0,180	2,003	98,444						
9	0,140	1,556	100,000						

Extraction Method: Principal Component Analysis.

In factor analysis, factor loads of all items are above 0.5. The first factor consists of 4 items and is named Intention1. The second factor consists of 3 items and is named Intention2. The third factor consists of 2 items and is named Intention3.

Table 3.12: Rotated Component Matrix[a]

	Component		
	1	2	3
Int 1	0.870		
Int 2	0.865		
Int 3	0.653		
Int 4	0.738		
Int 6		0.887	
Int 7		0.940	
Int 8		0.869	
Int 9			0.857
Int 10			0.861

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization

a. Rotation converged in 4 iterations.

To determine the reliability of the scale, the most appropriate Cronbach's Alpha Coefficient for Likert type scales was calculated with the SPSS program. In this analysis:

- If 0.00 < 0.40, the scale is not reliable.
- If 0.40 < 0.50 the scale has very low reliability.
- If 0.50 < 0.60, the scale is of low reliability.
- If 0.60 < 0.70, the scale is at sufficient confidence level.
- If 0.70 < 0.90, the scale is highly reliable.
- If 0.90 < 1.00, the scale is very reliable.

is accepted. (Özdamar, 2015: 575) In the reliability analysis, Cronbach's alpha coefficient was calculated as 0.786 in all Intention questions, 0.795 in Intention1 sub-dimension, 0.896 in Intention2 sub-dimension, 0.658 in Intention3 sub-dimension. This result shows that the survey questions and research data are reliable.

Table 3.13: Reliability Analysis Results of Intention and Its Sub-dimensions

	Number of Items	Items	Cronchbach's α
Intention1	4	1, 2, 3, 4	0.795
Intention2	3	6, 7, 8	0.896
Intention3	2	9, 10	0.658
Intention	10		0.786

Attitude:

About attitude, participants were asked 7 5-point Likert-type (0- Strongly disagree, 4-Strongly agree) questions. Attitude score was evaluated by calculating the mean of these 7 questions. The mean of the attitude score is 2.82 ± 0.53. The mean of the items is generally above 2. This means that most of the participants stated that they agree with the items. The item with the highest mean is ‘I do my best to reduce the electricity bill (turning off unnecessary lights, running devices at certain hours, etc.)’. The item with the lowest mean is ‘I am not sufficiently informed by my electricity supplier’

Table 3.14: The mean and standard deviation of attitude scores

Items	Mean	Std. Dev.
Using smart grid reduces electricity consumption, do you agree?	2,61	0,69
I am not sufficiently informed by my electricity supplier	2,40	0,87
If my supplier offers a discount on my bill, I use a smart meter.	3,00	0,74
If there was a smartphone app that alerted me in case of above-average consumption, I would use it.	2,83	0,77
If there was a smartphone app that alerted me when a cheaper supplier was found, I would use it	2,86	0,77
I do my best to reduce the electricity bill (turning off unnecessary lights, running devices at certain hours, etc.)	3,15	0,77
When there is a supplier that will lower my electricity bill, I immediately change my supplier.	2,88	0,77
Attitude	**2,82**	**0,53**

Explanatory factor analysis was applied to 7 items here. In the analyze, $p<0.05$ in the Barnett Test of Sphericity and KMO value were found to be 0.769. These values show that the data are suitable for factor analysis.

Table 3.15: KMO and Bartlett's Test for Attitude

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,769
Bartlett's Test of Sphericity	Approx. Chi-Square	2737,828
	df	21
	Sig.	,000

Varimax rotation technique was used in factor analysis. As a result of factor analysis, it is seen that there are 2 factors with eigenvalues greater than 1. With these 2 factors found, it explains 72.251 % of the total change in the data set, which is a high rate in factor analysis. After applying rotation to the data, homogeneous distribution of the variability between these 2 factors was ensured.

Table 3.16: Total Variance Explained-Attitude

Comp.	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,584	51,206	51,206	3,584	51,206	51,206	3,442	49,175	49,175
2	1,473	21,045	72,251	1,473	21,045	72,251	1,615	23,077	72,251
3	0,717	10,244	82,495						
4	0,460	6,573	89,068						
5	0,385	5,497	94,566						
6	0,271	3,870	98,436						
7	0,109	1,564	100,000						

Extraction Method: Principal Component Analysis.

In factor analysis, factor loads of all items are above 0.5. The first factor consists of 2 items and is named Attitude1. The second factor consists of 5 items and is named Attitude2.

Table 3.17: Rotated Component Matrix[a]

	Component	
	1	**2**
Using smart grid reduces electricity consumption, do you agree?		0,879
I am not sufficiently informed by my electricity supplier		0,894
If my supplier offers a discount on my bill, I use a smart meter.	0,647	
If there was a smartphone app that alerted me in case of above-average consumption, I would use it.	0,883	

If there was a smartphone app that alerted me when a cheaper supplier was found, I would use it	0,944
I do my best to reduce the electricity bill	0,777
When there is a supplier that will lower my electricity bill, I immediately change my supplier.	0,852

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 3 iterations.

In the reliability analysis, Cronbach's alpha coefficient was calculated as 0.814 in all Attitude questions, 0.731 in Attitude1 sub-dimension, 0.885 in Attitude2 sub-dimension. This result shows that the survey questions and research data are reliable.

Table 3.18: Reliability Analysis Results of Attitude and Its Sub-dimensions

	Number of Items	Items	Cronchbach's α
Attitude1	2	1, 2	0.731
Attitude2	5	3,4,5,6,7	0.885
Attitude	7		0.814

Behavior:

About behavior, participants were asked 9 questions. Participants answered all questions as ‘Yes’(2) and ‘No’(1). Behavior score was evaluated by calculating the mean of these 9 questions. When behavior score was evaluated, the question “I'm not doing anything to save electricity” calculated reversely. (Yes: 1 and No: 2) The mean of the behavior score is 1.47 ± 0.17. The item with the highest mean is “I try to turn off unnecessary lights.”. The item with the lowest mean is “I apply alternative methods such as solar or wind energy.” and “I'm not doing anything to save electricity”.

Table 3.19: The Mean and Standard Deviation of Behavior Scores

Items	Mean	Std. Dev.
I'm using a saving bulb	1,23	0,42
I try to turn off unnecessary lights.	1,81	0,39
I am using a smart meter	1,08	0,26
I run the appliances at certain times	1,47	0,50
I apply alternative methods such as solar or wind energy	1,09	0,29
I care about building insulation	1,38	0,49
I raise awareness of people living at home about saving	1,37	0,48

I run the dishwashers and washing machines fully loaded.	1,83	0,38
I'm not doing anything to save electricity	1,01	0,11
Behavior	**1,47**	**0,17**

Explanatory factor analysis was applied to 9 items here. In the analyze, $p<0.05$ in the Barnett Test of Sphericity and KMO value were found to be 0.565. These values show that the data are suitable for factor analysis.

Table 3.20: KMO and Bartlett's Test for Behavior

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,565
Bartlett's Test of Sphericity	Approx. Chi-Square	785.326
	df	36
	Sig.	,000

Varimax rotation technique was used in factor analysis. As a result of factor analysis, it is seen that there are 4 factors with eigenvalues greater than 1. With these 4 factors found, it explains 63.802 % of the total change in the data set, which is a high rate in factor analysis. After applying rotation to the data, homogeneous distribution of the variability between these 4 factors was ensured.

Table 3.21: Total Variance Explained-Behavior

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Comp.	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,057	22,853	22,853	2,057	22,853	22,853	1,935	21,503	21,503
2	1,331	14,784	37,637	1,331	14,784	37,637	1,361	15,121	36,625
3	1,240	13,781	51,418	1,240	13,781	51,418	1,311	14,572	51,197
4	1,115	12,384	63,802	1,115	12,384	63,802	1,134	12,605	63,802
5	0,943	10,483	74,285						
6	0,758	8,419	82,704						
7	0,681	7,562	90,266						
8	0,562	6,248	96,514						
9	0,314	3,486	100,000						

Extraction Method: Principal Component Analysis.

In factor analysis, factor loads of all items are above 0.5. The first factor consists of 3 items and is named Behavior1. The second factor consists of 2 items and is named Behavior2. The third factor consists of 2 items and is named Behavior3. The fourth factor consists of 2 items and is named Behavior4. As the questions here were Yes/No questions, the reliability analysis produced poor results.

Table 3.22: Rotated Component Matrix[a]

	Component			
	1	**2**	**3**	**4**
I care about building insulation	0,824			
I raise awareness of people living at home about saving	0,865			
I run the dishwashers and washing machines fully loaded.	0,547			
I am using a smart meter		0,805		
I run the appliances at certain times		0,729		
I'm not doing anything to save electricity			0,800	
I try to turn off unnecessary lights.			0,680	
I'm using a saving bulb				0,614
I apply alternative methods such as solar or wind energy				0,672

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 3 iterations.

Behavior with Positive Feedback as PFB:

About PFB, participants were asked 3 questions. In this section, the participants were asked about the monthly average electricity bills, the last electricity bills and whether they think that there will be a decrease in bill amounts when they use smart grid applications. The mean of the participants' monthly average electricity bills is 247.54 ± 67.00 TL. The mean of the participants' last electricity bills is 256.81 ± 60.89 TL. While 91.9 % of the participants think that their bill amount will decrease when they use smart grid applications, 7.0 % of the participants not sure about this and 1.1 % do not think will decrease.

Table 3.23: The Mean and Standard Deviation of PFB Questions

	Minimum	Maximum	Mean	Std. Dev.
The monthly average electricity bill	70,00	480,00	247,5363	67,00082
The last electricity bill	25,00	425,00	256,8080	60,88960

Do you think that your bill amount will decrease when you use smart grid applications?	0,00	2,00	1,9075	0,32684

Table 3.24: The Frequency of the Question ‘Do you think that your bill amount will decrease when you use smart grid applications?’

	Frequency	Percent	Valid Percent	Cumulative Percent
No	8	1,1	1,1	1,1
Not sure	49	7,0	7,0	8,1
Yes	646	91,9	91,9	100,0
Total	703	100,0	100,0	

C. SEM and Logistic Regression Analysis for the Revised Sample

Exploratory Factor Analysis

Exploratory factor analysis technique is used to determine the construct validity of the scale statistically. KMO and Bartlett tests are performed primarily to understand whether the scale is suitable for factor analysis. The KMO coefficient is calculated to test the sample size. Kaiser indicates that the value found is excellent as it approaches 1, and unacceptable below .50 (excellent at .90s, very good at .80s, mediocre at .70s and .60s, poor at .50s) (Tavşancıl, 2005). In the factor analysis, it is expected that the distribution in the universe is normal. This is also examined with the Bartlett test. In this context, the KMO test measurement result should be 0.50 and above, and the Bartlett sphericity test result should be statistically significant. The Scree Plot graph, which is the scatter diagram of the eigenvalues of the factors, is used to determine the total factor number of the scale. In the factor analysis process, factor load values are considered in the assignment of scale items to factors or their removal from the scale. The factor loading value is a coefficient that explains the relationship of the items with the factors. It is expected that the load values in the factor in which the items take place are high. If there is a cluster of items that are highly correlated with a factor, this finding means that those items together measure a concept, construct-factor.

Table: Intention Scale Exploratory Factor Analysis Results

Sub Scale	**Item no**	**Factor Load**	**AVO**	**CA**
Intention to Use	Intention 3	0,927	32,607	0,842
	Intention 2	0,900		
	Intention 1	0,888		
	Intention 4	0,658		
	Intention 5	0,580		
Intention to Recommend	Intention 8	0,910	27,850	0,771
	Intention 7	0,906		
	Intention 6	0,798		
	Intention 9	0,488		
	Intention 10	0,408		
Total			60,457	0,776
KMO=0,756 ; Barlett: X^2=2051,363 , p=0,000<0,05, *AVO: Explained rate of variance, CA: Cronbach Alpha*				

According to KMO and Barlett test results, In the Intention (KMO=0.756) scale, the KMO value was greater than 0.500 and the Bartlett X2 test was significant ($p<0.05$). Accordingly, the scales are suitable for Exploratory Factor Analysis and show normal distribution. In the analysis, it was determined that the scale was suitable for the 2-dimensional structure. The scale was evaluated over 2 sub-dimensions.

The Intention to Use sub-dimension consists of 4 items with factor loads ranging from 0.927 to 0.580. The explained variance rate of the dimension is 32,607%. Intention to Recommend sub-dimension consists of 4 items with factor loadings ranging from 0.910 to 0.408. The explained variance rate of the dimension is 27.850%. The reliability level of the sub-dimensions and the total scale is high (Cronbach Alpha>0.600). There are no items with low factor loading in the sub-dimensions (Factor load>0.300).

Table: Attitude Scale Exploratory Factor Analysis Results

Sub Scale	**Item no**	**Factor Load**	**AVO**	**CA**
Attitude	Attitude 5	0,935	51,987	0,823
	Attitude 4	0,877		
	Attitude 7	0,835		
	Attitude 6	0,777		
	Attitude 3	0,690		
	Attitude 2	0,350		

Attitude 1	0,309		
Total		51,987	0,776
KMO=0,778 ; Barlett: X^2=1272,592 , p=0,000<0,05			

AVO: Explained rate of variance, CA: Cronbach Alpha

According to KMO and Barlett test results, In the Intention (KMO=0.778) scale, the KMO value was found to be greater than 0.500 and the Bartlett X2 test was significant ($p<0.05$). Accordingly, the scales are suitable for Exploratory Factor Analysis and show normal distribution. In the analysis, it was determined that the scale was suitable for one-dimensional structure. The scale was evaluated on a single dimension.

The attitude scale consists of 7 items with factor loads ranging from 0.935 to 0.309. The explained variance rate of the scale is 51,987%. The reliability level of the scale is high (Cronbach Alpha>0.600). There is no item with a low factor load (Factor load>0.300).

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA), supported by a theoretical basis, is an analysis to evaluate how well the factors (latent variables) formed from many variables correspond with the real data. In other words, CFA aims to examine the extent to which a predetermined or constructed structure is confirmed by the collected data. In exploratory factor analysis, while the factor structure of the data is determined on the basis of factor loads without a certain preliminary expectation or hypothesis, CFA is based on testing a prediction that certain variables will take place predominantly on predetermined factors on the basis of a theory (Sümer, 2000). Many fit indices are used to determine the adequacy of the model tested in CFA. Since the fit indices have strengths and weaknesses in evaluating the fit between the theoretical model and the real data, it is recommended to use many fit index values to reveal the fit of the model. The most commonly used ones (Cole, 1987) are Chi-Square Fit Test (Chi-Square Goodness), Goodness Fit Index (GFI), Adjusted Goodness Fit Index (AGFI), Comparative Fit Index (CFI), Root Mean Errors (RMR) and it is the Root Mean Square Error (RMSEA) of Approximate Errors. For scale validity, DFA analyzes were performed with the AMOS 21.0 program.

Table: Attitude and Intention Scales Confirmatory Factor Analysis Results

Indices	Good Fit	Acceptable Fit	Intention	Attitude
X2	x	x	103,651	51,935
sd	x	x	31	13
X2/sd	≤ 3	≤ 5	3,344	3,987
RMR	≤ 0,05	≤ 0,08	0,021	0,017
GFI	≥ 0,95	≥ 0,90	0,941	0,960
AGFI	≥ 0,90	≥ 0,85	0,898	0,915
CFI	≥ 0,97	≥ 0,90	0,964	0,969
RMSEA	≤ 0,05	≤ 0,08	0,080	0,075

The CFA index results of the scales were examined. Intention scale goodness of fit (X2/sd=3.344), RMR (0.021), CFI (0.964), GFI (0.941), and AGFI (0.898), RMSEA (0.080) indices were fully provided. Attitude scale goodness of fit (X2/sd=3.987), RMR (0.017), CFI (0.969), GFI (0.960), and AGFI (0.915), RMSEA (0.075) indices were fully provided. The scales are compatible with the data.

Table: Attitude and Intention Scales Confirmatory Factor Analysis Factor-Item Load Distributions

Scale	Item	β	t	p
Intention to Use	Intention1	0,870		
	Intention5	0,391	7,371	**0,000***
	Intention4	0,467	9,006	**0,000***
	Intention3	0,959	26,497	**0,000***
	Intention2	0,924	24,966	**0,000***
Intention to Recommend	Intention6	0,774		
	Intention10	0,196	3,553	**0,000***
	Intention9	0,254	4,642	**0,000***
	Intention8	0,842	17,380	**0,000***
	Intention7	0,987	18,643	**0,000***
Attitude	Intention 7	0,800		
	Intention 6	0,739	15,369	**0,000***
	Intention 5	0,991	22,309	**0,000***
	Intention 4	0,839	18,278	**0,000***
	Intention 3	0,567	11,101	**0,000***
	Intention 2	0,208	3,803	**0,000***
	Intention 1	0,166	3,028	**0,002***

**p<0,05*

CFA item-factor load distribution and item significance of the Intention and Attitude scales are given. All items for the scales have statistically significant significance (p<0.05) for intention and attitude.

Table: Structural Equation Modeling Fit Indices

Indices	**Good Fit**	**Acceptable Fit**	**Model2**
X2	x	x	16,307
sd	x	x	6
X2/sd	≤ 3	≤ 5	2,718
RMR	≤ 0,05	≤ 0,08	0,043
GFI	≥ 0,95	≥ 0,90	0,984
AGFI	≥ 0,90	≥ 0,85	0,945
CFI	≥ 0,97	≥ 0,90	0,893
RMSEA	≤ 0,05	≤ 0,08	0,072

An error occurred in the model when taking both scaled and non-scaled parameters for SEM together. For this reason, the scores calculated from the scales defined in the model, and item-based analysis was not used.

Goodness of model fit (X2/sd=2.718), RMR (0.043), CFI (0.893), GFI (0.984), and AGFI (0.945), RMSEA (0.072) indices were fully provided. The data is compatible with the model.

Table: SEM Model Results

Dependent Variable	**Independent Variable**	**β**	**t**	**p**
Attitude	Awareness	0,155	2,861	**0,004***
Intention to Use	Attitude	0,032	0,580	**0,562**
Intention to Recommend	Attitude	0,166	3,069	**0,002***
PFB	Intention to Recommend	-0,020	-0,370	**0,712**
PFB	Intention to Use	-0,036	-0,655	**0,512**
Behavior	Intention to Recommend	-0,091	-1,659	**0,097**
Behavior	Intention to Use	0,095	1,726	**0,084**
PFB	Behavior	0,014	0,262	**0,793**

**p<0,05 significant effect, p>0,05 no significant effect; YEM*

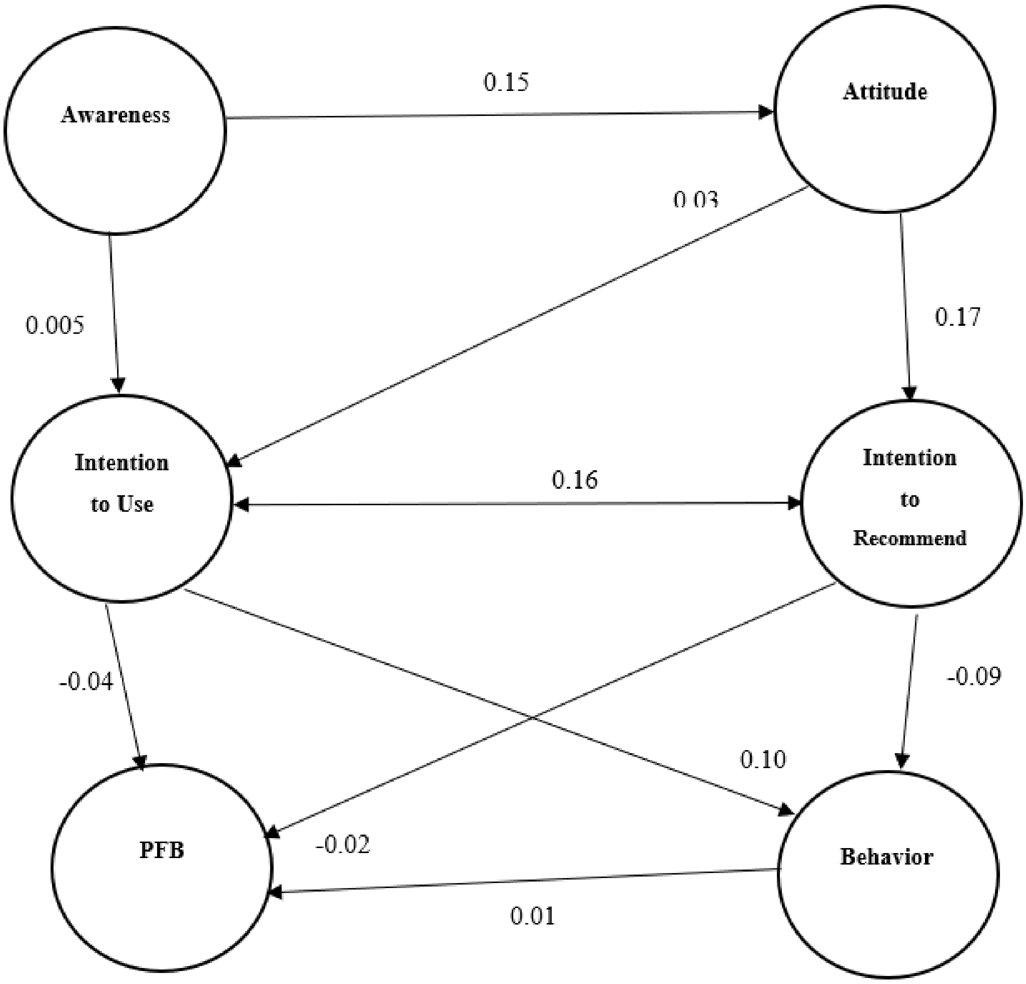

Figure: SEM Results for Revised Sample with Standard Estimates

Awareness (β=0.155) has a positive and significant effect on Attitude (t=2.861;p<0.05). Attitude (β=0.166) has a significant positive effect on Intention to Recommend (t=3.069;p<0.05). The effect of intention on PFB and Behavior on PFB was not statistically significant (p>0.05).

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PUBLICATIONS

1. Ulusoy Yılmaz R., Soytaş U. (2022) ‘Social Acceptance of Smart Energy Systems’, Handbook of Smart Energy Systems. Springer, Cham. https://doi.org/10.1007/978-3-030-72322-4_98-1

2. Ulusoy R. (2011), ‘Evolution of Turkish Electricity Distribution Network Under the Effects of Renewables: A Data-Based Study’, Journal of Energy Experts Association, Energy, Market and Regulation, Volume 10, p. 22-35.

Tennis, Playing Piano.