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Consumer's Adoption Of Smart Devices To Prevent Household Food Waste

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Dissertation

Presented as partial requirement for obtaining the Master Degree Program in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
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CONSUMER'S ADOPTION OF SMART DEVICES TO PREVENT HOUSEHOLD FOOD WASTE

By

Cláudia Alexandra Pedro Dos Santos

Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Intelligence.

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

DEDICATION

To all the people who, due to burnout, have given up on their dreams.

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I want to thank my parents, who apart from the emotional support were my biggest sponsors for me to study marketing for the last 5 years, even not knowing what marketing means, no matter how many times I explained it to them and kept explaining.

I thank my brothers, the other two elements of the three musketeers, because before I got to the moment of doing a dissertation, there was a whole journey of tests and exams over the years and the reason for part of my academic success derived from the fact that they on the previous days took my notes and asked me questions about the subject so that I could prepare better (sometimes against their desires). During the dissertation process, they covered for me by doing some of my day-to-day tasks, taking a load off my mind and leaving me only focused on getting it done, as well as making me laugh.

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Sometimes good opportunities come when you least expect them or are available. I am deeply grateful to my new colleagues for their support, understanding and for giving me the freedom to pursue not only the team's goals, but also my individual goals.

ABSTRACT

In some cases the consumer buys food, prepares it, consumes it, and unfortunately sometimes ends up wasting it, generating household food waste. This small action, repeated several times and on a global scale, has made food waste a worldwide problem. The fast technological development has opened up opportunities for the emergence of IoT devices, such as smart refrigerators as a promising tool to prevent food waste. This study aimed to investigate the main factors influencing the adoption of smart refrigerators as a technology to prevent household food waste. By applying and adapting the UTAUT2 model with three new constructs, namely privacy concerns, green self-identity, and attitude towards technology. An online survey was applied to 498 individuals residing in the United States of America. A Partial Least Squares Structural Equation Modeling (PLS-SEM) tool was applied to analyze the participants' data. The main influencers of behavioral intention to use smart refrigerator to prevent food waste were identified as social influence, performance expectancy, attitude, habit, and hedonic motivation, in this respective order. Privacy concerns and green self-identity were shown to play a role in shaping consumers' attitudes and their consequent behavioral intention. This research provides significant theoretical and managerial implications for the adoption of IoT technology to prevent food waste by highlighting both consumer drivers and barriers to technology adoption.

KEYWORDS

Food Waste; Green Self-Identity; Smart Home; Smart Refrigerator; Technology Adoption; UTAUT2

Sustainable Development Goals (SGD):

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LIST OF ABBREVIATIONS AND ACRONYMS

ATT	Attitude
BI	Behavioral Intention
BOGOF	Buy One, Get One Free
EE	Effort Expectancy
FAO	Food and Agriculture Organization
FC	Facilitating Conditions
GSI	Green Self-Identity
HM	Hedonic Motivation
HT	Habit
IoT	Internet of Things
IP Address	Internet Protocol Address
KG	Kilogram
PC	Privacy Concerns
PE	Performance Expectancy
PV	Price Value
RFID	Radio Frequency Identification
SDGs	Sustainable Development Goals
SI	Social Influence
UB	Use Behavior
USA	United States of America
USD	United States Dollar
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2

1 INTRODUCTION

Did you waste 74 kg of food last year? Statistically, that is what happens! Because the global average amount of food wasted each year is 74 kg per capita, and it was estimated that about 931 million tons of food waste were generated in 2019, of which 61% originated from households (FAO, 2021). Additionally, one-third of food is lost or wasted annually along the entire supply chain, causing serious environmental, economic, and social damages (Principato et al., 2021).

Food waste has become a worldwide problem, and since we live in a world where resources are limited, these tragic statistics have led us to the "sustainable development goal 12.3", which defines that food waste per capita should be reduced by half until 2030 (Lipinski, 2022). By doing simple math, consumers must reduce their food waste to 37kg per year per person.

At the same time, as we watch this human-made disaster, fortunately, the advances in the Internet of Things open up many opportunities to develop a set of innovations that support smart home users across many industries (Zielonka et al., 2021). Inclusively in the combat against food waste, where digital tools using Internet of Things technologies are creating new opportunities to change attitudes and influence consumer behavior to reduce food waste, like smart refrigerators (UNEP DTU Partnership & United Nations Environment Programme, 2021). The smart refrigerator, due to its amazing capabilities, is able to do many tasks such as helping to plan meals and create shopping lists, monitor food packages and their contents, measure and regulate environmental conditions to optimize storage conditions, alert consumers about food expiration dates (Liegeard & Manning, 2020; Vanderroost et al., 2017). Consumers may address the causes of food waste by incorporating these intelligent applications into daily household activities such as planning, purchasing, storage, preparation, and consumption (Hebrok & Boks, 2017; Liegeard & Manning, 2020).

The market size for Smart refrigerators was worth USD 2.66 billion in 2021 and is expected to grow to USD 6.39 billion by 2030. Geographically speaking, North America's market is mature in contrast to other regional markets due to the rapid adoption of technology (Verified Market Research, 2022).

Some authors (Liegeard & Manning, 2020) highlight the potential of certain smart technologies to prevent household food waste. However, despite the clear benefits, these technologies present substantial challenges, such as concerns over data privacy and hacking, as well as the potential loss of autonomy in food-related decision-making, which may influence the planning or purchasing of food. This author still emphasizes that it is necessary to conduct more investigations about consumer acceptance of smart approaches, such as the smart refrigerator, to reduce household food waste. There is an urgent need to understand better the attitudes, perceptions, and obstacles that influence consumer relations between food and technology by using social marketing (Galanakis et al., 2021).

Considering this gap, this research aims to identify the key factors that influence the acceptance of smart refrigerators as a technology to prevent household food waste. To conduct this study, a conclusive research was developed, which aims to obtain data through a survey questionnaire, from members of households living in the USA, based on scales previously developed in the literature.

From a theoretical point of view, this dissertation will extend the literature in the following ways: First, to fill the gap in the literature regarding consumer acceptance of smart refrigerators during household food routines to prevent household food waste (Liegeard & Manning, 2020). Second, to support the literature on the acceptance of smart refrigerators (Alolayan, 2014; Coughlan et al., 2012; Rothensee, 2008) and with updated and relevant information, identifying new factors for their adoption, especially for food waste purposes. Third, this research will contribute to supporting the literature regarding UTAUT2(Venkatesh et al., 2012) by studying the adoption of a specific technology to solve a specific purpose it is capable of doing, fourth by introducing new relationships such as privacy concerns (Marikyan et al., 2019; Wilson et al., 2017), attitude (Davis, 1989; Rothensee, 2008), and green-self identity (Barbarossa et al., 2015, 2017; Neves & Oliveira, 2021) relative to other variables under study since the authors have not provided a more comprehensive understanding of the factors influencing the adoption of this technology, namely discovering new indirect paths.

From a managerial point of view, it is expected that companies in this industry will know the factors most valued and least by consumers to adapt their products and marketing strategies so that they can have higher revenue and contribute to the solution of this problem. Since the industry can play a vital role by providing solutions that meet consumers' needs and preferences, it is crucial that both companies and consumers work together towards this common goal by 2030.

This dissertation follows a systematic structure. Starting with an in-depth literature review analysis and model development in section 2. Followed by a delineation of the research methodology in section 3. Then an analysis of the results obtained in the survey in section 4. After that, section 5 offers a comprehensive discussion of these findings. Ending with the conclusions of the study in section 6.

2 LITERATURE REVIEW AND MODEL DEVELOPMENT

2.1 CONTEXTUALIZATION OF FOOD WASTE

It is known that food can be lost in every stage of the supply chain (Lipinski et al., 2013), however not all of these lost are considered food waste. Food waste is the “decrease in the quantity or quality of food resulting from decisions and actions by retailers, food services and consumers” (FAO, 2019, p.5).

This research focus on household food waste, which occurs at the last stage of the chain and where currently 61% of consumer waste comes from the household, as indicated earlier in the introduction (FAO, 2021).

2.1.1 Causes of household food waste

All humans have the basic need to eat food in order to survive (Maslow, 1954). But, a lot of times, they buy the food, it is prepared, consumed and, unfortunately it can also end wasted (Quested et al., 2013).

To intervene effectively and efficiently in the problem of household food waste the first step is to find out what causes it (Graham-Rowe et al., 2015). The literature shows that food waste is not caused by a single variable, but by a set of variables that simultaneously influence food waste behaviour, making it a complex problem (Principato et al., 2021; Schanes et al., 2018), as illustrated in the following framework.

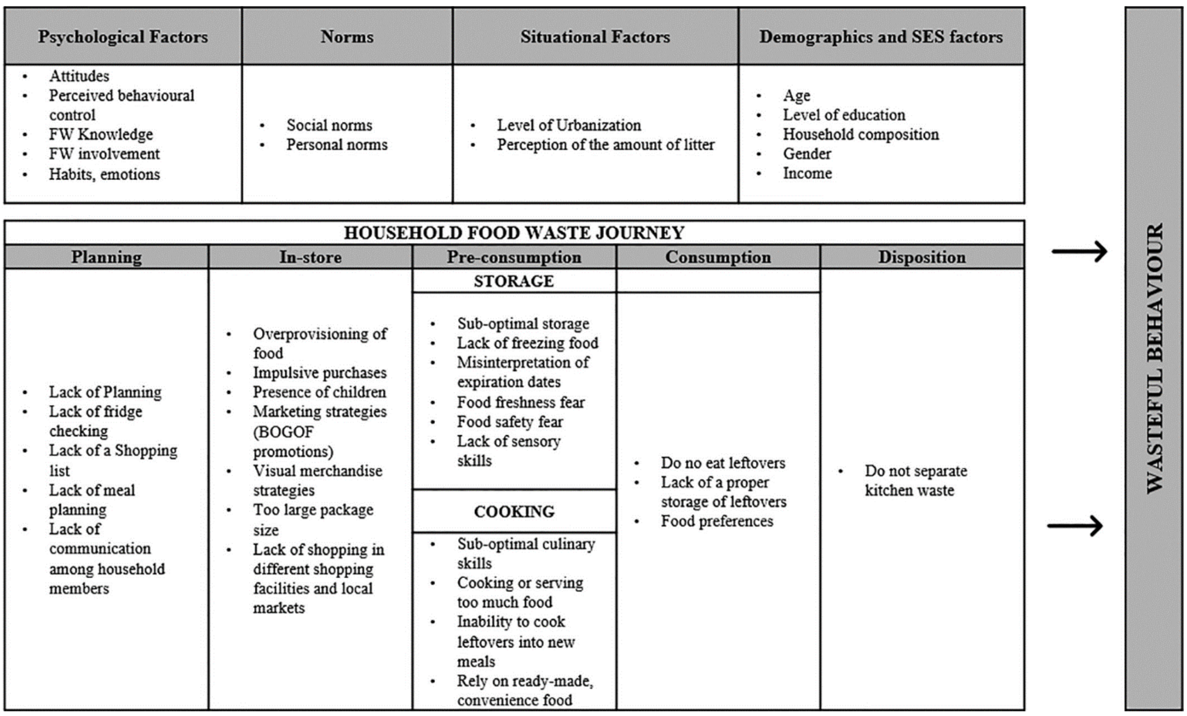


Figure 1 The household wasteful behaviour framework (Principato et al., 2021)

It is known that food-wasting behavior can be influenced by a combination of psychological factors, norms, situational factors, as well as demographic and socioeconomic characteristics (Principato et al., 2021). Only the household food waste journey was explored detail to better understand the causes of food waste already identified by the literature.

2.1.1.1 Household food waste journey

As shown before, as result of this complexity, the household food routines, such as planning, purchasing, storing, cooking, eating, as well as managing leftovers, play an important role in both food provisioning and food waste generation (Schanes et al., 2018).

- Planning

Research have shown that planning meals and creating shopping lists are two important behaviours for minimizing food waste (Parizeau et al., 2015). Consumers who plan their weekly meals have a lower probability of purchase more ingredients than they would consume and consequently waste them (Quested et al., 2013).

However, people with busy lifestyles and people who often shop opportunistically (e.g., after leaving work) tend not to know the exact amount of food they have stored in the fridge, and therefore end up overbuying (Ganglbauer et al., 2013). Good planning also requires good communication between household members, avoiding the risk of doubling up on the food purchased (Farr-Wharton et al., 2014a).

- In-store or Shopping

Food waste at home can also be caused by the difference between over-provisioning as opposed to over-consumption (Mallinson et al., 2016). Overprovisioning food is also related to time availability, in the sense that building a food stock reduces stress and saves time but might lead to purchasing more than one can eat (Graham-Rowe et al., 2014).

Previous research proved that this could happen due to some marketing strategies (such as “buy one, get one free” (BOGOF)) that lead to impulse buying, where the consumer buys more food than he needs (Principato et al., 2021). Sometimes, people also may not cook planned meals whose ingredients have already been bought because they don't have enough time (Schanes et al., 2018).

- Pre-consumption

The author has categorized the pre-consumption stage into two sub-phases: storing and cooking. These two sub-phases are discussed in detail below.

a. Storage

When customers purchase a lot of fresh food at widely spaced intervals, it is necessary a good food storage to increase their life, so they can be consumed instead of wasted. (Quested et al., 2013). Proper food storage can prevent or reduce food waste, but there are so many consumers who do not know how to manage shelf life, what is the proper place to store each type of food and maintain the recommended refrigerator temperature in order to get the most out of their food. This is compounded by the fact that most people set their refrigerators at higher than recommended temperatures, which promotes food degradation (Principato et al., 2021).

Most consumers are unaware of the optimal method and location for storing each type of food, so the way they organize their fridge might affect if the food is consumed or wasted. Some leftover ingredients are often stored at the bottom of the fridge, behind other items, and end up being forgotten because they are sometimes smaller and are not seen (Farr-Wharton et al., 2014; Schanes et al., 2018).

Previous studies have shown that a large number of consumers feel confused between "best before" and "use by" food expiration labels, leading them to misinterpretation of the food expiration date (Principato et al., 2021) which might influence them to decide to throw away the food (UNEP DTU Partnership & United Nations Environment Programme, 2021).

b. Cooking

Improving cooking and food preparation skills is another way to reduce food waste (Principato et al., 2021). A significant amount of food is wasted during the cooking process, primarily due to four reasons: an over-preparation of food, insufficient knowledge and skills for cooking leftovers, a limited repertoire of recipes and menus, and also a preference for convenience food. In turn, over-preparation behavior can be mitigated through training in cooking skills and using devices that help control food portions (Schanes et al., 2018).

- Consumption

According to (Schanes et al., 2018), very little research was done on the act of eating, and the waste that was created from it. From the studies done it was found that this is due to an unpredictability of how much food will actually be eaten given their appetite, regardless of whether they are adults or children. Given children's reasonably unpredictable eating habits and preferences, households with children tend to produce more food waste from meals. Lastly, Families with members who follow specific diets tend to waste less food overall.

When individuals do not eat everything on their plates and do not finish it later, it leads to food waste since it is discarded (Principato et al., 2021).

Giving leftovers a second chance requires a new set of actions, such as sorting, selecting, storing, and transforming the foods, however, eating the same foods repeatedly can be considered a sacrifice. (Cappellini, 2009; Schanes et al., 2018).

Although they are often considered less fresh or more susceptible to contamination, leftovers are perceived as time and money savers that are still tasty and good to eat (Waitt & Phillips, 2016). So, If people add to the leftovers some good decisions and good cooking skills, they can avoid wasting food (Stancu et al., 2016).

2.2 SMART DEVICES TO PREVENT HOUSEHOLD FOOD WASTE

According to Mezzina et al. (2023) the smart home concept was developed to provide its residents with an automated or semi-automated environment, where the goal of this design was to meet the residents' needs for well-being, safety, and comfort, as well as to minimize energy waste. To achieve these goals, robots have been introduced into the smart home environment as personal assistants to users assisting with daily tasks or gateways to centralize the interface for smart home devices (HUB). Also, these robots can be employed to meet the mentioned goals, but also for the purpose of reducing food waste.

Although some studies have already proved the effectiveness of these technological solutions in reducing food waste, their development is still immature because most of them are still in early-stage experimentation, prototyping or even limited launch phase (UNEP DTU Partnership & United Nations Environment Programme, 2021).

A study by Hanson & Mitchell (2017) on the impact of digital technologies on wastage during the consumption phase in services reveals that for every $1 invested, $14 was saved in operating costs. Due to this, the authors invite us to reflect on how much the household can save by using these technologies in their daily food routine.

The literature reports some possible solutions that can prevent household food waste by applying digital tools using the Internet of Things (IoT).

Among these, smart packaging emerges as a cutting-edge system designed to continuously monitor the quality of a product by collecting information from both the internal and external packaging environment and providing valuable information to actors in the food supply chain (Ghaani et al., 2016; Liegeard & Manning, 2020; UNEP DTU Partnership & United Nations Environment Programme, 2021).

Equally impactful, smart labeling acts as a preventive food waste by providing information about the shelf life, freshness, storage instructions, or recipe suggestions (UNEP DTU Partnership & United Nations Environment Programme, 2021).

Further along the same line of innovative solutions to prevent food waste, emerged the smart refrigerator, which is the technology that is discussed in depth in the following section and on which the research is based (Hebrok & Boks, 2017; Liegeard & Manning, 2020; Osisanwo et al., 2015; UNEP DTU Partnership & United Nations Environment Programme, 2021; Vanderroost et al., 2017).

2.2.1 Smart refrigerator

A smart refrigerator (also known as intelligent refrigerator, intelligent fridge, or smart fridge) is a smart home appliance, this device consists of a refrigerator that is equipped with a large and flat touchscreen interface for user interaction that uses Internet of Things (Alolayan, 2014). Typically, these devices are launched into the market already equipped with cameras that make it easy to view the contents stored inside without needing to be opened, they are also recognized as a combination of green, digital and IoT technology at the same time (UNEP DTU Partnership & United Nations Environment Programme, 2021).

Smart fridges, unlike regular refrigerators, possess distinctive features, as indicated by Osisanwo et al. (2015) and Liegeard and Manning (2020). These features include an IP address, enabling information exchange with a server via the internet, accessible through a user terminal (e.g. smartphone to access the refrigerant). Additionally, a control unit or microcontroller is present to manage the refrigerator's functions, acting as a small computer integrated on a single circuit with a processor, memory, and peripherals for input and output. The inclusion of sensors enables the measurement of conditions, like temperature and humidity, and then transforms the data into signals so that a control unit can read and interpret them. Also, communication devices like Bluetooth, Wi-Fi, or RFID technology facilitate wireless or wired network connections with other Internet of Things devices and appliances, converting received information into radio waves or signals (Liegeard & Manning, 2020; Osisanwo et al., 2015) .

Moreover, weight sensors (which allow the recording of incremental food intake) and voice interfaces (which allow easy recording of information by the user) are components that have been proposed to be added to smart refrigerators (UNEP DTU Partnership & United Nations Environment Programme, 2021).

2.2.1.1 Relationship between the smart refrigerator and household food waste routine

The smart refrigerator can be successfully integrated into household food routines and answer the causes of food waste addressed in the literature, namely in planning food routines, shopping, storage, preparation, and consumption (Hebrok & Boks, 2017; Liegeard & Manning, 2020).

Regarding food waste, some of the benefits of smart fridges that Osisanwo et al. (2015) mention are: that the consumer can remotely monitor the items inside the smart fridge and their current status, from anywhere using their smartphone. It allows the consumer to save cost by acquiring unnecessary or unneeded items, save time spent on reorganizing and verifying expiry dates manually, and save unnecessary energy spent. As well as better food management, no waste of food, more efficient shopping, and recording information on consumer purchases and information and their habits because, due to these components mentioned above, smart fridges are capable of performing functions such as: detecting and tracking food packaging and their inside contents; measure environmental conditions and establish ideal storage conditions; alerting customers about expiry dates, recommend recipes for food items or packages stored inside the fridge, is able to manage supply activities and helps create shopping lists (Vanderroost et al., 2017).

In a study conducted by Dekoninck and Barbaccia (2019) four alternative scenarios were developed to compare the difference in the environmental impact caused by smart fridges that employ IoT technology versus regular refrigerators. They found that smart fridges wasted the same amount of food as a regular fridge when used in a "least" scenario, but when used in an "average" scenario, they wasted approximately 30% less food, and when used in a "most" scenario were wasted 60% less food.

2.2.1.2 Consumer adoption of smart refrigerators

According to Liegeard and Manning (2020), smart fridges offer a range of tools and equipment to help consumers manage their household food, but its acquisition cost could lead to the risk of consumers characterizing it as an "unnecessarily expensive gadget". However, because of the numerous advantages of it, namely in terms of reducing food waste due to stock control, it has gained special interest in the literature. The author also laments that only a few studies have considered the degree of consumer acceptability and interest of smart fridges, alerting to the need for more empirical studies on this theme.

The success of new technologies strongly depends on user acceptance, and the smart refrigerator is no exception. The acceptance of smart fridges by consumers has already been studied (Alolayan, 2014), however, the data was collected in 2013 when its concept was still in the prototype phase and, unfortunately, to a tiny sample size. Nowadays, after 10 years, smart fridges have already had a significant evolution and have gone from prototypes to final products, in the same way there may have been a consumer change in their acceptance, so it becomes particularly challenging to investigate a more qualified sample that especially interacts with smart fridges in their daily life. This study, conducted by Alolayan (2014), only focused on consumers' general acceptance of smart fridges, but it did not specifically investigate the relationship between smart fridges and the prevention of household food waste.

Moreover, several studies (Baudier et al., 2020; Hubert et al., 2019; Kim et al., 2017; Nikou, 2019; Park et al., 2017; Shin et al., 2018; Yang et al., 2017) have focused on the acceptance of IoT technologies in smart homes in general, but none have specifically addressed the only the smart fridge, and neither have they contributed to any social cause, such as the reduction of food waste Given the studies previously done and the need to investigate consumer acceptance of smart fridges technology, as far as known, any previous research has investigated this relationship recently, and it becomes an interesting gap to investigate.

The Unified Theory of Acceptance and Use of Technology (UTAUT2) proposed by Venkatesh et al. (2012) was used as the main reference for this research because of its comprehensive empirical model witch is an evolution of the UTAUT(Venkatesh et al., 2003), which in turn was inspired by other theories such as the technology acceptance model (TAM)(Davis, 1989), theory of planned behaviour (TPB) (Ajzen, 1991), and others.

In UTAUT2 (Venkatesh et al., 2012) the author suggests that the actual use of technology is determined by behavioral intention, which in turn is influenced by factors such as: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and the habit.

There will also be study 3 extensions that have shown to have an impact on the adoption of technologies in other studies, namely: privacy concerns (Marikyan et al., 2019; Wilson et al., 2017) , attitude (Davis, 1989; Rothensee, 2008) and green self-identity (Barbarossa et al., 2015, 2017; Neves & Oliveira, 2021).

2.2.1.2.1 Performance expectancy

The performance expectancy can be defined as being "The degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh et al., 2012, p.159).

Venkatesh et al. (2003) proved in both UTAUT(Venkatesh et al., 2003) and UTAUT2(Venkatesh et al., 2012) to have a direct impact on the behavioral intention to use the technology.

Several research can show a significantly positive direct path between performance expectancy and behavioral intention towards technology in various fields, such as the adoption of mobile banking (Alalwan et al., 2017), acceptance of healthcare services (Cimperman et al., 2016), acceptance of shared e-scooters (Kopplin et al., 2021).

The smart fridge is a smart home service, and the literature in this context shows that people's performance expectancy about these devices contributes positively to the behavioral intention to use them, in other words, it means that the higher the performance expectancy, the higher the behavioral intention to use that device (Alaiad & Zhou, 2017; Pal, Funilkul, Charoenkitkarn, et al., 2018) leading to the following hypothesis:

H1. The consumer's performance expectancy about the smart refrigerator will positively influence their behavioral intention to use it.

2.2.1.2.2 Effort expectancy

The effort expectancy can be defined as being "the degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012, p.159).

The literature proved in both UTAUT(Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) that the effort expectation that the consumer has about a specific technology will influence the behavioral intention to use that technology. Being proven in several domains, as the adoption of mobile banking (Alalwan et al., 2017) or the acceptance of healthcare services (Cimperman et al., 2016), to have a significantly positive impact.

However, the literature is contradictory, because while some studies about IoT and smart homes demonstrate a positive relationship between effort expectancy and behavioral intention to use (Pal, Funilkul, Charoenkitkarn, et al., 2018), others reject this relationship (Alaiad & Zhou, 2017; Baudier et al., 2020) . For this study it was hypothesize:

H2. The consumer's effort Expectancy about the smart refrigerator will positively influence their behavioral intention to use it.

2.2.1.2.3 Social influence

The social influence can be defined as being "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" (Venkatesh et al., 2012, p.159).

In both UTAUT and UTAUT2 it has been proven that the social influence that exists over the consumer about a certain technology has a direct impact on the consumer's behavioral intention to use it (Venkatesh et al., 2003, 2012).

The literature shows in different contexts of the adoption of technologies that make up smart homes, an inconsistency of results because while some claim there is a significant relationship to the point of stating that social influence has a significant impact on the intention to use a particular technology (Alaiad & Zhou, 2017) , other studies have rejected this hypothesis (Baudier et al., 2020; Pal, Funilkul, Charoenkitkarn, et al., 2018).

According to (Alolayan, 2014) social influence is one of the key facts that influence the adoption of a smart fridge, due to the fact that when people are uncertain about their adoption decision, they tend to be uncomfortable with this uncertainty and therefore consult the opinions of their family members, friends and social network, about the subject. Taking into account that the smart fridge is used in a home environment, the members who live there can influence the need to adopt a smart fridge. The following hypothesis is formally proposed:

H3. The consumer's social influence towards the smart refrigerator positively influences their behavior in their intention to use it.

2.2.1.2.4 Facilitating conditions

The facilitating conditions can be defined as being “consumers’ perceptions of the resources and support available to perform a behavior” (Venkatesh et al., 2012, p.159).

The UTAUT and UTAUT2 models argue that the facilitating condition has a direct impact on the behavioral intention to use the technology and also its use behavior. However, in the context of IoT in smart homes (Pal, Funilkul, Charoenkitkarn, et al., 2018) it failed to prove that there was a significant relationship between facilitation conditions and behavioral intention to use that same technology.

Facilitating conditions encompass compatibility between technologies. Compatibility between IoT devices in a house is very important for its adoption, especially if people live in a smart home environment so that communication with other I0T devices is possible (Shin et al., 2018). Regarding this specific question about device compatibility in smart home environments, some studies have shown a significant direct relationship with intention to use technology (Hubert et al., 2019; Nikou, 2019; Pal, Funilkul, Vanijja, et al., 2018).

H4a. A consumer's facilitating conditions regarding the smart refrigerator positively influence his behavior to use it.

H4b. The consumer's facilitating conditions regarding the smart refrigerator positively influence its usage behavior.

2.2.1.2.5 Hedonic motivation

The hedonic motivation can be defined as being "The fun or pleasure derived from using a technology" (Venkatesh et al., 2012, p.161).

Venkatesh et al. (2012) in UTAUT2 established that an individual's fun or pleasure drive towards a specific technology has a direct impact on their intention to actually use it. Other research has supported this relationship when studying the adoption of other technologies, such as mobile banking.

However, in the context of smart home adoption, Baudier et al. (2020) reject this relationship, which suggests that the adoption of smart homes by students is influenced neither by fun nor by the pleasure obtained from using it.

Taking into account the components of a smart fridge and the numerous capabilities it has, previously shown in the literature, the following hypothesis was studied:

H5. Consumers' hedonic motivation about the smart refrigerator will positively influence their behavioral intention to use it.

2.2.1.2.6 Price Value

The price value can be defined as being "consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh et al., 2012, p.161).

The smart refrigerator provides a big amount of tools and equipment to help manage food, however, there is concern that due to its high acquisition cost compared to standard refrigerators, consumers may perceive the smart refrigerator as an "unnecessarily expensive gadget" (Liegeard & Manning, 2020). In fact, the adoption of the first smart refrigerator in the world was not successful, due to the fact that consumers perceive this technology as an unnecessary, expensive and luxury product (Aheleroff et al., 2020).

However, on the other hand, Osisanwo et al. (2015) says that the smart refrigerator can save costs by preventing people from buying unnecessary or unneeded food items. By utilizing smart home systems as smart refrigerators, it is possible to optimise power consumption and reduce costs (Aheleroff et al., 2020) which can be beneficial to the consumer.

Venkatesh et al. (2012) used empirical research to support the idea that there is a relationship between the price of a product associated with its quality level, however the consumer will feel that the price value is positive when the benefits they get from it are greater than its monetary cost. Stating that the price value of a technology is a predictor of the behavioral intention to use it.

Pal, Funilkul, Charoenkitkarn, et al. (2018) in the context of IoT devices in smart homes, found that there was a negative relationship between the price of these technological devices and behavioral intention. This leads to the following hypothesis:

H6. The price value a consumer feels about the smart refrigerator will sig negatively influence his behavioral intention to use it.

2.2.1.2.7 Habit

The habit can be defined as being “the extent to which people tend to perform behaviors automatically because of learn”(Venkatesh et al., 2012, p.161)

Venkatesh et al. (2012) in UTAUT2 established that habit is one of the predictors of behavioral intention to use as well as the use behavior of a given technology.

In the context of smart home adoption, some authors (Baudier et al., 2020) demonstrated that there is a significant relationship between habit and intention to use. Smart fridge users who end up using this technology to perform different tasks such as looking up recipes, making shopping lists, using the app to find out what they have stored in their fridges, and among other tasks, may generate a sense of habit towards the technology, which will influence their intention to use it, as well as their use behavior. Following this logic, you will be hyped:

H7a. The consumer's habit towards the smart refrigerator positively influences their behavioral intention to use it.

H7b. The consumer's habit towards the smart refrigerator positively influences their use behavior.

2.2.1.2.8 Privacy concerns

Smart Refrigerators, due to their multiple connected sensors and actuators, have the ability to collect and also generate data, transforming them into information, later into knowledge and finally into wisdom. Also, the home appliances industry has made significant advancements over the years, allowing manufacturers to collect incremental data from devices and their users, with the help of technologies such as IoT and big data (Aheleroff et al., 2020).

According to Marikyan et al. (2019) the risk of privacy intrusion is the main barrier to smart home acceptance, which has been corroborated by several other studies (Wilson et al., 2017). A study by Alaiad & Zhou (2017) proves that there is a negative relationship between privacy concerns and behavior intention regarding the use of a specific technology in a smart home environment.

But the user's opinion on this topic is divided, because while some studies about smart home services have found that privacy influences directly the attitude of the user toward technology (Yang et al., 2017), other studies about the smart home in general do not prove this relation (Shin et al., 2018).

Coughlan et al. (2012) addressed in a study of three IoT devices that could be used at home, including smart fridges addressed the privacy concerns variable, finding that the privacy issue refers to data sharing, but in a way it is also related to the usefulness of the technology, because if the technology is very useful to them there is a greater willingness to give in to data sharing. The author was intrigued to find that participants were more willing to share their data publicly than share it with commercial organizations. It was also possible to see that people who live with strangers are less willing to share their personal data with people living in the same house through the fridge, than people who live with their own families.

Also, in the context of smart home systems but specifically related to health, a negative relationship was detected between privacy concerns and the intention to use these technological systems. In other words, they found that privacy concerns are a barrier to the adoption of these technologies The following hypothesis will be investigated:

H8a. Consumers' privacy concerns about the smart refrigerator will negatively influence their attitude.

H8b. Consumers' privacy concerns about the smart fridge will negatively influence their behavioral intention to use them.

2.2.1.2.9 Green self-identity

Green self identity is defined as "an individual's overall perceived identification with the typical green consumer"(Barbarossa et al., 2017, p. 191).

According to Barbarossa et al. (2015) the green self-identity is a driver of environmentally friendly consumption, because people who consider themselves as green consumers may decide not to buy a specific product if they believe that such conduct does not appropriately represent their green ideology. In his studies about the adoption of environmentally friendly electronic cars, he found a positive correlation between green self-identity and: consumer attitude (Barbarossa et al., 2015) and intention to adopt (Barbarossa et al., 2015, 2017).

Based on the results of Barbarossa et al. (2017), another study conducted later also confirmed to have found a positive and significant relationship between green self-identity and the intention to use technology in the context of technology adoption (Cardoso-Andrade et al., 2022).

Neves & Oliveira (2021), in a slightly different study, not on behavioral intention to use but on behavioral intention to change, obtained data proving that green self-intention directly and positively influences the attitude towards technology and its behavioral intention to change to more energy-efficient technologies.

Also, other studies that specifically studied other similar identities found that Pro-environmental self-identity positively influences both pro-environmental intentions and behaviors (Carfora et al., 2017).

Transporting this empirical logic to the present study, it is believed that in the context of the adoption of smart refrigerators, the green self-identity has the capacity to significantly influence both attitude and behavioral intention. The study will propose to find out if:

H9a. The green self-identity of consumers will positively influence their attitude toward the smart refrigerator.

H9b. The green self-identity of consumers will positively influence their behavioral intention to use a smart refrigerator.

2.2.1.2.10 Attitude

Attitude toward using technology is defined as "an individual's overall affective reaction to using a system" (Venkatesh et al., 2003, p. 455)

The inclusion of attitude in theories of technology adoption has been studied over the years, according to Venkatesh et al. (2003) the literature shows some inconsistency about the relationship between attitude and behavioral intention because while some declare it to be the strongest predictor of behavioral intention, others say it was not significant relation. The author did not find any significant relationship between both constructs in the study where he established the UTAUT (Venkatesh et al., 2003) nor did he incorporate this hypothesis in UTAUT2 (Venkatesh et al., 2012).

However, studies on the adoption of smart refrigerators (Rothensee, 2008) state that attitude is able to positively influence behavioral intention. Also considering that the smart fridge is a smart home service, regarding the adoption of smart home services, some studies also prove a positive relationship between attitude and behavioral intention (Pal, Funilkul, Vanijja, et al., 2018).

Also, outside the context of technology adoption, we cannot forget that attitude is one of the psychological factors capable of influencing food waste attitude (Principato et al., 2021), So, it becomes interesting to investigate whether the attitude that consumers have towards technology to prevent food waste is or not an influential factor in the behavioral intention to use it. Thus, it was intended to study the following hypothesis:

H10. The consumers' attitude towards the smart refrigerator will positively influence their behavioral intention to use it.

2.2.1.2.11 Behavioral Intention to use

In the context of technology adoption, behavioral intention refers to the individual's willingness to use or continue to use a particular technology (Venkatesh et al., 2012).

It is important to note, that it is one thing to have the behavioral intention to use a technology, but it is another thing to actually use it. The literature has proven that behavioral intention is the strongest antecedent to the true use of technology (Davis, 1989; Venkatesh et al., 2003, 2012).

To conduct this research, the behavioral intention to use the smart fridge will be evaluated. This leads to the following hypothesis:

H11. The consumer's behavioral intention to use a smart refrigerator will positively influence its use behavior.

2.2.1.2.12 Use behavior

Use behavior can be described as the actual use of the system or technology (Venkatesh et al., 2003).

According Venkatesh et al. (2012) the author of UTAUT2, usage behavior is a dependent variable, directly influenced by behavioral intention, facilitation conditions and the habit of using a given technology. In other words, the greater the behavioral intention to use a technology, the facilitating conditions to use it and the individual's habit towards it, the greater will be the use of a technology.

2.3 RESEARCH MODEL

This section presents the theoretical model used in this research, in order to identify the main factors that influence the adoption of Smart Friends to prevent food waste.

The model was developed based on the research gap identified by Liegeard & Manning (2020), the literature review, and the technology adoption constructs presented earlier in this chapter.

The present research model is an adaptation of the UTAUT2 model(Venkatesh et al., 2012), in that none of the moderators suggested by the author, such as age, gender and experience, were considered. As a result of the previous research, three factors were added to the model, namely privacy concerns (Marikyan et al., 2019; Wilson et al., 2017), attitude (Davis, 1989; Rothensee, 2008) and green self-identity (Barbarossa et al., 2015, 2017; Neves & Oliveira, 2021).

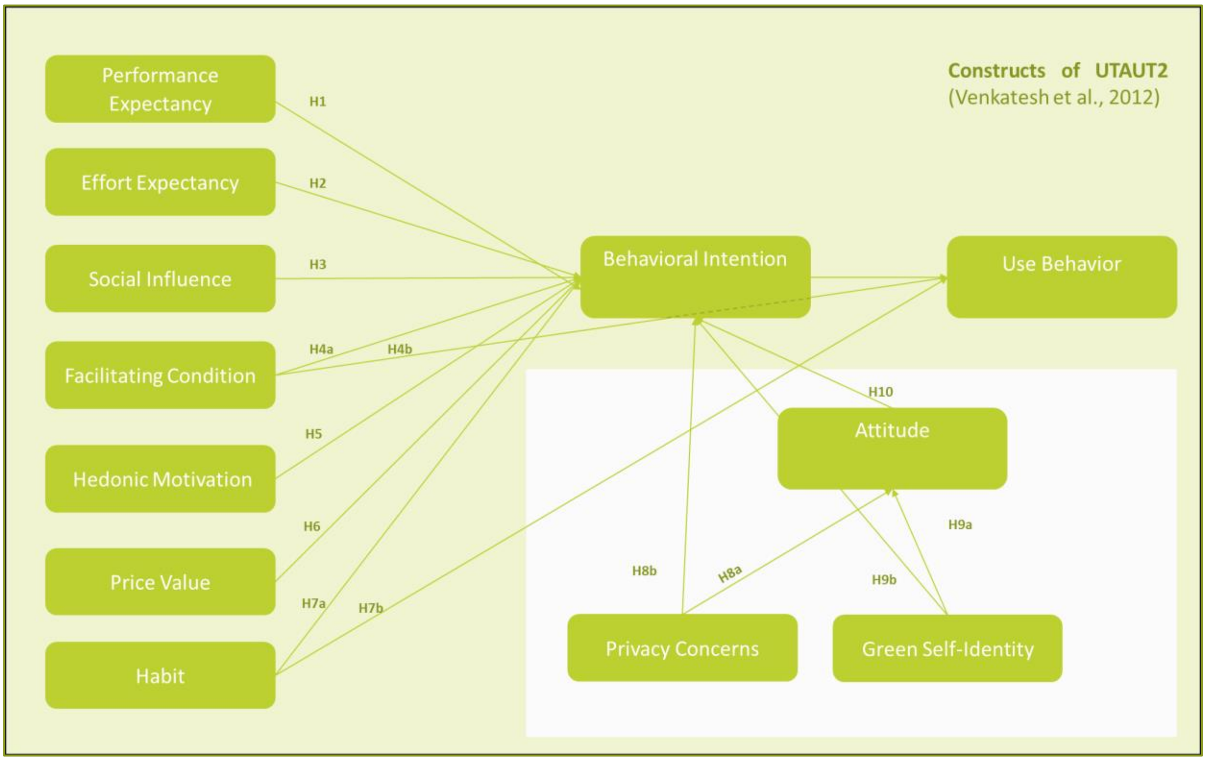


Figure 2 - Research model adapted from Venkatesh et al. (2012)

3 METHODOLOGY

To identify the key factors that influence the acceptance of smart refrigerators as a technology to prevent household food waste in the best way, the measurements, the data collection method, and the data analyses definition will be described.

3.1 MEASUREMENT

The item measures belonging to the constructs of the UTAUT2 model, namely Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Hedonic Motivation, Price Value and habit, will be adapted from the original author (Venkatesh et al., 2012). Attitude will be adapted from Taylor & Todd (1995), privacy concerns from Dinev & Hart (2006) and Green Self Identity llllllll by Barbarossa et al. (2015). Most of the item measures have undergone minor adaptations to suit this study.

All item measures used a 7-point Likert scale, except attitude which will use a 7-item semantinc scale. Attached is a table constructing the measurement items.

During the evaluation of the quality criteria, the cross-loadings of the item measures FC4 (from facilitating conditions construct) and UB1 (from the use behavior construct) had very low values, negatively affecting the AVE of the construct, thus being eliminated from the model analysis(Hair et al., 2017).

3.2 DATA COLLECTION

Data collection method: It is aimed to collect quantitative primary data through a structured survey questionnaire with closed-ended questions that test the hypothesis presented above in order to identify the key factors that influence the acceptance of smart refrigerators as a technology to prevent household food waste.

Materials: In order to collect the necessary data, three software were used, namely, the Qualtrics (2023) was used to develop the survey questionnaires, while Prolific (2023) was used as a paid platform to distribute the questionnaires to the research sample target. And also G*Power 3.1.9.7 (Buchner et al., 2020) to indicate the sample size.

When: The survey questionnaire was developed, applied first in pre-tests, and administered to the final respondents during March 2023, the data was further analyzed in April.

Research ethics: This study collected personal data from participants, however, this data was used only for academic purposes and treated with complete confidentiality and ethics. Participants were informed about the purpose of the research and were asked to give their consent to participate voluntarily for a pre-established payment. However, the researcher has the right to reject and consequently not pay the participant, based on failed attention checks, because the participant must also behave ethically and responsibly towards the researcher and athe rules established by the Prolific platform. The studies were also registered with the Nova ethics committee and Aspredicted.

Structure of the survey: First there was a page with the survey participation rules and consent form, then a page with smart fridge information presented as a video which was only allowed to advance after the duration of the video, followed by the construct section and some socio-demographic data about the participant.

Procedures to avoid common method bias: As suggested by Chang et al. (2010) to avoid possible biases during data collection, the survey questionnaire was structured with the following precautions:

a) Ensure the participant's anonymity, so that they provide as honest answers as possible and reduce their apprehension of response.

b) Ensure that there are no right or wrong answers, so that they do not feel biased in responding to any particular answer choice.

c) All questions were presented to the participant randomly in order to avoid fatigue or mood swings, considering that the measures selected to assess a particular construct may be similar.

Sample:

- Segmentation Method:
    a. Geographic limitation:

As mentioned in the introduction of this dissertation, in geographical terms, the North America's market is mature in contrast to other regional markets due to the rapid adoption of technology (Verified Market Research, 2022), making it the ideal place to find out what the main factors are that influence the adoption of smart refrigerators to prevent food waste.

b. Behavioral criterion:

To better understand the problem, the aim was to ensure that approximately half of the population had a high green self-identity. Additionally, it was desired that roughly half of the population had a smart refrigerator, while the remaining half did not. By implementing these criteria, it was possible to create a distributed population.

- Sample size:

To have a solid participant base in order to get credible results to answer our research question, it was chosen 2 different methods to define the minimum sample size.

In the first method, an A priori test was performed using the G*Power software. Since the research model is a PLS-SEM, it was decided to perform an F test, specifically the Linear multiple regression test, where the type of power analysis was an a priori sample size. Having specified the effect size ($f^2 = 0{,}15$), significance level ($\alpha = 0{,}05$), power level ($1 - \beta = 0{,}95$) and the number of predictors based on the construct behavioral intention (predictors =10), a total sample size of 172 participants was recommended. To check the results of this test, please refer to the attached document.

A minimum of 5 participants for each of the cited measurement items is recommended, however, it is generally the case that a ratio of at least 10 participants for each measurement item is the most appropriate minimum number for arbitrary distributions (Bentler & Chih-Ping Chou, 1987) . Since 44 measurement items have been defined, this suggestion informs that the minimum sample size can range from 220 to 440 participants.

However, despite the minimum data indicated, it was decided to establish a slightly higher value of 600 participants, because larger sample sizes increase the precision of PLS-SEM estimations (Hair et al., 2017), however due to time consuming responses and data cleaning, only 498 responses were considered.

3.3 DATA PREPATATION AND DATA ANALYSIS

Before starting the data analysis, it was necessary to prepare the initial raw dataset in order to obtain higher quality and more reliable data.

3.3.1 Data Prepatation

Several records have been received in the database, and it would be unwise to use them without treating them first, so this section will show what data treatment has been done. These tasks were performed the Microsoft Excel software.

3.3.1.1 Clean Data

- **Barred Participants:** There were participants who were barred from participating in the study due to: not giving consent to participate in the study (n=1), and not qualifying to begin the survey (n= 74), however their attempt to take the questionnaire was recorded in the database. The researcher chose to delete these records from the database.
- **Dropouts:** No participants dropped out of the study, and it was not necessary to delete participation records because of this. Thus, no action was required.
- **Inattentive people:** In the survey questionnaire, there were 3 attention checks, in order to find out which participants were attentive, and which were inattentive. All participants who failed at least 1 attention checks (n=8) were deleted from the database. The respective columns containing the data from each participant's attention checks have also been deleted, as they are not useful for the research.
- **Duplicates:** Repeated participations of the same participants were detected, so all records where the "Prolific ID" appeared duplicated (n=1) were eliminated. The choice criterion was to keep the first answer of the participant, because the first answer was more natural, while the second answer could be biased since the participant knew the questions.
- **Miscoded values:** All scales besides being numbered also contained text to facilitate the participant's response (e.g. "7. Strongly agree") it was necessary to transform the scale

names by their respective numerical values (e.g. "7"). In total 24853 data cells have been changed.

- **Outliers:** No treatment was done for the outliers, besides giving a more realistic picture of the current situation of each participant, it is also not an impeding factor because the software used for the analysis does not require that the data have a normal distribution.
- **Missing Data:** The survey was constructed in such a way that all questions were mandatory, avoiding questions being left unanswered. Due to a lapse of the researcher, only the construct "facilitating condition" was not placed as being mandatory, and in the item measurements of this construct, there were 81 missing values caused by 58 participants. As there were missing values, the researcher, in order to ensure data quality, chose to delete the records of the answers of the 58 participants, leaving the database without missing values.

3.3.2 Data analysis

This research applies the adapted UTAUT2 model to identify the factors influencing smart refrigerator adoption in the context of household food waste.

To test the model, Partial Least Squares Structural Equation Modeling (PLS-SEM) will be used as a data analysis technique. This option is mainly motivated by the fact that it is a prediction oriented model, which supports a large level of complexity and does not require a large sample size(Hair et al., 2017).

Materials: Excel was used for the data preparation, and the SmartPLS 4 (Ringle et al., 2022) was used to perform this analysis.

Analysis procedure: Firstly, the data was put into the software. Secondly, the model was examined to assess the reliability and validity of the constructs, and only then the structural model was tested.

4 RESULTS

4.1 SAMPLE CHARACTERISTICS

The researcher tried his best to have a sample as distributed as possible, mainly regarding age, gender, the number of people who own a smart fridge, and the level of environmental concern. This was done manually through the application of different dissemination of the study by applying filters to have a sample that was as distributed as possible.

Table 1 - Sample caracteristics

		Frequency	Frequency (%)
Age	18 – 23	57	11%
	24 – 29	97	19%
	30 – 35	108	22%
	36 – 41	70	14%
	42 – 47	34	7%
	48 – 53	58	12%
	> 54	74	15%
Gender	Female	211	42%
	Male	287	58%
Educational Level	None - 8th grade	0	0%
	9th - 11th grade	5	1%
	High school graduate	58	12%
	Some college, no degree	93	19%
	Associate's degree	56	11%
	Bachelor's degree	206	41%
	Master's degree	62	12%
	Professional degree	9	2%
	Doctoral degree	9	2%
Income	Less than $15,000 per year	21	4%
	$15,000 to $24,999 per year	21	4%
	$25,000 to $34,999 per year	34	7%
	$35,000 to $49,999 per year	56	11%
	$50,000 to $74,999 per year	102	20%
	$75,000 to $99,999 per year	101	20%
	$100,000 to $149,999 per year	101	20%
	$150,000 to $199,999 per year	35	7%
	$200,000 or more per year	27	5%
Household size	Living alone	62	12%
	Two people	199	40%
	Three people	112	22%

	Four people	71	14%
	Five or more people	54	11%
People live with	Family households	428	86%
	Nonfamily households	64	13%
	Family households and Nonfamily households	6	1%
Smart refrigerator own	Yes, I have	247	50%
	No, I do not have	251	50%
level of concern for environmental issues	High level (=4 or =5)	261	52%
	Not high level (≤ 3)	237	48%

4.2 MODEL ASSESSEMENT

To perform the analysis, a systematic process needed to be followed (Hair et al., 2017), where the first task was to assess the measurement quality of the scales used (measures of the relationships between the indicators and their constructs) through the metrics' reliability, convergent validity, and discriminant validity.

The second task was to evaluate the structural model (the relationships between the constructs) through metrics such as variance explained (R^2), and the size and statistical significance of the structural path coefficients (β).

4.2.1 Measurement Model Assessement

- Convergent validity and Reliability

Convergent validity is the degree to which an item's measurement correlates positively with the remaining item measurements of the same construct (Hair et al., 2017) .

To evaluate convergent validity of item measurements, two indicators were considered: the reliability indicators and the average variance extracted (AVE).

The reliability indicators considered were Cronbach's alpha and composite reliability. In terms of internal consistency reliability, Cronbach's alpha is typically considered the lower limit, while composite reliability is considered the upper limit, and it is recommended that the values of both measures be higher than 0.7 to indicate satisfactory reliability (Hair et al., 2017). In the case of this research model, all constructs have values higher than 0.7 for Cronbach's alpha and Composite reliability, which shows evidence of internal consistency.

The AVE should have a value greater than 0.5 to respect the general rule that a latent variable should explain a substantial part of each indicator's variance, usually at least 50%, that in other words, if the AVE is 0.5 or higher, it means that on average this construct explains more than half of the variance of this indicator (Hair et al., 2017). In this case, we can verify that all constructs presented a value superior to 0.5.

With regard to convergent validity, the model appears to be robust.

Table 2 - Validity and Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attitude	0.953	0.955	0.966	0.877
Behavioral Intention	0.970	0.970	0.980	0.943
Effort Expectancy	0.917	0.925	0.941	0.800
Facilitating Condition	0.784	0.788	0.874	0.698
Green Self-Identity	0.928	0.931	0.954	0.875
Hedonic Motivation	0.955	0.958	0.971	0.917
Habit	0.918	0.921	0.948	0.859
Privacy Concerns	0.975	0.977	0.981	0.930
Performance Expectancy	0.955	0.957	0.967	0.880
Price Value	0.963	0.971	0.976	0.931
Social Influence	0.968	0.968	0.979	0.940
Use Behavior	0.889	0.895	0.923	0.749

4.2.1.1 Discriminant Validity

Discriminant validity is a quality criteria to make sure that each indicator has a greater relationship with the respective construct and not with other constructs in the model (Hair et al., 2017).

Regarding discriminant validity, the outcomes of two analysis were consider: Cross-Loadings and Fornell-Larcker.

- Cross-loadings Analysis

Cross-loading is an indicator's correlation (factor loading) with all constructs in the model. For this criterion to be met, it is necessary that the item measurement has a higher correlation with its associated construct compared to its correlations with other constructs (Hair et al., 2017).

By performing a loadings and cross-loadings analysis it was possible to individually analyze the correlation between each of the item measurements with each of the constructs in the model. It was concluded that each item measurement had a higher factor loading with its own construct, and consequently a lower one with the other constructs. This analysis proved that there is discriminant validity in the scales used.

During the evaluation of the cross-loadings of the item measures FC4 (from facilitating conditions construct) and UB1 (from the use behavior construct) had very low values, negatively affecting the AVE of the construct, thus being dropped from the model analysis (Hair et al., 2017).

Table 3 - Loadings and cross-loadings

	ATT	BI	EE	FC	GSI	HM	HT	PC	PE	PV	SI	UB
ATT1	**0.948**	0.631	0.400	0.428	0.321	0.582	0.393	-0.195	0.731	0.503	0.453	0.496
ATT2	**0.940**	0.625	0.404	0.401	0.339	0.594	0.440	-0.234	0.710	0.524	0.473	0.496
ATT3	**0.938**	0.685	0.396	0.435	0.353	0.610	0.476	-0.235	0.734	0.532	0.518	0.502
ATT4	**0.920**	0.599	0.417	0.431	0.335	0.608	0.425	-0.183	0.697	0.501	0.454	0.504
BI1	0.662	**0.974**	0.495	0.461	0.398	0.664	0.607	-0.293	0.700	0.582	0.669	0.427
BI2	0.643	**0.963**	0.473	0.420	0.382	0.638	0.601	-0.285	0.685	0.574	0.654	0.449
BI3	0.676	**0.976**	0.490	0.437	0.411	0.655	0.621	-0.314	0.707	0.590	0.684	0.455
EE1	0.353	0.379	**0.888**	0.614	0.178	0.397	0.236	-0.216	0.424	0.261	0.297	0.330
EE2	0.426	0.502	**0.898**	0.586	0.266	0.502	0.341	-0.228	0.567	0.378	0.388	0.343
EE3	0.354	0.462	**0.904**	0.562	0.264	0.442	0.345	-0.256	0.476	0.324	0.399	0.268
EE4	0.401	0.429	**0.887**	0.613	0.197	0.449	0.254	-0.174	0.499	0.266	0.281	0.315
FC1	0.371	0.411	0.511	**0.852**	0.212	0.398	0.260	-0.189	0.391	0.292	0.319	0.172
FC2	0.338	0.348	0.640	**0.824**	0.183	0.394	0.179	-0.124	0.408	0.202	0.242	0.188
FC3	0.418	0.371	0.519	**0.830**	0.237	0.489	0.249	-0.173	0.448	0.336	0.289	0.296
GSI1	0.323	0.355	0.255	0.279	**0.912**	0.374	0.312	-0.027	0.370	0.318	0.387	0.279
GSI2	0.345	0.396	0.243	0.221	**0.942**	0.370	0.422	-0.072	0.365	0.346	0.492	0.325
GSI3	0.342	0.396	0.225	0.217	**0.951**	0.364	0.395	-0.046	0.370	0.318	0.463	0.316
HM1	0.611	0.639	0.479	0.503	0.363	**0.970**	0.482	-0.248	0.696	0.539	0.523	0.475
HM2	0.639	0.679	0.523	0.525	0.401	**0.957**	0.493	-0.258	0.734	0.547	0.532	0.472
HM3	0.583	0.610	0.443	0.444	0.367	**0.947**	0.488	-0.217	0.676	0.546	0.523	0.502
HT1	0.442	0.632	0.350	0.313	0.390	0.464	**0.921**	-0.261	0.470	0.462	0.578	0.339
HT2	0.383	0.535	0.261	0.220	0.342	0.443	**0.934**	-0.166	0.410	0.477	0.573	0.365
HT3	0.460	0.574	0.313	0.235	0.388	0.504	**0.926**	-0.187	0.495	0.549	0.602	0.447
PC1	-0.224	-0.293	-0.254	-0.192	-0.041	-0.246	-0.204	**0.965**	-0.254	-0.301	-0.246	-0.118
PC2	-0.207	-0.286	-0.214	-0.169	-0.042	-0.212	-0.212	**0.952**	-0.224	-0.284	-0.233	-0.097
PC3	-0.214	-0.283	-0.232	-0.193	-0.057	-0.253	-0.200	**0.967**	-0.247	-0.286	-0.244	-0.092
PC4	-0.230	-0.316	-0.246	-0.201	-0.062	-0.261	-0.239	**0.973**	-0.255	-0.314	-0.273	-0.120
PE1	0.718	0.731	0.560	0.487	0.358	0.728	0.495	-0.278	**0.930**	0.559	0.542	0.523
PE2	0.715	0.675	0.524	0.469	0.352	0.706	0.471	-0.249	**0.946**	0.527	0.514	0.537
PE3	0.721	0.642	0.493	0.462	0.384	0.650	0.435	-0.200	**0.933**	0.492	0.498	0.546
PE4	0.725	0.639	0.498	0.450	0.383	0.663	0.457	-0.223	**0.944**	0.504	0.518	0.565
PV1	0.482	0.516	0.300	0.298	0.319	0.499	0.476	-0.268	0.486	**0.951**	0.503	0.424
PV2	0.569	0.606	0.353	0.333	0.343	0.575	0.537	-0.309	0.558	**0.968**	0.563	0.473
PV3	0.536	0.604	0.352	0.338	0.349	0.563	0.535	-0.310	0.561	**0.976**	0.575	0.472
SI1	0.501	0.678	0.373	0.333	0.460	0.524	0.611	-0.268	0.544	0.555	**0.974**	0.400
SI2	0.490	0.668	0.392	0.337	0.473	0.549	0.620	-0.248	0.543	0.553	**0.963**	0.386
SI3	0.486	0.658	0.360	0.321	0.464	0.525	0.605	-0.235	0.520	0.546	**0.972**	0.390
UB2	0.453	0.427	0.301	0.223	0.327	0.458	0.430	-0.131	0.500	0.484	0.425	**0.872**
UB3	0.450	0.371	0.272	0.222	0.262	0.429	0.327	-0.081	0.471	0.400	0.306	**0.873**
UB4	0.495	0.411	0.359	0.266	0.262	0.444	0.362	-0.098	0.530	0.380	0.339	**0.875**

UB5	0.449	0.365	0.277	0.204	0.281	0.406	0.302	-0.067	0.497	0.367	0.317	**0.843**

- Fornell-Larcker criterion

The Fornell-Larcker criterion was the second approach used to assessing discriminant validity.

This criterion compares the square root of each construct's average variance extracted (AVE) with the correlation of all constructs (Hair et al., 2017). In table 3, the values of the square root of the diagonal bird are shown, and all other values refer to the correlation between the constructs. Since none of these correlations is higher than the square root of the AVE, we can say that the Fornell-lacker criterion is met and consequently the model has discriminant validity.

Table 4 - Fornell-larcker criterion

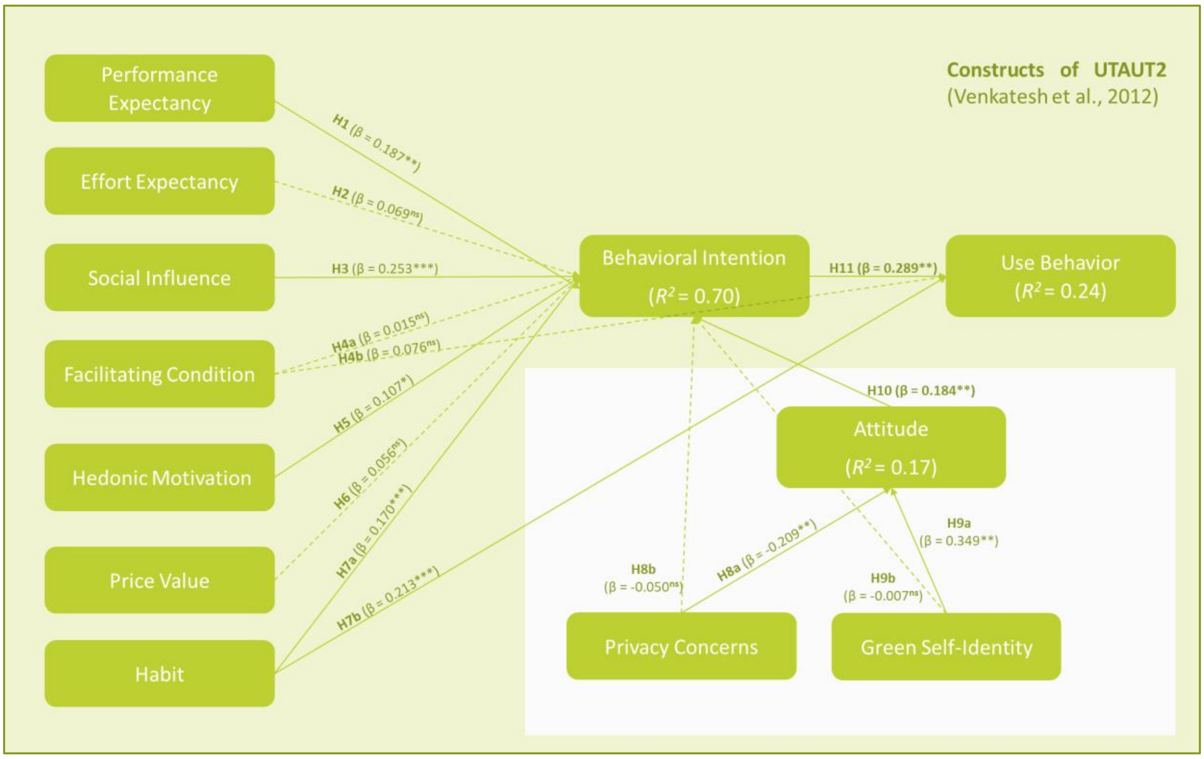
	ATT	BI	EE	FC	GSI	HM	HT	PC	PE	PV	SI	UB
ATT	**0.936**											
BI	0.680	**0.971**										
EE	0.431	0.500	**0.894**									
FC	0.453	0.452	0.662	**0.835**								
GSI	0.360	0.409	0.257	0.254	**0.935**							
HM	0.639	0.672	0.504	0.514	0.394	**0.958**						
HT	0.464	0.628	0.334	0.277	0.404	0.509	**0.927**					
PC	-0.227	-0.306	-0.246	-0.196	-0.052	-0.253	-0.222	**0.964**				
PE	0.767	0.718	0.555	0.499	0.393	0.734	0.496	-0.254	**0.938**			
PV	0.551	0.599	0.348	0.336	0.350	0.568	0.536	-0.308	0.557	**0.965**		
SI	0.508	0.689	0.386	0.341	0.480	0.549	0.631	-0.259	0.553	0.569	**0.969**	
UB	0.534	0.457	0.351	0.265	0.329	0.504	0.415	-0.111	0.578	0.474	0.405	**0.866**

After the analysis of these two quality criteria, it was concluded that the research model provides a very satisfactory degree of discriminant validity, showing that each construct is unique and describes things that the other constructs in the model don't.

4.2.2 STRUCTURAL MODEL

After the quality of the scales used had been measured and accomplished, it was possible to begin the evaluation of the structural model (the relationships between the constructs). The results of the estimation of the structural model are presented in the following framework:

Table 5 - Structural model



To estimate the structural model, metrics such as the variance explained (R^2), the size and statistical significance (p-value) of the structural path coefficients (β) were used.

4.2.2.1 Path Coefficients and determination coefficients:

It was necessary to analyze the path coefficients in detail, to find out if significant relationships exist between the constructs that form the investigated hypotheses. The significance levels of the path coefficients in the structural model were calculated using bootstrap with 5000 subsamples that were randomly generated (with replacement) from the original data set using the software.

A statistical description of the results obtained will be made. In order to facilitate the reader, it has been organized in two sections, one referring to the constructs of UTAUT2, another to the new constructs introduced. These findings are also summarized in the table 6.

- UTAUT2 constructs

Regarding the models introduced by UTAUT2, it was found that out of the 10 hypotheses without moderators, 6 of them were supported, while 4 were ultimately rejected by the analysis.

Focusing on the supported hypotheses, the results obtained show that the main use behavior is positive and significantly influenced by the behavioral intention (H11: $\beta = .289$; $p < .001$) and the habit (H7b: $\beta = .213$; $p < .001$). Moreover, the data revels that the behavioral intention is positive and significantly influenced by performance expectancy (H1: $\beta = .187$; $p = .005$), social influence (H3: $\beta = .253$; $p < .001$), hedonic motivation (H5: $\beta = .107$; $p = .043$) and by habit (H7a: $\beta = 0.170$; $p < .001$).

In contrast, due to the lack of significant statistical evidence, it was not possible to prove that behavioral intention was influenced directly by neither effort expectancy (H2: $\beta = .069$; $p = .099$), facilitating conditions (H4a: $\beta = .015$; $p = .712$) or price value (H4b: $\beta = .076$; $p = .146$). Similarly, it was not possible to prove that usage behaviour was influenced by facilitating conditions (H6: $\beta = .056$; $p = .189$).

- New constructs

Regarding the 5 hypotheses introduced by the new model, with the introduction of the constructs privacy concerns, green self-identity and attitude, three of them were supported and two were rejected.

Regarding the new constructs, a significant level of statistical evidence was found that allows stating that as a dependent variable attitude is negatively affected by privacy concerns (H8a: $\beta = -.209$; $p < .001$) and positively influenced by green self identity (H9a: $\beta = .349$; $p < .001$). Analyzing attitude as an independent variable, it can be stated that it influences the behavioral intention to use the smart refrigerator to avoid food waste (H10: $\beta = .184$; $p < .001$).

The results suggest that there is no direct relationship between privacy concerns and behavioral intentions (H8b: $\beta = -.050$; $p = .083$), nor between green self-identity and behavioral intentions (H9b: $\beta = -.007$; $p = .837$).

Of the total 15 hypotheses proposed by the model, 9 of them were supported and 6 were rejected. As can be seen in the following table:

Table 6 - Path Coefficients and determination coefficients

Hypothesis	Path: Independent Variable	Path: Dependent Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Statistical significance
H1	Performance Expectancy	Behavioral Intention	0.187	0.193	0.066	2.835	**.005**	**Supported**
H2	Effort Expectancy	Behavioral Intention	0.069	0.070	0.042	1.651	**.099**	**Rejected**
H3	Social Influence	Behavioral Intention	0.253	0.251	0.043	5.900	**<.001**	**Supported**
H4a	Facilitating Condition	Behavioral Intention	0.015	0.014	0.040	0.369	**.712**	**Rejected**
H4b	Facilitating Condition	Use Behavior	0.076	0.078	0.052	1.455	**.146**	**Rejected**
H5	Hedonic Motivation	Behavioral Intention	0.107	0.106	0.053	2.024	**.043**	**Supported**
H6	Price Value	Behavioral Intention	0.056	0.053	0.042	1.313	**.189**	**Rejected**
H7a	Habit	Behavioral Intention	0.170	0.171	0.033	5.156	**<.001**	**Supported**
H7b	Habit	Use Behavior	0.213	0.212	0.053	3.990	**<.001**	**Supported**
H8a	Privacy Concerns	Attitude	-0.209	-0.208	0.039	5.359	**<.001**	**Supported**
H8b	Privacy Concerns	Behavioral Intention	-0.050	-0.050	0.029	1.734	**.083**	**Rejected**
H9a	Green Self-Identity	Attitude	0.349	0.351	0.042	8.385	**<.001**	**Supported**
H9b	Green Self-Identity	Behavioral Intention	-0.007	-0.006	0.033	0.206	**.837**	**Rejected**
H10	Attitude	Behavioral Intention	0.184	0.182	0.051	3.635	**<.001**	**Supported**
H11	Behavioral Intention	Use Behavior	0.289	0.290	0.064	4.510	**<.001**	**Supported**

Specific Indirect effects: It is interesting to verify that although privacy concerns and green self-identity are not able to directly influence behavioral intention, it is possible to see (appendix B) that both are able to influence it through attitude which acts as mediator. Similarly, privacy concerns and green self-identity are both able to influence use behavior indirectly, using attitude and behavioral intention as mediators.

The R^2 was used to measure how well the independent variables explained the dependent variables. The variables social influence, performance expectancy, attitude, habit and hedonic motivation, were responsible for 70% of the variance of behavioral intention. The variables privacy concerns and green self-identity were responsible for 17% of the variance of attitude. The variables behavioral intention and habit were responsible for 24% of the variance of use behavior.

5 DISCUSSION

5.1 MAIN FINDINGS

This study aimed to investigate the key factors influencing the acceptance of smart refrigerators as a technology to prevent household food waste, using an adapted UTAUT2 (Venkatesh et al., 2012).

The findings indicate that the research model has strong predictive power regarding de behavioral intentions, and a moderate predictive power regarding the user's attitudes and use behavior toward using a smart refrigerator to prevent food waste in their household. Overall, the model explains 17% of attitude, 70% of behavioral intention and 24% of use behavior.

Based on the results, it was found that the more the consumer believes in the effectiveness (H1) of the smart refrigerator to prevent food waste, the higher their behavioral intention to use it, in accordance with findings reported by other authors when studying the adoption of other technologies (Alaiad & Zhou, 2017; Pal, Funilkul, Charoenkitkarn, et al., 2018; Venkatesh et al., 2003, 2012). The same happens with social influence (H3), since it was shown that is extremely beneficial for the decision of adopting a smart refrigerator to minimize their household's food waste, like Alolayan (2014) who states that when people are undecided about adopting a smart refrigerator, they tend to consult the opinion of their family members, friends or social network, before making the adoption decision (Alaiad & Zhou, 2017; Venkatesh et al., 2003, 2012).

Also, hedonic motivation (H5) and habits (H7a and H7b) appear as key drivers that influence the intention to use technologies, as previously discovered by Venkatesh et al. (2012). This means that if the consumer experiences a feeling of enjoyment or pleasure and are already accustomed to using technology the more likely they are to adopt the smart fridge to prevent their household food waste. However, it is important to note that although Baudier et al. (2020) corroborated the influence of habits on intention to use, he did not support the idea of hedonic motivation (H5) as a determining factor for technology adoption. In the same way that the habit (H7b) proves to influence the use behavior (Venkatesh et al., 2012).

As in UTAUT(Venkatesh et al., 2003) and UTAUT2(Venkatesh et al., 2012) it was proven that behavioral intention is significantly influential to use behavior. This means that when consumers have a strong intention to use the smart fridge to prevent food waste, they are more likely to use it during their household food routines.

The concern that consumers have about the exposure of their privacy (H8b) was not shown to significantly influence the intention to use the smart fridge through direct path, not supporting the research done by Alaiad & Zhou (2017). Privacy (H8b) has been shown to be a factor capable of shaping consumer attitude, as already demonstrated in a smart homes environment regarding other technologies (Yang et al., 2017). In addiction it was found that attitude plays a mediating role between the construct’s privacy concerns and behavioral intention. Likewise, attitude and behavioral intention play a mediating role between the construct privacy concerns and use behavioral, an evidence that has not been found in the previous literature review.

Green self-identity of consumers (H9b) did not have a significant impact on the intention to use a smart refrigerator. This suggests that even if consumers consider themselves to have a high green self-identity, it does not necessarily lead them to be more interested in using a smart refrigerator to prevent food waste in their household. Contrary to Barbarossa et al. (2015, 2017) (Barbarossa et al., 2015, 2017) who found a direct relationship between this construct and the intention to use other technologies. However, it was proved that green self-identity (H9a) is able to influence it indirectly using attitude as a mediating agent in this relationship. It was also verified that green self-identity influences the use behavior of the smart refrigerator to prevent food waste through an indirect path, in which attitude and behavioral intention play a mediating role. Previously this indirect pathway between green self-identity and behavioral intention to adopt has been found to be mediated by attitude towards technology (Barbarossa et al., 2015). However, the researcher did not find any relationship in the previous literature that said green self-identity was an influencing factor of use behavior through mediating attitude and behavioral intentions to use.

This research confirms that the attitude (H10) that consumers have towards this IoT technology to prevent food waste is an influential factor in the behavioral intention to use it, in agreement with other studies about the acceptance of smart refrigerators (Rothensee, 2008) and other IoT technologies used in smart homes environment (Pal, Funilkul, Vanijja, et al., 2018). Which means that if the consumer has a positive attitude towards the smart fridge to prevent food waste, they will be more likely to use it. Contrarily, if the consumer has a negative attitude towards the smart fridge to prevent food waste, they are more likely to have a lower intention to use it.

However, surprisingly, there is not enough evidence to claim that there is a relationship between Effort Expectancy (H2) and Behavioral Intention as existed in the UTAUT2 model (Venkatesh et al., 2012). Incidentally, other studies had also found scientific evidence about IoT technologies in smart home environments (Pal, Funilkul, Charoenkitkarn, et al., 2018) contrary to the study now done. The same happened with the variable Facilitating Conditions (H4b), which contrary to previous studies, no scientific evidence was found to prove that facilitating conditions cause significant influence use behavior (Venkatesh et al., 2003, 2012). Nor between facilitating conditions (H4a) and behavioral intention (Venkatesh et al., 2012) aligning with other research which did not support this relationship (Pal, Funilkul, Charoenkitkarn, et al., 2018). Lastly, no statistical relationship was found to indicate that customer perceived value (H6) and behavioral intention, as evidenced by Venkatesh et al. (2012). This rejection of the hypothesis may indicate that consumers' cognitive tradeoff is not a determining factor.

5.2 THEORETICAL CONTRIBUTIONS

From a theoretical point of view, this dissertation extends the literature in the following ways: First, it helps fill the gap in the literature (Liegeard & Manning, 2020) regarding consumer acceptance of smart refrigerators during household food routines to prevent household food waste, by providing evidence of what are the main factors influencing the acceptance of smart refrigerators as a technology to avoid household food waste. Specifically confirming the barrier of privacy concerns and highlighting the factors that determine performance expectancy, social influence, hedonic motivation, habit, attitude and green self-identity.

Second, to support the literature on the smart refrigerators (Alolayan, 2014; Coughlan et al., 2012; Rothensee, 2008) as well as other IoT technologies that make up the smart home concept studies (Baudier et al., 2020; Hubert et al., 2019; Kim et al., 2017; Nikou, 2019; Park et al., 2017; Shin et al., 2018; Yang et al., 2017), with updated and relevant information, identifying new factors for their adoption, especially for food waste purposes. The findings of this research extend Venkatesh et al. (2012) work by applying UTAUT2 and other constructs instead of tam and showing that behavioral intention to accept them, in addition to attitude and social influence, was also influenced by can also be influenced by performance expectancy, hedonic motivation, habit and green self-identity, as well as negatively by privacy concerns that the consumer may feel towards technology.

Third, this research will contribute to supporting the literature regarding UTAUT2 (Venkatesh et al., 2012) by studying a specific IoT technology, namely the smart refrigerator, applied to a specific purpose, which in this case is the prevention of food waste. To best of our knowledge, there is still no published literature on the use of UTAUT2 to investigate the acceptance of technologies to prevent food waste. By focusing on one specific application (e.g. preventing food waste, reducing energy costs, watching TV, searching the internet, seeing who is ringing the doorbell...) rather than the possible applications of a technology, it can provide a new perspective for using UTAUT2.

Fourth, this research provides a unique theoretical framework by extending UTAUT2 by adding three new constructs that have been shown to impact the adoption of other technologies, namely: privacy concerns (Marikyan et al., 2019; Wilson et al., 2017), attitude (Davis, 1989; Rothensee, 2008) and green self-identity (Barbarossa et al., 2015, 2017; Neves & Oliveira, 2021). Introducing these three constructs together it was discovered 3 indirect paths not highlighted in the literature, while one had already been discovered:

By introducing the privacy concerns construct into the model along with the attitude construct, it was found that attitude plays a mediating role between the privacy concerns and behavioral intention constructs, evidence that was not found in the researcher's previous literature review. Similarly, attitude and behavioral intention play a mediating role between privacy concerns and behavioral intention constructs, evidence that was also not found in the previous literature review.

In turn, by introducing green self-identity and simultaneously introducing the attitude construct, it allowed us to see that attitude also plays a mediating role between green self-identity and behavioral intention, a path already discovered by Barbarossa et al. (2015) and which this research supports. However, this research is able to reveal an even greater indirect pathway that was not found in the previous literature review, namely between the green self-identity and use behavior constructs, through a mediation made by the attitude developed towards technology and its use intention by the consumer.

5.3 MANAGERIAL CONTRIBUTIONS

From a management point of view, it is expected that companies in this industry will know the factors most valued and least valued by consumers, in order to adapt their products and marketing strategies, so that they can have greater revenue, as well as contribute to the solution of this problem. Since the industry can play a vital role in providing solutions that meet consumers' needs and preferences, it is crucial that both companies and consumers work together towards this common goal by 2030, thus this research aims to have a managerial contribution as follows:

Social influence is a predictor of behavioral intention (Alaiad & Zhou, 2017; Venkatesh et al., 2003, 2012), considering this information companies can make strategic partnerships with influencers who are influential with their target audience, create or participate in digital communities, and collaborate strategically with retailers of products of various brands or models in order to recommend a particular smart refrigerator.

The performance expectancy proved to be a predictor of behavioral intention (Alaiad & Zhou, 2017; Pal, Funilkul, Charoenkitkarn, et al., 2018; Venkatesh et al., 2003, 2012). Marketers should communicate the functionalities of smart refrigerators effectively to their target consumers, emphasizing on smart refrigerator efficiency in preventing food waste. For example, ads that highlight the usefulness of the IoT device to create shopping lists, set menus based on the ingredients the user has inside the smart fridge, or even show how buying unnecessary ingredients can be avoided by checking what is stored inside when the person is at the supermarket.

Given that habit positively influences behavioral intention (Nikou, 2019; Venkatesh et al., 2012) and use behavior (Venkatesh et al., 2012). Organizations should study which factors form technological habits, and with that in mind equip the smart refrigerator with features that promote the creation of habits related to household food routines. For instance, companies could invest in artificial intelligence and machine learning to customize smart refrigerators to household routines. Which in turn could suggest recipes based on the consumption habits of household members (for example, if the family has tomatoes near the expiration date, and it knows that household members often eat pasta and meat, it could suggest making a spaghetti Bolognese, including tomatoes in the sauce).

Hedonic motivations have proven to be a predictor of behavior intentions (Venkatesh et al., 2012). Having this information organizations can make smart refrigerators even more appealing in order to generate fun for the consumer, or even show numerical data or messages that stimulate the feeling of pleasure for preventing food waste in their household. It may for example include features such as a score board for less amount of food waste, achievements for consecutive days without waste, or even social sharing options to boast eco-friendly behaviors.

Although price value did not show a significant impact in this research (Venkatesh et al., 2012), it is important to consider the perceived value of smart refrigerators to prevent food waste. What can be evidenced is that, the consumer perceives this IoT technology as an unnecessary, expensive and luxury product (Aheleroff et al., 2020; Liegeard & Manning, 2020). The monetary cost of this IoT smart device may be more affordability, marketers may choose to reduce the price or create different payment options such as payment in lower installments but in return for extended payment time, or even leasing.

Privacy concerns negatively influence the attitude towards the smart refrigerator (Alaiad & Zhou, 2017), taking into account that companies can ensure transparency of communication by revealing data collection and storage procedures, as well as make their data indecipherable by using the most advanced encryption techniques in case third parties try to inappropriately access the data (such as post-quantum cryptography to prevent indecipherability of both quantum and traditional computers). In this way, they can provide more security to the consumer, which will in turn reduce their concerns about the use of this IoT device.

Supporting the literature on green self-identity and attitude in a smart home environment (Pal, Funilkul, Vanijja, et al., 2018). Supporting the literature on green self-identity and attitude in a smart home environment the green self-identity is thus significant in shaping consumer attitudes toward the use of smart refrigerators to prevent food waste. Organizations should target this group, study how they behave, what motivates them, and what repels them, and develop a marketing strategy tailored to them (for example, developing appealing campaigns highlighting the benefits of IoT devices in terms of reducing their ecological footprint). Organizations can also play a role in encouraging behavioral change, to make the consumer aware of the importance of sustainable behaviors.

By performing these tasks, many households can be prevented from wasting food, and food waste can be cut in half by 2030, and preferably this habit will be instilled and consumers will have behaviors that prevent food waste in their household in the long term.

5.4 LIMITATIONS AND FUTURE WORK

Despite the valuable insights provided by this study, it does contain some limitations that should be noted.

First, this study used a sample of persons residing in the United States, due to the fact that this is the geographic location where the smart fridges market is most developed, as opposed to other geographic points. This proves to be a limiting factor in that the findings may not be applicable to other geographic regions with different technological, cultural, and economic contexts. Future research can investigate what factors influence this acceptance in other geographic regions.

The fact that a balanced sample was selected both in terms of whether or not they owned a smart refrigerator and whether or not they had a green self-identity was a limiting factor of the research as it was set as a criterion. Future research should test different percentages of these criteria, or even add some criterion related to privacy concerns, in order to get more insights to better understand this technological acceptance.

The fact that the survey included a video to better show the characteristics of smart refrigerators may have biased the results, insofar as the hedonic motivation may have been more positively evaluated, since the consumer could imagine himself in the situation of the actors and imagine a pleasure resulting from the tasks they were performing. It may also have caused the participants to respond more with the emotional side rather than the rational side, pondering the issue of the facilitating conditions of technology use, which proved to be unsupported. Future research should only describe in writing the features or benefits of the technology, so that the instrument is as neutral as possible.

As this research is the first on the adoption of technologies to prevent food waste, it achieved satisfactory initial results, but the variance of attitude and use behavior are low, indicating that these constructs are influenced by other constructs that were not considered in this research. Future research should look into what factors influence the acceptance of this IoT technology to prevent food waste, such as technology anxiety (Alolayan, 2014; Pal, Funilkul, Charoenkitkarn, et al., 2018), to understand whether people who live with housemates are more concerned about exposing their data (Coughlan et al., 2012), environmental beliefs and environmental concerns (Schill et al., 2019), or even other antecedents of food waste at the household level already evidenced by Principato et al. (2021). As well as study acceptability of other technologies considering attitude as a mediator.

6 CONCLUSIONS

This study aimed to investigate the main factors influencing the acceptance of smart refrigerators as a technology to prevent household food waste. By applying and adapting the UTAUT2 model of Venkatesh et al. (2012), with three new constructs based on the literature review, namely privacy concerns (Marikyan et al., 2019; Wilson et al., 2017), green self-identity (Barbarossa et al., 2015, 2017; Neves & Oliveira, 2021) and attitude towards technology (Davis, 1989; Rothensee, 2008).

The results revealed several significant findings related to the UTAUT2 model constructs as well as the new introduced constructs of privacy concerns, green self-identity, and attitude. Notably the model suggests that the main influencers of behavioral intention were social influence, performance expectancy, attitude, habit and hedonic motivation, in this respective order considering the level of influence.

Moreover, the consumer's behavioral intention and the consumer's habits towards technology were identified as significant predictors of behavioral use of technology to prevent food waste. Nevertheless, no evidence was found that Behavioral Intention was significantly influenced by effort expectancy, price value and facilitating conditions for technology use. Also the facilitating conditions have not been shown to significantly influence use behavior.

Regarding the new constructs, neither privacy concerns nor green self-identity directly influences behavioral intention. But the indirect effects of privacy concerns and green self-identity on behavioral intention highlight the significant role of attitude as a mediator. Similarly, the indirect effects of privacy concerns and green self-identity on use behavior emphasize the crucial roles of attitude and behavioral intention as mediators. This means that the presence of privacy concerns in a consumer's mind regarding a smart fridge undermines their overall attitude towards the technology, which will ultimately influence their behavioral intention towards its use, and subsequently determine the use behavior of the technology to prevent food waste. Similarly, the consumer's green identity plays a crucial role in the consumer's attitude towards the technology as a promoter of food waste reduction, consequently influencing the behavioral intention to use it and the subsequent use behavior.

Based on the results of the 2 models it is concluded that consumers are more likely to adopt smart refrigerators if they perceive them as beneficial, influenced by social factors, driven by pleasure, if they remain consistent with their usual behaviors, faithful to their attitudes and usage intentions. The attitude that consumers develop toward technology may be influenced by privacy concerns and green-self identity.

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APPENDIX

APPENDIX A

Development of the measurement items of the constructs used

Construct	Items	Measurement items	Scale	Adapted from
Performance Expectancy	PE1	I find the smart refrigerator useful in my household food routines.	7-Point Likert Scale	(Venkatesh et al., 2012)
	PE2	Using smart refrigerators makes me more efficient in dealing with my household food management.		
	PE3	Using smart refrigerators increases my ability to prevent food waste.		
	PE4	I find smart refrigerator useful to prevent household food waste.		
Effort Expectancy	EE1	Learning how to use a smart refrigerator is easy for me.	7-Point Likert Scale	(Venkatesh et al., 2012)
	EE2	My interaction with the smart refrigerator is clear and understandable.		
	EE3	I find smart refrigerators easy to use.		
	EE4	It is easy for me to become skillful at using smart refrigerators.		
Social Influence	SI1	People who are important to me think that I should use a smart refrigerator to prevent food waste.	7-Point Likert Scale	(Venkatesh et al., 2012)
	SI2	People who influence my behavior think I should use a smart refrigerator to prevent food waste		
	SI3	People whose opinions I value prefer that I use a smart refrigerator to prevent food waste		

Facilitating Conditions	FC1	I have the resources necessary to use a smart refrigerator.	7-Point Likert Scale	(Venkatesh et al., 2012)
	FC2	I have the knowledge necessary to use smart refrigerators.		
	FC3	Smart refrigerator is compatible with other technologies I use.		
	FC4	I can get help from others when I have difficulties using smart refrigerators. **(Dropped)**		
Hedonic Motivation	HM1	Using a smart refrigerator is fun.	7-Point Likert Scale	(Venkatesh et al., 2012)
	HM2	Using a smart refrigerator is enjoyable.		
	HM3	Using a smart refrigerator is very entertaining.		
Price Value	PV1	Smart refrigerator is reasonably priced.	7-Point Likert Scale	(Venkatesh et al., 2012)
	PV2	The smart refrigerator is a good value for the money.		
	PV3	At the current price, the smart fridge offers good value.		
Habit	HT1	The use of smart refrigerators has become a habit for me.	7-Point Likert Scale	(Venkatesh et al., 2012)
	HT2	I am addicted to using smart refrigerator.		
	HT3	I must use smart refrigerator.		
Attitude	ATT1	Using the smart refrigerator to prevent food waste is a (bad...good) idea.	7-Item Semantic Differential Scale	(Taylor & Todd, 1995)
	ATT2	Using the smart refrigerator to prevent food waste is a (foolish ...wise) idea.		
	ATT3	I (dislike…like) the idea of using the smart refrigerator to prevent food waste		
	ATT4	Using the smart refrigerator to prevent food waste is a (unpleasant ...pleasant) idea.		
Privacy Concerns	PC1	I am concerned that the information I submit on the smart refrigerator could be misused.	7-Point Likert Scale	(Dinev & Hart, 2006)

	PC2	I am concerned that a person can find private information about me on the smart refrigerator.		
	PC3	I am concerned about submitting information on the smart refrigerator because of what others might do with it.		
	PC4	I am concerned about submitting information on smart refrigerator because it could be used in a way I did not foresee		
Green Self-Identity	GSI1	I think of myself as someone who is concerned about environmental issues	7-Point Likert Scale	(Barbarossa et al., 2015)
	GSI2	I think of myself as a "green" consumer		
	GSI3	I would describe myself as an ecologically conscious consumer		
Behavioral Intention	BI1	I intend to use smart refrigerators to prevent food waste.	7-Point Likert Scale	(Venkatesh et al., 2012)
	BI2	I intend to use smart refrigerators in the next months to prevent food waste.		
	BI3	I plan to use smart refrigerators frequently to prevent food waste		
Use Behavior	What is your actual frequency of use of the following smart refrigerator capabilities? - (1) Never; to (7) Every time.		7-Point Likert Scale	(Venkatesh et al., 2012)
	UB1	a) Store food **(Dropped)**		
	UB2	b) Plan meals		
	UB3	c) Create shopping lists		
	UB4	d) Use its features to know what's stored inside		
	UB5	e) Track expiration dates		

APPENDIX B

The table below gives the result of the specific indirect paths

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Statistical significance**
PV -> BI -> UB	0.016	0.015	0.013	1.229	0.219	Rejected
PE -> BI -> UB	0.054	0.058	0.027	2.024	0.043	Supported
SI -> BI -> UB	0.073	0.072	0.018	4.111	0.000	Supported
GSI -> ATT -> BI -> UB	0.019	0.018	0.007	2.794	0.005	Supported
GSI -> ATT -> BI	0.064	0.064	0.020	3.292	0.001	Supported
PC -> ATT -> BI -> UB	-0.011	-0.011	0.004	2.615	0.009	Supported
GSI -> BI -> UB	-0.002	-0.002	0.010	0.202	0.840	Rejected
EE -> BI -> UB	0.020	0.020	0.013	1.551	0.121	Rejected
ATT -> BI -> UB	0.053	0.052	0.017	3.047	0.002	Supported
HM -> BI -> UB	0.031	0.031	0.017	1.801	0.072	Rejected
FC -> BI -> UB	0.004	0.004	0.012	0.363	0.717	Rejected
HT -> BI -> UB	0.049	0.049	0.015	3.363	0.001	Supported
PC -> BI -> UB	-0.014	-0.014	0.009	1.635	0.102	Rejected
PC -> ATT -> BI	-0.038	-0.038	0.013	3.056	0.002	Supported