

EVALUATION OF CONSUMERS' USE OF SMART ROBOTIC VACUUM CLEANERS UNDER EXTENDED EXPECTATION-CONFIRMATION MODEL

VREDNOVANJE PROVEDENO MEĐU POTROŠAČIMA PAMETNIH ROBOTSКИH USISAVAČA U OKVIRU PROŠIRENOGA MODELA POTVRDE OČEKIVANJA

M Market-Tržište
Vol. 36, No. 1, 2024, pp. 25-42
UDK 658.89:004.896
DOI <http://dx.doi.org/10.22598/mt/2024.36.1.25>
Preliminary communication

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Abstract

Purpose – The present research study extends the Expectation-Confirmation Model (ECM) by focusing on satisfaction, continuance intention, and recommendation intention among smart robotic vacuum cleaner users. The impacts of battery life concern and perceived privacy factors on satisfaction and continuance intention of the smart robotic vacuum cleaner were investigated by adding the variables of battery life concern, perceived privacy, and recommendation intention in the ECM.

Design/methodology/approach – The participants of this study consisted of smart robotic vacuum cleaner users in Turkey. The snowball sampling method, as one of the non-random sampling methods, was used to reach the participants; data was collected using an online survey created with Google Forms, asking the participants to share the survey link with people around them who have smart robotic vacuum cleaners. A total of 218 smart robotic vacuum cleaner users participated in the study between March 1 and May 1, 2023.

Sažetak

Svrha – Istraživanje proširuje Expectation-Confirmation Model (ECM) (hrv. model očekivanje – potvrda) usredotočujući se na zadovoljstvo korisnika pametnog robotskog usisavača, namjeru nastavka korištenja i namjeru preporuke. Istraživano je kako zabrinutost oko trajanja baterije i čimbenika percipirane privatnosti utječe na zadovoljstvo i namjeru da se i dalje koristi ovaj uređaj dodavanjem u ECM model varijabli zabrinutost oko trajanja baterije, percipirana privatnost i namjera preporuke.

Metodološki pristup – Sudionici istraživanja bili su korisnici pametnog robotskog usisavača u Turskoj. Kako bi se došlo do ispitanika, korištena je metoda snježne grude, jedna od metoda uzorkovanja koja nije zasnovana na vjerojatnosti, a podaci su prikupljeni korištenjem online anketnog upitnika izrađenog pomoću Google Forms alata. Sudionici su zamoljeni da podijele poveznicu ankete s ljudima koji imaju pametni robotski usisavač. U istraživanju je sudjelovalo 218 korisnika, a trajalo je od 1. ožujka do 1. svibnja 2023.

Findings and implications – Structural equation modeling (SEM) was used as the data analysis technique in the study. While the ECM was confirmed as a result of the SEM analysis, an important finding was that consumers with battery life concerns intend to continue using the smart robotic vacuum cleaner despite a negative relationship between battery life concern and satisfaction. While the effect of perceived privacy on continuance intention was not significant, satisfaction was found to have a significant effect on continuance intention. Given that artificial intelligence-related businesses face fierce competition, organizations that wish to prosper in this environment must excel in a variety of areas, ranging from product design to marketing and from sales policies to post-sales assistance. Considering the findings, determining the factors that affect the satisfaction and intention to continue using robot vacuum cleaners will be a guide for smart robot vacuum cleaner manufacturers and marketers. At the same time, the fact that the issue has been investigated within the framework of a model will also make significant contributions to the literature.

Limitations – Different factors influence smart robotic vacuum cleaner users' satisfaction and desire to continue using them, but only battery-life concerns and perceived privacy variables were incorporated into the ECM model in this research study. Another limitation is connected to the research sample. Because the snowball sampling method was employed to obtain data for the research, its findings cannot be generalized as they cover only smart robotic vacuum cleaner users who participated in the survey.

Originality/value – The ECM employed in the study was expanded by including the variables of battery-life concern, perceived privacy, and recommendation intention. A general lack of information among potential consumers regarding artificial intelligence and smart robotic vacuum cleaners, which is highly fascinating and a source of curiosity, as well as the lack of research on this issue in the literature, underscore the significance of this research study. By integrating and expanding the ECM for application to consumers using smart robotic vacuum cleaners, this study adds a fresh viewpoint to the literature.

Keywords: artificial intelligence, smart robotic vacuum cleaners, Expectation-Confirmation Model, continuance intention, recommendation intention

Rezultati i implikacije – Korišten je SEM kao metoda analize podataka. Iako je ECM model potvrđen kao rezultat SEM analize, važno je otkriće da potrošači zabrinuti za trajanje baterije namjeravaju nastaviti koristiti pametni robotski usisivač unatoč činjenici da postoji negativan odnos između zabrinutosti oko trajanja baterije i zadovoljstva. Iako učinak percipirane privatnosti na namjeru nastavka korištenja nije bio značajan, utvrđeno je da zadovoljstvo ima značajan učinak na namjeru nastavka korištenja. Poduzeća koja koriste umjetnu inteligenciju suočavaju se s oštrom konkurencijom, a ako žele napredovati u ovom okruženju, trebaju se isticati u raznim područjima, od dizajna proizvoda, marketinga i prodajne politike pa do poslijeprodajne usluge. Uzimajući u obzir rezultate, određivanje čimbenika koji utječu na zadovoljstvo i namjeru daljnjeg korištenja robotskih usisavača bit će vodilja proizvođačima i trgovcima pametnog robotskog usisavača. Istodobno, činjenica da je predmet istražen u okviru ECM modela također će pružiti značajan doprinos literaturi.

Ograničenja – Iako različiti čimbenici utječu na zadovoljstvo korisnika pametnog robotskog usisavača i želju za nastavkom korištenja, u ovom su istraživanju u ECM model uključeni samo zabrinutost oko trajanja baterije i varijable percipirane privatnosti. Sljedeće ograničenje istraživanja povezano je s uzorkom. Budući da je za dobivanje podataka korištena metoda snježne grude, rezultati se ne mogu generalizirati, a obuhvaćaju samo korisnike pametnog robotskog usisavača koji su sudjelovali u istraživanju.

Doprinos – ECM model potvrde očekivanja proširen je uključivanjem varijabli zabrinutost oko trajanja baterije, percipirana privatnost i namjera preporuke. Neinformiranost potencijalnih potrošača o umjetnoj inteligenciji i pametnim robotskim usisavačima, što je vrlo fascinantly i izvor znatiželje, kao i nedostatak istraživanja ove problematike u literaturi, upućuje na značaj istraživanja. Integracijom i proširenjem ECM modela u kontekstu potrošača pametnih robotskih usisavača pružen je novi uvid u literaturu.

Ključne riječi – umjetna inteligencija, pametni robotski usisavači, Expectation-Confirmation Model, namjera nastavka korištenja, namjera preporuke

1. INTRODUCTION

Throughout history, mankind has pondered how to complete its chores more quickly and easily; as a consequence, it has come up with new ideas, inventions, and discoveries while also constructing machines as a result of the research it has done. This evolution and transformation have persisted from the past to the present day and will continue into the future. Because of the rapid advancement and dissemination of technology, new concepts have emerged, and the actual and virtual worlds have been linked. Because of the increasing usage of the internet and the emergence of wireless internet, gadgets may now be operated remotely. Physical locations have given way to "virtual", "online", and "mobile" environments, while physical devices have been replaced by "smart" and "robot" gadgets. Although robot technologies, artificial intelligence, and automation systems are incredibly intriguing concepts all around the world, most people are unaware of them. Artificial intelligence and smart robot technologies have lately been studied in a variety of domains (Gursoy, Chi, Lu & Nunkoo, 2019; Talukder, Chiong, Bao & Hayat Malik, 2019; Gupta, Dhiman, Yousaf & Arora, 2020; Aiolfi, 2023). Because these applications are utilized in so many different domains and hence have distinct meanings in each particular one, it is difficult to provide a single description. These systems rely on data analysis to generate new outputs based on the data fed into the computers.

Artificial intelligence, one of the most recent outcomes of this research, is an interdisciplinary subject that requires a comprehensive approach. Artificial intelligence, which can mimic human intelligence, is designed to perform specific tasks and can improve itself with the information it has gathered; from engineering to philosophy, science to health services, e-commerce to robot applications, defense industry to cyber security systems; in short, most disciplines are being used to their full potential. Given the scope of the effect of artificial intelligence on every aspect of our life, it has shown potential

to be applied in daily work as well. Robotic devices have recently been favored in many fields; thanks to smart devices coupled with smart home appliances following smartphones, there is hope about minimizing the workforce and saving time. This technique has also been successfully incorporated into smart robotic vacuum cleaners using a particular robotic coding method. Consumers are increasingly inclined to acquire such items not only because of their technology but also the ease of cleaning benefits they provide, such as not taking up much room, charging itself, reaching hard-to-reach areas, and being remotely operated without the need for people. As a result, a new market has formed for companies looking to transform this desire into an opportunity.

One of the reasons for doing research in this field is the observed growth in the use of service robots in households, which is one of the areas where robot technologies are employed the least. A research study by Tor-Kadioğlu (2020) devoted to smart robotic vacuum cleaners was designed to identify why users utilize these products. The purpose of this research is to establish consumer satisfaction levels and their willingness to continue using and promoting the product via the smart robotic vacuum cleaners they have used. To accomplish this goal, an Expectation-Confirmation Model (ECM), designed to explain the influence on consumer repurchase behavior, was utilized to assess the level of satisfaction with the product. This idea has also been applied to research on intelligent robots (Pal, Funilkul & Vanijja, 2020; Çağlar Çetinkaya and Kartal, 2022).

The ECM employed in the present study was expanded by including the variables of battery-life concern, perceived privacy, and recommendation intention. A general lack of information among potential consumers regarding artificial intelligence and smart robotic vacuum cleaners, which is highly fascinating and remains a source of curiosity, as well as the lack of research on this issue in the literature underscore the significance of this research. By integrating and

expanding the ECM for application to consumers using smart robotic vacuum cleaners, this study adds a fresh viewpoint to the literature. According to practitioners, the results in terms of revealing existing problems (such as battery life and privacy concerns against perceived benefits, etc.) related to smart robotic vacuum cleaners (Pal et al., 2020) and meeting consumer expectations in this respect will benefit manufacturers striving to survive in the artificial intelligence-oriented sector in an intensely competitive environment; it will also provide support for brands in many areas, ranging from product design to marketing and from sales policy to product development. As a result, the study is expected to be a source of knowledge for enthusiasts, a resource for practitioners, and a contribution to the literature.

The following sections are included in the present paper. The conceptual framework, literature evaluation, and hypothesis development procedure are all covered in the next section. Then, information regarding the research technique is provided, followed by the findings. Discussion, theoretical and managerial implications, limitations, and future research prospects are included in the concluding part.

2. CONCEPTUAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

With recent technical advancements, the creation and application of AI-based gadgets have gained traction. AI technology is employed in a variety of sectors, ranging from automotive robots to clinical decision support systems in hospitals. As outlined by Gursoy et al. (2019), AI-powered machines may now readily execute tasks that were previously solely handled by humans, such as driving a car, understanding human language, identifying faces in photographs, analyzing massive data, or searching online. Since the 1960s, robots have been replacing human bodily duties and doing monotonous tasks.

Simultaneously, robots are utilized in a wide range of automation systems for mass manufacturing. Nonetheless, despite countless efforts to bring robotic technology into our homes, consumer adoption of “consumer robots” or “domestic robots” has been gradual. In general, robots are utilized in high-tech toys, with the exception of floor-cleaning items (Yoon & Jetter, 2014). Another related concept that comes to mind when robots and home technology are mentioned is the internet of things. To put it simply, the Internet of Things application, which was first used by a group of academics at Cambridge University in 1991, is a communication network that allows us to control, monitor, and analyze the physical elements in the environment (Lopez-de-Armentia, Casado-Mansilla & Lopez-de-Ipina, 2012). It is now used in many areas, as well as in the field of home technologies. All objects in the home technology system communicate with each other through wireless networks (Jiang, Yang & Zhang, 2015). With the introduction of home service robots into people’s homes, it is becoming increasingly vital to understand the long-term adoption process while also taking into account consumer demands (Fink, Bauwens, Kaplan & Dillenbourg, 2013).

The research model in this study was built using the ECM, as shown in Figure 1. ECM is considered an important theory in the field of information systems and technologies that explains post-adoption behavior by users and is based on the Expectation-Confirmation Theory, which proposes that expectations and perceived performance lead to post-purchase satisfaction and influence repurchase intention (Park, 2020; Hsu and Lin, 2015). ECM is a theoretical framework used to understand and explain such things as consumer satisfaction, purchase, trust, and switching decisions, as well as the acceptance, use, or adoption of technology (Eveleth, Baker-Eveleth & Stone, 2015). Oliver initially proposed the Expectation-Confirmation theory to investigate customer satisfaction and post-purchase behavior. According to Oliver (1980), cus-

tomers' repurchase intentions are mostly determined by their satisfaction with their past use of the product or service. The ECM attempts to explain satisfaction as a consequence of confirming or not confirming expectations, perceived performance, and beliefs when a consumer purchases or adopts a certain product or service (Pal et al., 2020). This model is frequently applied to exploring consumer satisfaction and post-purchase behavior (Bhattacharjee, 2001a). In ECM, it is thought that the level of satisfaction with the product or service impacts the consumer's desire to repurchase (Thong, Hong & Tam, 2006). In this context, ECM is used to achieve consumers' repurchase intentions in five phases (Bhattacharjee, 2001a). First, before acquiring a product or service, buyers develop their first expectations. Furthermore, before making a purchasing choice, consumers form expectations about specific goods or services. After acquiring a product or service, users gain experience with it, and their perception of performance arises after the first consumption time. Third, based on pre-purchase references, consumers assess the perceived performance of the product or service and judge the extent to which those expectations are confirmed. Fourth, satisfaction or mood is developed based on the degrees of approval and the expectations that are the basis for the approval. Finally, when a product or service works as predicted, consumers' expectations are verified, and a repurchase intention is generated. When a product or service performs poorly, consumers' expectations are disappointed, and further usage is discontinued. In short, the amount of approbation determines satisfaction (Churchill and Surprenant, 1982; Bhattacharjee, 2001a; Lin, Wu & Tsai, 2005; Hong, Thong & Tam, 2006; Thong et al. 2006; Huang and Yu, 2023). Consequently, satisfaction is a key determinant in the research model.

Cleaning is a daily activity expected by consumers to be made simpler using promoted items. When it comes to facilitation, the first thing that springs to mind is smart robotic vacuum cleaners (Tor-Kadioğlu, 2020). Smart robotic vacuum cleaners were created with the goal of minimiz-

ing human labor and replacing regular vacuum cleaners (Yoon and Jetter, 2014). The main distinction between smart robotic vacuum cleaners and ordinary vacuum cleaners is that they do the cleaning themselves (Tor-Kadioğlu, 2020). Smart robotic vacuum cleaners have affected consumers and modified their cleaning habits as compared to traditional vacuum cleaners (Forlizzi, 2007). Furthermore, certain smart robotic vacuum cleaners have been discovered to clean more thoroughly than regular ones (Fink et al., 2013). As a result, the main determinants of the research model are perceived usefulness, satisfaction, and continuance intention. Many factors influence consumer satisfaction (Tam, Santos & Oliveira, 2018; Çağlar Çetinkaya & Kartal, 2022). The criteria utilized to assess satisfaction in this research include consumers' perceived benefit from smart robotic vacuum cleaners, worry about their battery life, and confirmation. It is anticipated that consumers' battery-life concerns, perceived usefulness, perceived privacy, and satisfaction play a role in their continuance intention and that consumers who have this intention will also have the recommendation intention.

Perceived Usefulness

The amount to which a person feels that employing a certain technology would increase work performance (Davis, Bagozzi & Warshaw, 1989; Pal et al., 2020) is referred to as perceived usefulness. Perceived usefulness determines consumer satisfaction and confirmation of expectations (Thong et al., 2006). It is a measure of consumers' extrinsic motivation and anticipation of results (Pal et al., 2020), or the perception of performance that happens to consumers after utilizing the product (Çağlar Çetinkaya and Kartal, 2022). The more benefits consumers acquire, the happier they will be and the more likely they will be to continue using the product (Pal et al., 2020). Many researchers have discovered a link between perceived usefulness and satisfaction, and/or continuance intention (Bhattacharjee, 2001a; Bhattacharjee, 2001b; Thong et al., 2006;

Oghuma, Libaque-Saenz, Wong & Chang, 2016; Susanto, Chang & Ha, 2016; Pal et al., 2020; Çağlar Çetinkaya & Kartal, 2022). However, Gupta et al. (2020) discovered no beneficial association between perceived usefulness and continuance intention in their research. The following hypotheses were developed in this context.

H1a: The perceived usefulness of smart robotic vacuum cleaners has a positive effect on satisfaction with these products.

H1b: The perceived usefulness of smart robotic vacuum cleaners has a positive effect on continuance intention with these products.

Satisfaction

Post-adoption behavior is heavily influenced by satisfaction (Pal et al., 2020). It is a straightforward evaluation of a consumer's initial (trial) encounter with a product or service. It can be expressed as a positive feeling (satisfaction), an indifferent mood (indifference), or a negative emotion (dissatisfaction). Satisfaction and continuance intention are related (Bhattacharjee, 2001b). High satisfaction is seen as a crucial aspect in effective long-term partnerships because it might lead to further purchases. A number of prior research studies demonstrated a link between satisfaction and continuance intention (Susanto, Chang & Ha, 2016; Bhattacharjee, 2001a; Oghuma et al., 2016; Gupta et al., 2020; Çağlar Çetinkaya and Kartal, 2022). Based on these studies in the literature, the following hypothesis has been developed.

H2: The satisfaction of smart robotic vacuum cleaners has a positive effect on the continuance intention of using these products.

Confirmation

The psychological condition of the consumers occurs when the emotion around unverified expectations is combined with their past sentiments about the consuming experience. A psychological or emotional condition arising from satisfaction is the cognitive assessment of expectation-performance confirmation. With

lower expectations and/or greater performance leading to more approval, this condition has a favorable effect on satisfaction and continuance intention; conversely, it generates disapproval, discontent, and intention to stop. Confirmation is closely connected to perceived performance and has an inverse relationship with anticipation (Bhattacharjee 2001a). Confirmation can be positive or negative at the same time; positive confirmation improves the perceived effectiveness of any system, whereas negative confirmation diminishes it (Pal et al., 2020). Many studies argue that there is a relationship between confirmation on the one hand and perceived usefulness and satisfaction on the other (Bhattacharjee, 2001b; Huang, 2019; Gupta et al., 2020; Pal et al., 2020). Since perceived usefulness is the reference for approving a product or service, there is a relationship between usefulness and confirmation (Ashraf, Jaafar & Sulaiman, 2017). Confirmation leads to user satisfaction if users believe that a technology is useful and their expectations are met or exceeded after using it (Oghuma et al., 2016). As a result, the hypotheses listed below have been formulated.

H3a: The confirmation of smart robotic vacuum cleaners has a positive effect on the perceived usefulness of these products.

H3b: The confirmation of smart robotic vacuum cleaners has a positive effect on satisfaction with these products.

Continuance Intention and Recommendation Intention

Consumers who are pleased with the outcome of approval or favorable approval are more inclined to repurchase items or services in the future. Consumers who are unsatisfied with a product or service following rejection or negative approval will not utilize it again (Susanto et al., 2016). There is also a close relationship between wearable technology and smart robots. Through wearable technology consumers can easily establish a connection to their various connected home devices, including refrigerators, washing machines, robot vacuum cleaners,

etc. from anywhere (Kim, Hong, Kim, Kim, Kim & Chun, 2014). The use of wearable devices in smart home appliances makes human life even easier (Volety & Geethanjali, 2022). Considering that the use of wearable technology has both direct and indirect effects on recommendation intention (Talukder et al., 2019), the same may be true for smart robotic vacuums. Gupta et al. (2020) discovered that the continuance intention has a favorable influence on the recommendation intention, leading to the following hypothesis.

H4: The continuance intention of using smart robotic vacuum cleaners has a positive effect on the recommendation intention of these products.

Battery-Life Concern

Battery life may be the most critical success criterion for smartwatches to get market acceptance. The failure of Microsoft's SPOT (Smart Personal Objects Technology) due to battery restrictions demonstrates the need to take battery life into account more seriously (Rawasizadeh, Price & Petre, 2015). The way in which smartphone battery life affects user experience has been explored (Pal et al., 2020, p. 271). Battery life is critical because consumers frequently use wearables such as smartwatches for a variety of reasons. Users have an unfavorable opinion of smart watches with a limited battery life, which may cause them to be disappointed and quit using them. Battery life worries are users' concerns regarding the battery lifetime while using all of the device's features and functionalities to their maximum capability on a single full

charge (Pal et al., 2020). Graaf, Allouch, and Dijk (2019) discovered that utilitarian attitudes had no influence on continuance intention, but Pal et al. (2020) discovered that battery-life concern had a negative effect on satisfaction and continuance intention, so the following hypotheses were developed.

H5a: Battery-life concern about smart robotic vacuum cleaners has a negative effect on satisfaction with these products.

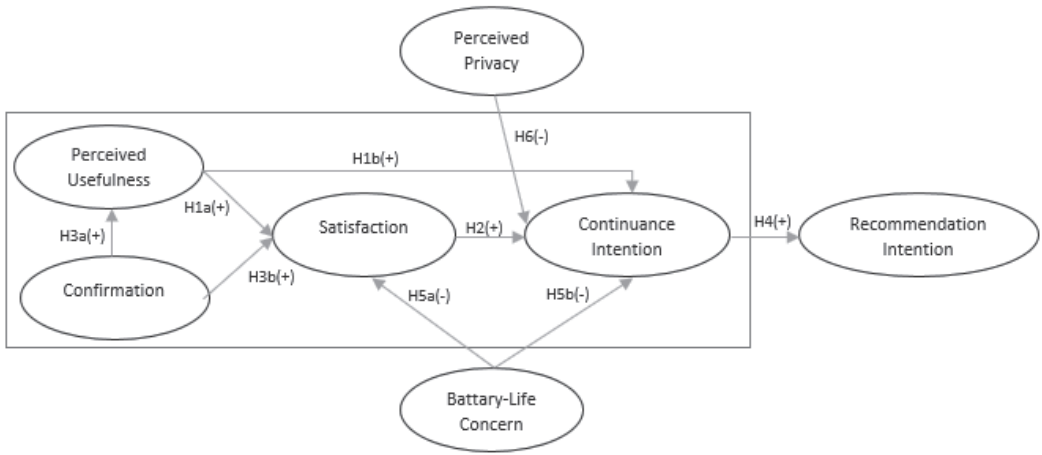
H5b: Battery-life concern about smart robot vacuum cleaners has a negative effect on the continuance intention of using these products.

Perceived Privacy

The practical requirement for human rights protection and the unavoidable need for information technology growth is privacy protection (Liu, Wu, Yang, Zhao & Sun, 2022). Harmful persons can hijack the robot without the user's awareness by using harmful software. Just as a robot that can record photos in violation of private life privacy may instantaneously broadcast recorded video over the internet (Bozkurt Yüksel, 2017), this can also be valid for smart robotic vacuum cleaners. Susanto et al. (2016) discovered that perceived security and privacy influence trust but not satisfaction. Pal et al. (2020) discovered, however, that perceived privacy had a negative influence on continuance intention. As a result, the following hypothesis was created.

H6: The perceived privacy of smart robotic vacuum cleaners has a negative effect on the continuance intention of using these products.

FIGURE 1: Research Model



3. RESEARCH METHODOLOGY

3.1. Data Collection and Sample Characteristics

Participants of the research study consisted of smart robotic vacuum cleaner users in Turkey. The snowball sampling method, which is among the non-random sampling methods, was used to garnish participation because it saves time and money for researchers (Brickman Bhutta, 2012). The data were collected using an online survey created with Google Forms, inviting participants to share the survey link with persons in their vicinity who had smart robotic vacuum cleaners. Given that only the users of

smart robot vacuum cleaners were eligible to participate in the survey, a “Do you have a smart robot vacuum?” filter question was added, so the participants who replied “Yes” to this question were permitted to continue with the survey. A total of 218 smart robotic vacuum cleaner users took part in the research between March 1 and May 1, 2023, but as five questionnaires were found to be incomplete and erroneous, 213 questionnaires were approved as legitimate. Because a sample size of 10 times the number of items used in the questionnaire is deemed acceptable to estimate sample size (Hair, Black, Babin & Anderson, 2010), the number of samples obtained in the current investigation was sufficient. The demographic information of survey participants is presented in Table 1.

TABLE 1: Demographic statistics of the sample

Demographic characteristics		Total number of participants (N) = 213 Frequency	Percentage
Gender	Male	131	61.5
	Female	82	38.5
Marital status	Married	162	76.1
	Single	51	23.9
Age	18-28	48	22.5
	29-39	123	57.7
	40-50	35	16.5
	51 and older	7	3.3
Education status	Primary	6	2.8
	Secondary	15	7
	Undergraduate	111	52.2
	Postgraduate	81	38
Income	360 EUR and below	13	6.1
	361-600 EURo	31	14.6
	601-840 EUR	43	20.2
	841-1,080 EUR	42	19.7
	1,081 EUR and higher	84	39.4
Occupation	State-employed	116	54.5
	Private	42	19.7
	Housewife	21	9.9
	Retired	2	0.9
	Student	25	11.7
	Not working	7	3.3
Living place	District	31	14.6
	Province	182	85.4

3.2. Measures

The data was gathered using an online questionnaire created with Google Forms. The first section of the questionnaire, which is divided into three sections, included filter questions; the second section contained 21 items regarding the research scales, while the third section consisted of questions about the participants' demographic data. The research employed validated multi-item measures modified from prior studies on the issue, and a 5-point Likert-type scale (1 – Strongly Disagree to 5 – Strongly Agree) was selected for grading these scales. The scale

information used in the research is as follows: perceived usefulness with three items (Davis, 1989; Bhattacharjee, 2001a), confirmation with three items (Bhattacharjee, 2001a), satisfaction with three items (Bhattacharjee, 2001; Kang & Lee, 2010), and continuance intention with three items (Bhattacharjee, 2001a; Venkatesh, Thong & Xu, 2012); recommendation intention with three items (Alexandris, Zahariadis, Tsorbatzoudis & Grouios, 2004; Gupta et al., 2020), battery-life concern with three items (Pal et al., 2020), and perceived privacy with three items (Malhotra, Kim & Agarwal, 2004; Pavlou, Liang & Xue, 2007).

Because the scales used in the research were in a different language, the items were translated into Turkish using the translation-back translation method, and a pre-test was conducted on nine consumers after the content validity was ensured by two academicians who are experts in the field and users of smart robotic vacuum cleaners. Following input from the pretest, a few changes were made to the questionnaire in terms of form and meaning, and the data-collecting phase began. To prevent skewness issues, the data gathered during the pre-testing phase were excluded from the research.

4. RESULTS

4.1. Measurement model

The data gathered in the research was analyzed using the Statistical Package for the Social Sciences (SPSS 21) and Analysis of Moment Structures (AMOS 24) tools. First, normality analysis

was conducted to determine if the research data was normally distributed, and the kurtosis and skewness values of all variables were calculated. The normality analysis found the skewness values of all variables to be in the range of -2 to +2, while the kurtosis values were in the range of -7 to +7, proving that the data had a normal distribution (Curran, West, & Finch 1996; George & Mallery, 2016). While Cronbach's alpha (α) and composite reliability (CR) tests were employed to assess the construct reliability of the scales, the extracted mean-variance (AVE) values were utilized to establish the discriminant and convergent validity of the research components (Hair, Hult, Ringle & Sarstedt, 2013). Factor loadings for all indicators must be larger than 0.5 (Hair et al., 2010), CR values must be greater than 0.7 (Bagozzi and Yi, 1988), and AVE must be greater than 0.5 (Fornell and Larcker, 1981). The results of testing on the research scales to determine these values is summarized in Table 2.

TABLE 2: Results of internal consistency and convergent validity tests

Construct	Item	Standardized Factor Loading	Cronbach alfa (α)	CR	AVE
Perceived usefulness	My robot vacuum cleaner assists me in cleaning the house.	.944	.942	.944	.848
	A robot vacuum cleaner enables me to accomplish my job more efficiently.	.911			
	Using a robot vacuum cleaner makes house cleaning easier.	.907			
Confirmation	The robot vacuum cleaner was better than I expected.	.839	.915	.917	.886
	The performance of my robot vacuum cleaner was better than I expected.	.921			
	Overall, the robot vacuum cleaner met most of my expectations.	.898			
Satisfaction	I believe I made the correct choice in employing a robot vacuum cleaner.	.903	.836	.850	.659
	I am delighted to have a robot vacuum cleaner.	.632			
	I consider my decision to utilize a robot vacuum cleaner to be sound.	.873			

Construct	Item	Standardized Factor Loading	Cronbach alfa (α)	CR	AVE
Recommendation intention	I am prepared to speak positively about robot vacuum cleaners.	.953	.950	.950	.864
	I am confident in recommending robot vacuum cleaners to others.	.944			
	I intend to urge my friends and family to utilize robot vacuum cleaners.	.890			
Continuance intention	In the future, I intend to use my robot vacuum cleaner frequently.	.682	.882	.846	.651
	In the future, I plan to utilize my robot vacuum cleaner on a regular basis.	.781			
	I intend to continue using my robot vacuum cleaner.	.937			
Battery-life concern	It irritates me to have to charge the robot vacuum cleaner every day.	.654	.762	.789	.562
	I wish my robot vacuum cleaner had a larger battery capacity so it could run for longer periods of time.	.643			
	I use the robot vacuum cleaner with caution so that the battery does not run out while cleaning.	.919			
Perceived privacy	My personal information could be misused by a robot vacuum cleaner, infringing on my privacy.	.940	.913	.914	.781
	My personal data may be lost if I use a robot vacuum cleaner.	.884			
	The information gathered by the robot vacuum cleaner might be monitored or abused.	.824			

Table 2 displays standardized factor loads, α , CR, and AVE values for each factor. All of the obtained values are greater than the reference values, demonstrating the reliability and convergent validity of the scales utilized. The discriminant validity of the factors, on the other hand, was also investigated. The statistical difference between the two constructs is determined in

discriminant validity by comparing the square root of the AVE value of each construct with the correlation coefficients of that construct with the other constructs. Each construct's square root of the AVE should be bigger than the correlational values it shares with other constructs (Chin, 1998). As shown in Table 3, the research scales have acceptable discriminant validity.

TABLE 3: Correlation of the constructs and test for discriminant validity

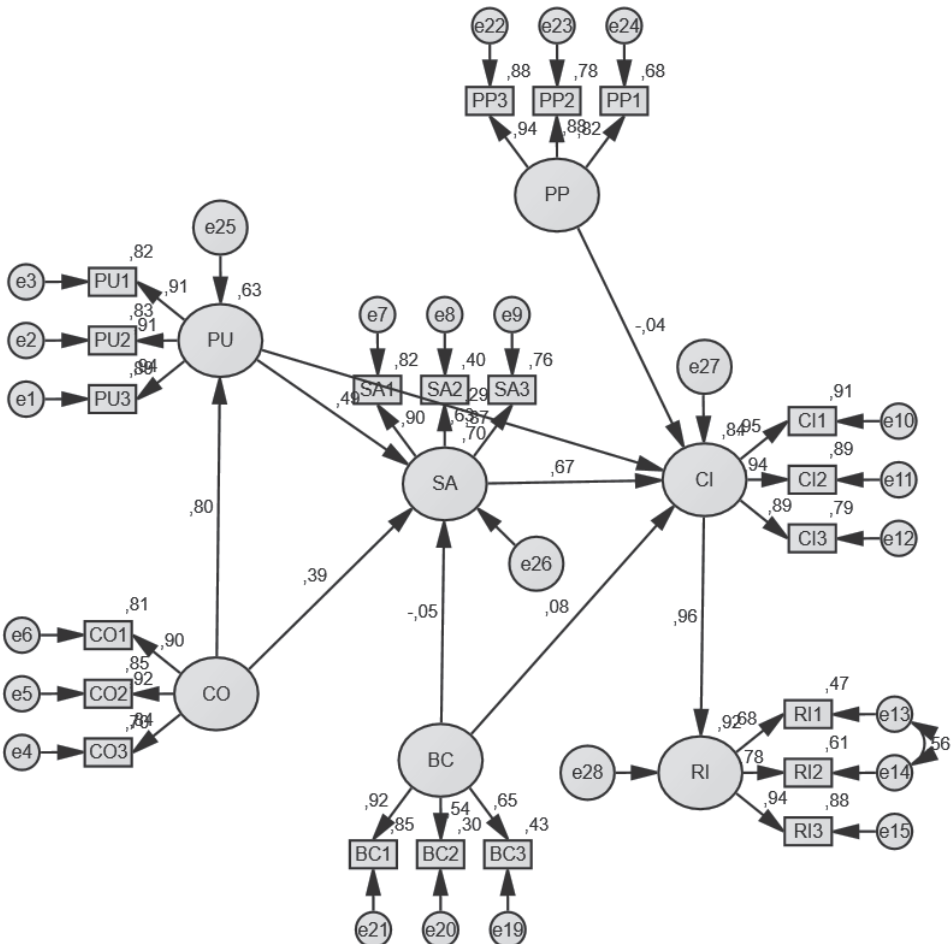
	PU	CO	BC	PP	SA	CI	RI
PU	.921						
CO	.735	.942					
BC	.045	.017	.749				
PP	-.133	-.088	.301	.883			
SA	.724	.653	-.059	-.122	.811		
CI	.639	.653	.082	-.061	.691	.806	
RI	.681	.662	.052	-.116	.678	.730	.929

4.2. Structural Model and Hypothesis Tests

Structural Equation Model (SEM) analysis was done using the AMOS software to assess the

proposed research model and research hypotheses. Figure 2 depicts the structural model that was evaluated using the data obtained. The goodness-of-fit values are used to determine if the structural model fits the data. The df (ratio of

FIGURE 2: Conceptual model results



chi-square statistics to the degree of freedom), RMSEA (root mean square error of approximation), GFI (goodness-of-fit index), AGFI (adjusted goodness-of-fit index), CFI (comparative fit index), NFI (normed fit index), IFI (incremental fit index), and TLI (Tucker-Lewis index) are the most commonly used goodness of fit values in the literature. Given that some of the fit values were not within acceptable values when the model was originally run (GFI: 0.847), covariance connections were constructed in accordance with the recommendations' adjustments. The model was run again after building covariance links between the error components e13-e14 with the recommendation intention scale.

Running the final model yielded the following goodness of fit values: X2/df: 1.957, AGFI: 0.831, GFI: 0.869, CFI: 0.958, NFI: 0.919, and RMSEA: 0.067. When these structural model's goodness of fit values are reviewed, all can be seen to fall within the sound and acceptable goodness of fit range (Sümer, 2000; Tabachnick and Fidell, 2013), indicating that the structural model is a good fit to the research data. Standardized direct effect coefficients and p-values were used to evaluate the hypotheses developed within the scope of the research model. Table 4 shows the outcomes of the research hypothesis.

The findings show that two of the research hypotheses were not supported due to non-significant results, while the remaining hypotheses were supported. The smart robotic vacuum cleaner confirmation influences and supports perceived usefulness ($\beta=.795$; $p<.001$) and satisfaction ($\beta=.390$; $p<.001$). While the positive effect of perceived usefulness on satisfaction was established and supported ($\beta=.488$; $p<.001$), a supporting result could not be obtained despite battery-life concern having a negative influence on satisfaction ($\beta=-.053$; $p>.005$). When it comes to the impact on the continuance intention of using the smart robotic vacuum cleaner, satisfaction ($\beta=.669$; $p<.001$), perceived usefulness ($\beta=.288$; $p<.001$), and battery-life concern ($\beta=.078$; $p<.05$) were all found to have a favorable impact and promote the continuance intention. While the negative effect of perceived privacy on continuance intention was confirmed ($\beta=-.044$; $p>.005$), no meaningful result was obtained. Finally, a positive and significant effect ($\beta = .669$; $p<.001$) was determined and supported the continuance intention of using smart robot vacuums on the recommendation intention.

TABLE 4: Hypothesis results

Hypothesis	Standardized coefficients (β)	S.E.	p-value	Result
H1a: PU \rightarrow SA	0.488	0.096	***	Supported
H1b: PU \rightarrow CI	0.288	0.073	***	Supported
H2: SA \rightarrow CI	0.669	0.072	***	Supported
H3a: CO \rightarrow PU	0.795	0.065	***	Supported
H3b: CO \rightarrow SA	0.390	0.103	***	Supported
H4: CI \rightarrow RI	0.961	0.062	***	Supported
H5a: BC \rightarrow SA	-0.053	0.051	0.285	Not supported
H5b: BC \rightarrow CI	0.078	0.037	0.041*	Supported
H6: PP \rightarrow CI	-0.044	0.024	0.213	Not supported

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

5. DISCUSSION AND CONCLUSION

5.1. Discussion

Smart robotic vacuum cleaners have made it simpler for many individuals, particularly the elderly and working women, to clean their homes. While reaching Turkey in 2013 for the first time, smart robotic vacuum cleaners did not enter homes until the 2020s (Avci, 2022). Thus, the perspectives of users of smart robotic vacuum cleaners, which have gained popularity in recent years, are critical. A model that describes the attitudes of smart robotic vacuum cleaner users thoroughly was constructed by expanding the ECM in this research study. The battery-life concern, perceived privacy, and recommendation intention were all included in the ECM. What makes this research distinct are the opinions of users of smart robotic vacuum cleaners within the scope of the extended ECM. The emphasis is on smart robotic vacuum cleaner user satisfaction, as well as their determination to continue using and recommending them. Research results confirmed the existence of favorable and substantial connections between the perceived usefulness of smart robotic vacuum cleaners and satisfaction (H1a) and continuance intention (H1b). Many studies in the literature support the link between perceived usefulness of smart robotic vacuum cleaners and user satisfaction and continuance intention (Bhattacharjee, 2001b; Thong et al., 2006; Huang, 2019; Gupta et al., 2020; Çağlar Çetinkaya and Kartal, 2022). Simultaneously, it was determined that consumers who are satisfied with smart robotic vacuum cleaners want to continue using them (H2). A number of earlier research studies (Susanto et al., 2016; Pal et al., 2020) claimed that satisfied consumers are more likely to continue using a technology product. A considerable influence of confirmation, as one of the essential variables in the ECM, was identified on both perceived usefulness (H3a) and satisfaction (H3b), so the ECM was validated as a consequence of these hypotheses. In validation, users place a higher value on perceived usefulness than satisfaction,

which is consistent with the findings of several relevant studies (Bhattacharjee, 2001a; Oghuma et al., 2016; Susanto et al., 2016; Pal et al., 2020; Çağlar Çetinkaya and Kartal, 2022). Significant results were also obtained when the continuance intention variable was included in the model. Users who expect to continue using the smart robotic vacuum cleaner also aim to recommend it (H4), and the strongest correlation was found between these two factors. This finding validates the findings of Gupta et al. (2020). There were also significant connections observed between perceived battery-life concerns regarding smart robotic vacuum cleaners on the one hand and satisfaction and continuance intention on the other. Although there is a negative link between battery-life concerns and satisfaction, there is no significant effect (H5a), so consumers expect to continue using the smart robotic vacuum cleaner despite the battery-life concern (H5b). This may be explained by the fact that, although smart robotic vacuum cleaners have battery problems, consumers wish to keep using them thanks to the larger benefits they bring. According to the final hypothesis (H6), while the perceived privacy of smart robotic vacuum cleaners is predicted to have a negative and substantial influence on the continuance intention, no significant result could be obtained despite the existence of a negative association.

5.2. Implications

When the research findings were theoretically evaluated, the ECM was expanded by integrating variables for battery life concern, perceived privacy, and recommendation intention, and the model was tested in the context of a smart robotic vacuum cleaner. The most significant scientific contribution is the expansion of ECM specifically to smart robot vacuum cleaners, as well as the model validation. As a result, the innovative aspect of this research is the incorporation and expansion of the ECM among smart robotic vacuum cleaner users. Although there is a negative correlation between worry about smart robotic vacuum cleaner battery life and

satisfaction, and therefore consumers are dissatisfied with this condition, their intention to continue using smart robotic vacuum cleaners contributes significantly to the literature. This can be explained by the fact that the benefits of smart robotic vacuum cleaners outweigh their drawbacks. Furthermore, the negative correlation between smart robotic vacuum cleaners' perceived privacy in terms of personal information of users being leaked to outsiders and the intention to continue using it adds to the findings of prior research. Otherwise, consumers who are satisfied with smart robotic vacuum cleaners intend to continue using them; at the same time, one of the main outcomes is their desire to promote smart robotic vacuum cleaners to others. When consumers are satisfied with smart robotic vacuum cleaners, they not only continue to use them but also aim to advocate the use of smart robotic vacuum cleaners to others. Finally, our findings confirm the literature on the support of smart robotic vacuum cleaners while also adding a unique perspective.

When the research findings are assessed in practical terms, they provide a significant contribution to the disclosure of challenges associated with smart robotic vacuum cleaners and to the promotion of their utilization. AI-related businesses face fierce competition, and organizations that wish to prosper in this environment must excel in a variety of areas, ranging from product design to marketing and from sales policies to post-sales assistance. The findings of this study will also help brands achieve their objectives in this regard by expanding on extant research. To begin with, while no significant connection was believed to exist between battery-life concerns and satisfaction with smart robotic vacuum cleaners, a negative link was now discovered. Similarly, there is a negative connection between consumers' perceived privacy and their continuance intention. Taking both outcomes into account, smart robotic vacuum cleaner manufacturers must work on alleviating the issue of charging associated with their products or, in other words, lengthen the battery life.

As a result, the satisfaction levels of smart robotic vacuum cleaner users are likely to be raised, so this will also help buyers contemplating the purchase of a robot vacuum cleaner stop worrying about charging issues. Another critical topic is the problem of privacy, which has become increasingly important to consumers nowadays. Smart robotic vacuum cleaners with cameras, in particular, make consumers nervous since they mirror their personal information to the outside world. Therefore, smart robot manufacturers must reassure consumers about privacy protection and make changes to prevent outsiders from obtaining personal information such as users' voices and images via smart robotic vacuum cleaners. Furthermore, in order to continue using smart robotic vacuum cleaners, consumers must first be satisfied with them; because the desire to continue using them influences the intention to promote them to others, it is vital to ensure consumer satisfaction first. It is critical for consumer satisfaction to expand the benefits of the smart robotic vacuum cleaner and to have it accepted. It will be difficult for a disappointed consumer to continue using or recommending it. In this regard, it is vital to continue improving consumer satisfaction by addressing the aforementioned issues plaguing smart robotic vacuum cleaners.

6. LIMITATIONS AND FUTURE RESEARCH

In addition to its significant theoretical and practical contributions, this paper has various limitations. First and foremost, the ECM model was used to measure the satisfaction and continuous usage of smart robotic vacuum cleaners by customers. Of course, there are additional factors influencing smart robotic vacuum cleaner users' satisfaction and desire to continue using them, but in the current research, only battery-life concerns and perceived privacy variables were incorporated into the ECM model. Hence, future academics who undertake research on this topic may be advised to repeat the research with new factors. Furthermore, it may be determined

to investigate the existence of potential demographic differences in satisfaction, intention to continue, and intention to suggest smart robotic vacuum cleaners. Although information such as the participants' financial status and place of residence were gathered in the current research, the moderator function of these factors was not investigated. As a result, by adding important factors to the current model, researchers may explore the moderator roles of these variables. Another weakness of the research is connected to the research sample. Because the snowball sampling method was employed to obtain data for the research, its findings cannot be general-

ized as they cover only smart robotic vacuum cleaner users who participated in the survey. Furthermore, given that the present research is not limited to a particular brand of smart robotic vacuum cleaner, any smart robotic vacuum cleaner users are welcome to participate. Thus, future researchers should select any smart robotic vacuum cleaner brand in order to conduct their research on consumers who use that brand or else include the brand variable as a regulatory variable in the ECM model. In conclusion, the current research will serve as a significant signal for future research on smart robotic vacuum cleaners.

REFERENCES

1. Aiolfi, S. (2023). How shopping habits change with artificial intelligence: smart speakers' usage intention. *International Journal of Retail & Distribution Management*, 51(9/10), 1288-1312.
2. Alexandris, K., Zahariadis, P., Tzorbatzoudis, C., & Grouios, G. (2004). An Empirical Investigation of the Relationships among Service Quality, Consumer Satisfaction and Psychological Commitment in a Health Club Context. *European Sport Management Quarterly* 4(1), 36–52.
3. Ashraf, M., Jaafar, N. I., & Sulaiman, A. (2017). The Mediation Effect of Trusting Beliefs on the Relationship Between Expectation-Confirmation and Satisfaction with the Usage of Online Product Recommendation. *The South East Asian Journal of Management*, 10(1), 75–94.
4. Avci, N. (2022). Technology, Human and Culture Relation: The Lazy Life of Fashionable Consumption with Smart Home Appliance. *International Peer-Reviewed Journal of Cultural Science and Management Research*, 2(2), 61-91.
5. Bagozzi, R.P., & Yi, Y. (1988). On the Evaluation of Structural Equation Models. *Journal of Academy of Marketing Science*, 16(1), 74–94.
6. Bhattacherjee, A. (2001a). Understanding Information Systems Continuation: An Expectation-Confirmation Model. *MIS Quarterly*, 25(3), 351–370.
7. Bhattacherjee, A. (2001b). An Empirical Analysis of the Antecedents of Electronic Commerce Service Continuation. *Decision Support Systems*, 32(2), 201-214.
8. Bozkurt Yüksel, A. E. (2017). Robot hukuku. *TAAD*, 7(29), 85-112.
9. Brickman Bhutta, C. (2012). Not by the Book: Facebook as a Sampling Frame. *Sociological Methods & Research*, 41(1), 57–88.
10. Chin, W. W. (1998). The Partial Least Squares Approach for Structural Equation Modeling. In: G. A. Marcoulides (Ed.), *Methodology for Business and Management. Modern Methods for Business Research* (pp. 295–336). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.
11. Churchill, G. A., & Surprenant, C. (1982). An Investigation into the Determinants of Consumer Satisfaction. *Journal of Marketing Research*, 19(4), 491–504.
12. Curran, P. J., West, S. G. & Finch, J. F. (1996). The Robustness of Test Statistics to Nonnormality and Specification Error in Confirmatory Factor Analysis. *Psychological Methods* 1(1), 16–29.
13. Çağlar Çetinkaya, N., & Kartal, C. (2022). Factors Affecting Consumers' Continuation Intention Online Home Appliances under the Expectation Confirmation Model. *Journal of Emerging Economies and Policy*, 7(2), 483-495.

14. Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 35(8), 982–1003.
15. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319–340.
16. Eveleth, D. M., Baker-Eveleth, L. J. & Stone, R. W. (2015). Potential Applicants' Expectation-Confirmation and Intentions. *Computers in Human Behavior*, 44, 183–190.
17. Fink, J., Bauwens, V., Kaplan, F. & Dillenbourg, P. (2013). Living with a Vacuum Cleaning Robot. *International Journal of Social Robotics*, 5, 389–408.
18. Forlizzi, J. (2007). How Robotic Products Become Social Products: An Ethnographic Research of Cleaning in the Home. In *Proceedings of the ACM/IEEE international conference on Human-robot interaction (HRI '07)*. Association for Computing Machinery, New York, NY, USA, (pp. 129–136).
19. Fornell, C., & Larcker, D.F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research*, 18(3), 382–388.
20. George, D., & Mallery, P. (2016). *IBM SPSS Statistics 23 Step by Step: A Simple Guide and Reference* (14th ed.). New York: Routledge.
21. Graaf, M. M. A., Allouch, S. B. & Dijk, J. A. G. M. (2019). Why Would I Use This in My Home? A Model of Domestic Social Robot Acceptance. *Human-Computer Interaction*, 34(2), 115–173.
22. Gupta, A., Dhiman, N., Yousaf, A. & Arora, N. (2020). Social Comparison and Continuation Intention of Smart Fitness Wearables: An Extended Expectation Confirmation Model Perspective. *Behaviour & Information Technology*, 40(13), 1341–1354.
23. Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers Acceptance of Artificially Intelligent (AI) Device Use in Service Delivery. *International Journal of Information Management*, 49, 157–169.
24. Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2013). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. California: Sage Publication.
25. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis A Global Perspective* (7th ed.). Pearson.
26. Hong, S.-J., Thong, J. Y. L., & Tam, K. Y. (2006). Understanding Continued Information Technology Usage Behavior: A Comparison of Three Models in the Context of Mobile Internet. *Decision Support Systems*, 42(3), 1819–1834.
27. Hsu, C.-L., & Lin, J. C.-C. (2015). What Drives Purchase Intention For Paid Mobile Apps? – An Expectation Confirmation Model With Perceived Value. *Electronic Commerce Research and Applications*, 14(1), 46–57.
28. Huang, Y.-M. (2019). Examining Students' Continued Use of Desktop Services: Perspectives from Expectation-Confirmation and Social Influence". *Computers in Human Behavior*, 96, 23–31.
29. Huang, Y., & Yu, Z. (2023). Understanding the Continuance Intention for Artificial Intelligence News Anchor: Based on the Expectation Confirmation Theory. *Systems*, 11(9), 438.
30. Jiang, T., Yang, M., & Zhang, Y. (2015). Research and Implementation of M2M Smart Home and Security System. *Security and Communication Networks*, 8(16), 2704–2711.
31. Kang, Y.S., & Lee, H. (2010). Understanding The Role of an IT Artifact in Online Service Continuation: An Extended Perspective of User Satisfaction. *Computers in Human Behavior*, 26(3), 353–364.
32. Kim, S., Hong, J., Kim, S., Kim, S., Kim, J., & Chun, J. (2014). Restful Design and Implementation of Smart Appliances for Smart Home. *2014 IEEE 11th Intl Conf on Ubiquitous Intelligence and Computing and 2014 IEEE 11th Intl Conf on Autonomic and Trusted Computing and 2014 IEEE 14th Intl Conf on Scalable Computing and Communications and Its Associated Workshops*, Bali, Indonesia, 2014, pp. 717–722.
33. Lin, C. S., Wu, S., & Tsai, R. J. (2005). Integrating Perceived Playfulness Into Expectation-Confirmation Model for Web Portal Context. *Information & Management*, 42(5), 683–693.

34. Liu, D., Wu, C., Yang, L., Zhao, X., & Sun, O. (2022). The Development of Privacy Protection Standards for Smart Home". *Wireless Communications and Mobile Computing*, 1-10. 9641143.
35. Lopez-de-Armentia, J., Casado-Mansilla, D., & Lopez-de-Ipina, D. (2012). *Fighting Against Vampire Appliances Through Eco-Aware Things*. In *Proceedings of the 2012 Sixth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS)*, Palermo, Italy, 4–6 July 2012, pp. 868–873.
36. Malhotra, N., Kim, S., & Agarwal, J. (2004). Internet Users' Information Privacy Concerns: The Construct, the Scale, and a Causal Model. *Information Systems Research*, 15(4), 336–355.
37. Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., & Chang, Y. (2016). An Expectation-Confirmation Model of Continuation Intention to Use Mobile Instant Messaging. *Telematics and Informatics*, 33(1), 34-47.
38. Oliver, R. L. (1980). A Cognitive Model for the Antecedents and Consequences of Satisfaction. *Journal of Marketing Research*, 17(4), 460–469.
39. Pal, D., Funilkul, S. & Vanijja, V. (2020). The Future of Smartwatches: Assessing the End-Users' Continuous Usage Using an Extended Expectation-Confirmation Model. *Universal Access in the Information Society*, 19, 261–281.
40. Park, E. (2020). User Acceptance of Smart Wearable Devices: An Expectation-Confirmation Model Approach. *Telematics and Informatics*, 47, 101318.
41. Pavlou, P. A., Liang, H. G., & Xue, Y. J. (2007). Understanding and Mitigating Uncertainty in Online Exchange Relationships: A Principal Agent Perspective. *MIS Quarterly*, 31(1), 105–136.
42. Rawassizadeh, R., Price, B. A. & Petre. M. (2015). Wearables: Has the Age of Smartwatches Finally Arrived?. *Communications of the ACM*, 58(1), 45-47.
43. Susanto, A., Chang, Y., & Ha, Y. (2016). Determinants of Continuation Intention to Use The Smartphone Banking Services: An Extension to The Expectation-Confirmation Model". *Industrial Management & Data Systems*, 116(3), 508-525.
44. Sümer, N. (2000). Yapısal Eşitlik Modelleri: Temel Kavramlar ve Örnek Uygulamalar. *Türk Psikoloji Yazıları*, 3(6), 49-74.
45. Tabachnick, B. G. and Fidell, L. S. (2013). *Using Multivariate Statistics*. Boston: Pearson Education Limited.
46. Talukder, M. S., Chiong, R., Bao, Y., & Hayat Malik, B. (2019). Acceptance and Use Predictors of Fitness Wearable Technology and Intention to Recommend: An Empirical Research. *Industrial Management & Data Systems*, 119(1), 170-188.
47. Tam, C., Santos, D., & Oliveira, T. (2018). Exploring the Influential Factors of Continuance Intention to Use Mobile Apps: Extending the Expectation Confirmation Model. *Information Systems Frontiers*, 22, 243 - 257.
48. Thong, J. Y. L., Hong, S-J., & Tam, K. Y. (2006). The Effects of Post-Adoption Beliefs on The Expectation-Confirmation Model for Information Technology Continuation. *International Journal of Human-Computer Studies*, 64(9), 799-810.
49. Tor-Kadioğlu, C. (2020). Tüketicilerin Akıllı Robot Süpürge Satın Alma Motivasyonları Üzerine Bir Araştırma. *Üçüncü Sektör Sosyal Ekonomi Dergisi*, 55(4), 2515-2537.
50. Venkatesh, V., Thong, J.Y., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending The Unified Model of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157–178.
51. Volety, R., & Geethanjali, P. (2022). Smart Home Automation Using Wearable Technology. In: G. D. Gargiulo & G. R. Naik (Eds.), *Wearable/Personal Monitoring Devices Present to Future*. Springer, Singapore.
52. Yoon, B. S. & Jetter, A. J. (2014). Investigation of different perspectives between developers and consumers: Robotic vacuum cleaners, *Proceedings of PICMET '14 Conference: Portland International Center for Management of Engineering and Technology; Infrastructure and Service Integration*, Kanazawa, Japan, (pp. 2307-2313).