Koç, F.; Giray, C.; Yön, B. ve Okşar, G. (2026). Generational Differences in the Acceptance of Consumer Robots: A Technology Acceptance Model Approach, *Tüketici ve Tüketim Araştırmaları Dergisi,* 18(1), 219-266
Doi: 10.15659/ttad.18.1.224

Generational Differences in the Acceptance of Consumer Robots: A Technology Acceptance Model Approach

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Abstract

The research addresses the growing integration of innovative technologies like consumer robots into daily life, particularly focusing on smart robotic vacuum cleaners, within the Technology Acceptance Model (TAM) framework. This study examines the increasing integration of innovative technologies, specifically consumer robots such as smart robotic vacuums, within the framework of the Technology Acceptance Model (TAM). The primary objective of the study is to investigate whether the strength of the structural relationships among perceived usefulness (PU), perceived ease of use (PEoU), attitude (ATT), and behavioral intention (INT) differs across generations (X, Y, and Z). In addition to this objective, we analyzed the direct and indirect effects

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Makale Türü / Paper Type: Araştırma Makalesi / Research Paper
Makale Geliş Tarihi / Received: 25.08.2025
Makale Kabul Tarihi / Accepted: 08.06.2026

among the variables, independent of generational differences. Data for the research were collected through an online survey administered to 357 participants. The data were evaluated using PLS-based structural equation modeling, specifically via multi-group analysis (MGA) and path analysis. Although generational mean perception levels for the respective variables remained statistically similar (based on ANOVA results), the strength of psychological transitions and effects among these variables varied significantly across generations. Results of the multi-group analysis indicate tha the structural impacts (path coefficients) of PEoU on ATT and of ATT on INT were significantly stronger in Generation Y than in other generations. Furthermore, within Generation Y, PEoU was found to influence ATT and INT, mediated by PU, while PU influenced INT, mediated by ATT. These findings offer critical insights for businesses seeking to understand the underlying mechanisms that drive the purchasing intentions of Generation Y consumers and to develop targeted strategies accordingly.

Keywords**:** Robotic Technologies, TAM, Generations, Smart Robotic Vacuum Cleaners, Consumer Perception

Tüketici Robotlarının Kabulünde Kuşaklar Arası Farklılıklar: Teknoloji Kabul Modeli Yaklaşımı

Öz

Bu araştırma, akıllı robot süpürgelere odaklanarak, tüketici robotları gibi yenilikçi teknolojilerin günlük yaşama artan entegrasyonunu Teknoloji Kabul Modeli (TAM) çerçevesinde ele almaktadır. Bu çalışma; akıllı robot süpürgeler gibi tüketici robotları özelinde, yenilikçi teknolojilerin artan entegrasyonunu Teknoloji Kabul Modeli (TAM) çerçevesinde incelemektedir. Çalışmanın temel amacı; algılanan fayda (PU), algılanan kullanım kolaylığı (PEoU), tutum (ATT) ve davranışsal niyet (INT) arasındaki yapısal ilişkilerin gücünün kuşaklara (X, Y ve Z) göre farklılık gösterip göstermediğini araştırmaktır. Bu amaca ek olarak, kuşaksal farklılıklardan bağımsız olarak, değişkenler arasındaki doğrudan ve dolaylı etkiler de analiz edilmiştir. Araştırma verileri, 357 katılımcıya uygulanan çevrimiçi bir anket aracılığıyla toplanmıştır. Veriler, PLS tabanlı yapısal eşitlik modellemesi, özellikle de çoklu grup analizi (MGA) ve yol (path) analizi kullanılarak değerlendirilmiştir. İlgili değişkenlere yönelik kuşaksal ortalama algı düzeyleri (ANOVA sonuçlarına göre) istatistiksel olarak benzer kalmasına rağmen, bu değişkenler arasındaki psikolojik geçişlerin ve etkilerin gücü kuşaklar arasında önemli ölçüde farklılık göstermiştir. Çoklu grup analizi sonuçları; PEoU'nun ATT üzerindeki ve ATT'nin INT üzerindeki yapısal etkilerinin (yol katsayılarının), Y kuşağında diğer kuşaklara kıyasla önemli ölçüde daha güçlü olduğunu göstermektedir. Ayrıca, Y kuşağı içinde PEoU'nun, PU aracılığıyla ATT ve INT'yi etkilediği; PU'nun ise ATT aracılığıyla INT'yi etkilediği bulunmuştur. Bu bulgular, Y kuşağı tüketicilerinin satın alma niyetlerini yönlendiren temel mekanizmaları anlamak ve buna göre hedefli stratejiler geliştirmek isteyen işletmeler için kritik bilgiler sunmaktadır.

Anahtar Kelimeler: Robotik Teknolojiler, Teknoloji Kabul Modeli(T-KM), Kuşaklar, Akıllı Robot Süpürgeler, Tüketici Algısı

Introduction

Modern and innovative technologies have become increasingly common for convenience and to reduce time spent on household chores (Asafa, Afonja, Olaniyan and Alade, 2018). Futuristic scenarios about robot nannies, robot maids, robot guards, and robot companions have been around since the early 1950s (Vaussard et al., 2014). Human-robot interaction (HRI) is a field of study that aims to understand, evaluate, and design robotic technologies. The concept is not only for robots operated by humans but also autonomous systems because they operate with humans, and humans set targets to achieve goals (Setchi, Dehkordi, and Khan, 2020). Robotic technology has become integrated into our lives and continues to develop. Studies on home HRI are crucial for revealing managerial and strategic approaches and increasing access to robot use (Fink, Bauwens, Kaplan, and Dillenbourg, 2013).

Changes in the social and living environment have expanded the areas in which robots are used in our daily lives and increased their frequency of use (De Graaf and Allouch, 2013; Vishaal, Raghavan, Rajesh, Michael, and Elara, 2018; Nicholls and Strengers, 2019). The statement in one of the publications is quite striking; the concepts of "Artificial

Intelligence (AI) and Robotics" evoke science fiction movies, or one can imagine a robot vacuum cleaner that can clean the house without hitting furniture and scaring pets (Haenlein and Kaplan, 2020). Indeed, the "digital revolution" in domestic life has been perpetuated by technologies such as, which have been present in households for years and are now commonplace. The feasibility of implementing wireless automatic charging has been established (Kore, Patil, Sapkal, Itkarkar, and Jain, 2022). Moreover, individuals can remotely control robotic vacuum cleaners through the Android application, demonstrating not only speed and agility but also autonomous management of different floor dirt and stains, surpassing the convenience of manual counterparts (Parmar, Meena, Bhovaniya and Priyadarshi, 2019; Naptsoksch, 2022).

The global market for robotic vacuum cleaners has demonstrated an extraordinary growth rate, consistently outperforming earlier forecasts. According to Fortune Business Insights (2025), the market, initially projected by Prabakaran, Elara, Pathmakumar and Nansai (2018) to achieve a value of $2.50 billion by 2020, experienced a remarkable surge, reaching approximately $8 billion in 2019. This upward trend continued, with the market value expanding to $18 billion in 2020. Furthermore, forecasted growth for the market suggests an increase from $11.97 billion in 2021 to a substantial $50.65 billion by 2028, representing a compound annual growth rate of 27.2% the forecast period. The demand for robotic cleaners is evident, with sales figures anticipated to climb from 19 million units in 2019 to over 74 million units by 2024, indicating strong and sustained market expansion. Delgosha and Hajiheydari (2021) projected an expansion in the market size, forecasting global sales of domestic vacuum cleaners to reach 130 million units by the end of 2026, indicating a robust growth trend in this sector. Parallel to this global trend, the Turkish market has also witnessed emerging academic interest in domestic robotics. For instance, Avci, Kocan, and Kirmizibiber (2024) investigated consumer evaluations of smart robotic vacuum cleaners in Turkey through an extended Expectation-Confirmation Model (ECM), highlighting how post-adoption satisfaction and confirmation play pivotal roles in continuous usage intentions. More recently, Emec (2025) unveiled user preferences in robotic vacuum cleaner selection using the FUCOM methodology, demonstrating that criteria weights and consumer preferences are crucial factors in device adoption.

The adoption and integration of robotic technologies into daily life have been influenced by various factors. Among these, generational differences play a critical role in determining the acceptance and usage of such technologies. Studies have indicated that different generational cohorts exhibit varying perceptions (Alkire, O'Connor, Myrden, and Köcher, 2020), and attitudes toward new technological products, particularly robotics (Figà-Talamanca, Tanzi, and D'Urzo, 2022). Research indicates that older individuals experience more difficulties in adopting new technologies compared to younger generations (Klimova and Poulova, 2018), and engage in limited interaction with in-store technologies (Pantano, Viassone, Boardman, and Dennis, 2022).

The younger generations, who are enthusiasts of technology, have been observed to have a positive attitude towards robots in restaurants (Eksiri and Kimura, 2015). In their study on financial advisor robots, Figà-Talamanca, Tanzi, and D'Urzo (2022) revealed that Generation Y (GEN Y) and Generation Z (GEN Z) accept this technology based on perceived ease of use, while GEN X does so based on perceived usefulness. Besides studies that indicate variations in technology acceptance according to generations, some studies claim the opposite. In a study on the adoption of information communication technologies (Güner and Acartürk, 2020), it has been observed that older and younger adults exhibit similar behaviors. This complexity is further compounded by the fact that different groups hold inherently divergent perspectives on domestic robotics; as Yoon and Jetter (2014) pointed out, there is often a significant perceptual gap between technology developers and end-use customers regarding the value and features of robotic vacuum cleaners.

The field of human-robot interaction (HRI) has garnered substantial academic interest, predominantly focusing on the operational, technical, and functional aspects of robotics (Setchi et al., 2020). However, research specifically exploring consumer-centric acceptance and daily usage dynamics of home-based robotic technologies, such as smart robotic vacuum cleaners, remains notably scarce. While early foundations examined the alignment between developer and customer viewpoints (Yoon and Jetter, 2014), and recent pioneering studies have begun to map consumer satisfaction (Avci, Kocan, and Kirmizibiber, 2024) and multi-criteria preference priorities (Emec, 2025) toward smart vacuum cleaners, empirical research that dissects these behavioral patterns across distinct socio-technological cohorts is still in its nascent stages. Crucially, the current literature exhibits two major gaps: First, although overarching consumer preferences and confirmation dynamics are being explored, how these structural relationships vary when moderated specifically by generational differences remains unexamined. Second, prior studies offer fragmented or contradictory evidence regarding cohort behaviors toward technology (Klimova and Poulova, 2018; Güner and Acartürk, 2020). Consequently, a comprehensive model that systematically evaluates how generational differences (GEN X, Y, and Z) moderate the core TAM paths in the domestic robotics sector is missing.

To bridge these distinct gaps, this study explores these generational variations by employing the Technology Acceptance Model (TAM), a framework that has demonstrated significant efficacy in examining technology acceptance across various contexts (Davis, 1989). The model's emphasis on perceived usefulness (PU) and perceived ease of use (PEoU) provides a robust basis for understanding consumer attitudes toward smart robotic vacuum cleaners.

This research, with three primary objectives, pioneers the evaluation of consumer robotics across generations. The study aims: (1) to investigate and analyze potential variations among different generations (GEN X, GEN Y, and GEN Z) concerning perceived usefulness (PU), perceived ease of use (PEoU), attitude (ATT), and intention (INT) to adopt smart robotic vacuum cleaners; (2) to establish an understanding of the relationships between PU, PEoU, ATT, and INT in the context of smart robotic vacuum cleaners, while considering generational differences.; (3) to explore the indirect effects and variations in the relationships between PEoU, PU, ATT, and INT related to smart robotic vacuum cleaners, taking into account generational differences.

The next sections review the literature on robots and smart robotic vacuum cleaners and on TAM, highlighting the importance of adaptability, ease of use, and usefulness in HRI, introducing the unique characteristics of different generations -GEN X, GEN Y, and GEN Z - and underscoring the relevance of understanding generational traits in the context of smart robotic systems and adaptation. Following that, we discuss our research model, data collection technique, and findings. Finally, we summarize the study's findings and their relevance to producers of Smart Robotic Vacuum Cleaners and to the retail market, and we suggest directions for future research. It aspires to contribute valuable insights to the field of consumer robotics, offering guidance for future technological developments and marketing strategies.

Literature Review and Hypotheses Development

Robotic Systems and Smart Robotic Vacuum Cleaners

Defined by Duffy (2003) as "the physical manifestation of a system in our physical and social space," robots embody mechanical beings designed to perform tasks in a human-like manner. These innovative systems play a multifaceted role in supporting and enhancing our daily activities across various domains. Robots have been ingeniously adapted to replace human involvement in hazardous and labor-intensive tasks, notably in healthcare and recently in controlling the COVID-19 pandemic (Vishaal et al., 2018). Their use extends from healthcare to sectors like hospitality and tourism, where they help mitigate the impact of social distancing (Wang and Wang, 2021). In the medical field, robotic surgery offers precision and control, significantly reducing potential complications (Alamdar, 2019; Onofrio and Trucco, 2020; Eshaghi, Ghasemi, and Khorshidi, 2021). Beyond healthcare, robots assist in food handling, elderly care, agriculture, construction, and even cleaning public spaces (Bader and Rahimifard, 2020; Shishehgar, Kerr, and Blake, 2018; Bu, Hu, Chen, Sugirbay, and Chen, 2020; Cai, Ma, Skibniewski, and Bao, 2019; Vega-Heredia et al., 2019; Verma and Mishra, 2020). They are becoming indispensable in diverse workspaces, fostering human-robot collaboration (Mohammed and Wang, 2018; Franklin, Dominguez, Fryman, and Lewandowski, 2020).

Addressing everyday chores, especially mundane tasks like floor cleaning, robots have emerged as practical solutions (Vishaal et al., 2018; Asafa et al., 2018). Known as 'Consumer Robots' they are increasingly used for cleaning, entertainment, and companionship in personal spaces (Delgosha and Hajiheydari, 2021). The degree of interaction between humans and robots varies, with autonomy levels ranging from minimal to complete, where robots can operate independently based on pre-set schedules (Nicholls and Strengers, 2019; Setchi et al., 2020). For instance, a robotic vacuum cleaner programmed to clean at specific times demonstrates this level of autonomy, efficiently managing its tasks without human intervention.

A robotic vacuum cleaner is "an automated cleaning machine with AI software programming, a smart navigation and mapping system, an adjustable suction power, and a scheduling mechanism" (Fortune Business Insights, 2025) that works without human intervention (Manasa, Vidyashree, Bindushree, Rao, and Gowra, 2021). Some of their initiatives underscore a commitment to advancing the technological capabilities of such devices, contributing to their overall effectiveness in autonomous cleaning operations. A vacuum cleaner must search its paths without colliding (Gupta, Sangeeta, Mishra, Singal, Badal, and Garg, 2020). In this sense, Considerable efforts in research and development have been made to augment their productivity, functionality, and efficiency of navigation and coverage (Muthugala et al., 2020).

Robotic vacuum cleaners represent the pinnacle of this autonomous technology. They are equipped with AI software, advanced navigation systems, and adaptable suction power (Manasa et al., 2021). Research efforts focus on enhancing their efficiency, navigation, and coverage capabilities (Muthugala et al., 2020). Technologies like optical path prediction, infrared sensors, and ultrasonic sensors play a pivotal role in their functionality (Gupta et al., 2020; Yakoubi and Laskri, 2016; Prabakaran et al., 2018). These robots can adapt to various cleaning tasks, from floors to walls, and navigate spaces with precision.

Despite the technical complexity of these robots, their usage is becoming increasingly user-friendly and intuitive, aligning with the expectation that they will soon be a standard household item (Prabakaran et al., 2018). The market for these devices is expanding, driven by technological advancements in hardware, AI, and smart navigation systems (McGinn, Sena, and Kelly, 2017; Fortune Business Insights, 2025).

The Technology Acceptance Model (TAM) and Smart Robotic Vacuum Cleaners

The Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) have been extensively used in exploring behaviors and intentions in technology usage (Cheng, 2019). Both theories, extensions of the Theory of Reasoned Action (TRA), have been instrumental in understanding how individuals adapt to new technologies. Studies have often blended TAM and TPB to gain a more comprehensive insight into technology adoption, especially in educational contexts (Cheng, 2019).

TAM developed by Davis has been the most employed model with its high level of predictive and exploratory power for examining technology acceptance (Davis, 1989; Ghazali, Ham, Barakova, and Markopoulos, 2020). The widespread use of the TAM can be attributed to its simplicity, IT-specific focus, well-established measurement scales, and strong empirical support. TAM effectively predicts user acceptance of various technologies across different contexts, making it a leading model in the field of technology acceptance (De Graaf, Ben Allouch, and Van Dijk, 2019; Ge, Qi, and Qu, 2023). It describes actual technology use and uses intentions (Scherer, Siddiq, and Tondeur, 2019). The model predicts acceptance and the corresponding use of technologies (Bröhl, Nelles, Brandl, Mertens, and Nitsc, 2019). Research also indicates that perceived usefulness significantly influences the acceptance of technological trend applications (Rese, Ganster, and Baier, 2020).

The robotic vacuum cleaner has a capability called path planning of the coverage region (PPCR), which ensures that it sweeps every accessible point in the area. Sensory data obtained from different sensors combined with an algorithm to create a PPCR (Yakoubi and Laskri, 2016). PEoU, PU, attitude toward using, and intentions to use are the model's components (Davis, 1989). According to TAM, perceived information is crucial both for accepting innovative technology and for its relationship with consumers' intentions to benefit from a new technology system. Perceived usefulness and perceived ease of use are the dimensions of perceived information (Ge et al., 2023). Davis (1989) describes the PEoU as "the degree to which a person believes that using a particular system would be free from effort," while perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance". Literature reveals that high PU and a positive attitude indicate an intention to use technology (Kelly, Kaye, and Oviedo-Trespalacios, 2022; Rejali, Aghabayk, Esmaeli, and Shiwakoti, 2023). The results of Lotz, Himmel, and Ziefle' (2019) study on robotic systems showed that PU was a significant predictor of behavioral intentions. On the other hand, Ghazali et al. (2020) study results revealed that perceived usefulness was not the predicting factor for behavioral intentions. Behavioral intentions are listed as the sole predictor of actual system usage in the model. Motives to use technology, environmental factors, and expected outcomes and habits are the determinants that explain use behavior (De Graaf et al., 2019).

Adopting robotic vacuum cleaners is influenced by several key determinants, including their financial benefits, cleaning methodologies, social acceptability/subjective norms, alignment with daily routines, spatial compatibility, PU, and PEoU (Fink et al., 2013).

Relationships between Generations, Technology Acceptance Model and Smart Robotic Vacuum Cleaners

In the academic literature, distinct characteristic features of different generations are emphasized. In the context of smart robotic systems and adaptation, highlighting specific traits of generations can be beneficial for the focus of the study. GEN X (1965–1980) (Kotler, Kartajaya, and Setiawan, 2021) is referred to as the "middle child" and "forgotten" generation (Cecily, 2019) faced economic shifts in the 1980s, now attractive to marketers for their financial success and conspicuous consumption. Defined as individuals born between 1981 and 1996, Generation Y—often labeled "the cool generation"—grew up alongside the success of democratic capitalism (Kotler et al., 2021; Kotler et al., 2022). Characterized by a strong online presence and contradictory traits, this cohort has become a major target for marketers (Canavan, 2020; Lv et al., 2024). GEN Z (1997–2009) (Kotler, Kartajaya, and Setiawan, 2021) is also known as 'the digital natives' generation (Persada, Miraja and Nadlifatin, 2019), shaped by events like the 2008 crisis and COVID-19, is resilient, proactive, and demands meaningful changes, expecting respectful treatment from marketers (Canavan, 2020). Personalization, conversational engagement, informational and emotional support are factors that influence Gen Z's purchase intentions (Guo and Luo, 2023). GEN Y and GEN Z are frequently grouped together due to their shared characteristics, particularly their adeptness with technology and their ease in navigating the global environment (Wood, 2013).

Younger generations are more accepting of Automated Vehicles (AVs) compared to older generations, indicating a generational difference in AVs acceptance (Wang, Wang, and Wyatt, 2022). Generation Y(-GEN Y) exhibited higher levels of smartphone addiction compared to Generation X (GEN X) and Generation Z (GEN Z) (Zhitomirsky-Geffet and Blau, 2016).

The dynamics of technology acceptance and usage across different generational cohorts have been a focal point in recent scholarly research. Priporas, Stylos, and Fotiadis (2017) employed a qualitative methodology, engaging 38 university students in the UK to understand the impact of smart technologies on GEN Z. Their findings highlight that GEN Z consumers show a significant inclination towards smart technologies, with an expectation for the widespread availability of new devices and a preference for autonomy and expedited transactions, expect the widespread availability of new devices, and prefer autonomy and expedited transactions. Complementing this perspective, Morais (2022) extended the analysis to include three generational cohorts – Generation X (GEN X), Generation Y (GEN Y), and GEN Z – with a specific focus on their perceptions and adaptations to emerging technologies in the hospitality sector. Interestingly, while all three generations demonstrated technological proficiency, it was Gen X that predominantly considered technology when selecting hotels, indicating a nuanced approach to technology adoption based on generational contexts. In a similar exploration of generational technology behavior, Calvo-Porral and Pesqueira-Sanchez (2020) delved into the motivational factors driving technology use among Millennials (GEN Y) and GEN X. Their study revealed distinct preferences: Millennials tend to use technology primarily for entertainment purposes, while GEN X leans towards utilitarian applications, emphasizing the retrieval of information. This research underscores the moderating role of generational differences in shaping technology utilization patterns and preferences.

Based on this theoretical foundation, we suggest the following hypothesis:

H1: *(a) PU, (b) PEoU, (c) attitude, and (d) intention to use smart robotic vacuum cleaners differ according to generations.*

H2: *(a) PU has a significant and positive effect on the intention to use smart robotic vacuum cleaners; (b) the effect of PU on the intention to use smart robotic vacuum cleaners differs across generations.*

H3: *(a) PU has a significant and positive effect on attitude toward smart robotic vacuum cleaners. (b) The effect of PU on attitude toward smart robotic vacuum cleaners differs according to generations.*

H4: *(a) PEoU has a significant and positive effect on PU. (b) The effect of PEoU on PU differs according to generations.*

H5: *(a) PEoU has a significant and positive effect on attitude towards smart robotic vacuum cleaners. (b) The effect of PEoU on attitude toward smart robotic vacuum cleaners differs according to generations.*

H6: *(a) Attitude toward smart robotic vacuum cleaners has a significant and positive effect on intention to use. (b) The effect of attitude toward smart robotic vacuum cleaners on adoption intention smart robotic vacuum cleaners differs according to generations.*

H7: *(a) PEoU indirectly affects attitude towards smart robotic vacuum cleaners through PU. (b) The indirect effect of PEoU on attitude toward smart robotic vacuum cleaners through PU differs according to generation.*

H8: *(a) PEoU indirectly affects the intention to use a smart robotic vacuum cleaner through PU and attitude. (b) The indirect effect of PEoU on the intention to use a smart robotic vacuum cleaner through PU and attitude differs across generations.*

H9: *(a) PU indirectly affects the intention to use a smart robotic vacuum cleaner through attitude. (b) The indirect effect of PU on the intention to use a smart robotic vacuum cleaner through attitude towards using it differs according to generations.*

H10: *(a) PEoU indirectly affects the intention to use a smart robotic vacuum cleaner through attitude. (b) The indirect effect of PEOU on intention to use a smart robotic vacuum cleaner through attitude differs across generations.*

H11: *(a) PEOU indirectly affects the intention to use a smart robotic vacuum cleaner through PU. (b) The indirect effect of PEOU on the intention to use a smart robotic vacuum cleaner through PU differs across generations.*

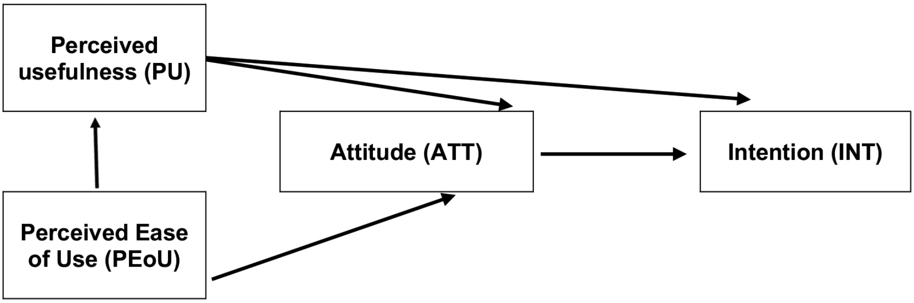

Figure 1: Research Model for the Purchase Intention of Smart Robotic Vacuum Cleaners

Methodology

The Research Process and Form of Questionnaire

The survey process began with questions regarding participants' demographic information. Following this, participants were asked to indicate their year of birth to classify them into generational cohorts. To ensure that all respondents had a clear understanding of the technology in question, an explanation of the smart robotic vacuum cleaner and its features was provided. After this informational stage, participants were shown a video demonstrating the features of the smart robotic vacuum cleaner. The rationale behind providing both the explanation and video was to standardize participants' knowledge, as some may have had limited familiarity with technology. This approach ensured that respondents could make informed evaluations. Following the video, participants were presented with items designed to measure the key variables of the Technology Acceptance Model (TAM).

Sample and Data Collection

The principal objective of this study is to examine individuals' opinions regarding the use of smart robotic vacuum cleaners within the Technology Acceptance Model. The study explores whether the variables and relationships in the technology acceptance model differ according to generation. To achieve these objectives, an online survey form was developed. The target population of this study consists of individuals from Generation X (born 1965-1980), Generation Y (born 1981-1996), and Generation Z (born 1997-2009). These generational cohorts were selected to explore differences in technology acceptance, particularly regarding the use of smart robotic vacuum cleaners. The sampling method employed was convenience sampling, using an online survey distributed via social media platforms. This method allowed the researchers to collect responses from a wide range of participants.

Three control questions were integrated into the survey in response to challenges encountered in online survey applications. These questions were framed as follows: "This is a control question. Please check the ..... option". Respondents providing incorrect answers to one or more of these questions were deemed to have not thoroughly read or considered the survey, and their responses were excluded from the analysis.

The survey was conducted online, and the survey link was distributed on social media. Within the scope of this research, 490 questionnaires were answered. After rigorous examination, the responses of 133 individuals with incomplete submissions or erroneous answers to the control questions were excluded, resulting in a total of 357 questionnaires included in the analysis (Cochran, 1977; Sekaran and Bougie, 2016; Hair et al. 2017). The reference intervals provided by Kotler, Kartajaya, and Setiawan (2021) were utilized in creating the GEN X (1965-1980), GEN Y (1981-1996), and GEN Z (1997-2009) groups in this study.

This study was approved by the Ethics Board of Istanbul Galata University (2025-06) on July 21st, 2025; protocol number: E-77300296-050.04-18272.

Measures

The scales used in the study were taken from various sources. The 7-item perceived usefulness (PU) scale and the 5-item perceived ease of use (PEOU) scale were adapted from Davis (1989). The 5-item attitude scale was adapted from Bagheri, Bondori, Allahyari, and Surujlal,

(2021) and Muk and Chung (2015). The 6-item intention scale used in the study was taken from Venkatesh and Davis (2000) and Venkatesh, Morris, Davis, and Davis, (2003). All items were measured on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

Method of Data Analysis

PLS-SEM was selected as the primary analytical technique due to its suitability for prediction-oriented research and its capability to estimate complex structural models involving multiple latent constructs, mediating relationships, and multi-group comparisons. Given that the primary aim of this study is to examine and predict behavioral intentions within the Technology Acceptance Model (TAM), PLS-SEM provides an appropriate framework for analysis. In addition, the presence of multiple structural paths and the inclusion of generational multi-group analysis (MGA) further justify the use of PLS-SEM.

Results

SPSS and Smart PLS 4 were used to analyze the data. Smart PLS 4 was used to test the research model (Path Analysis) and to determine whether the relationships between variables differed according to generation (Multigroup Analysis). ANOVA was used to determine whether the variables in the model differed according to generation.

Demographic Characteristics of the Participants

Age, gender, educational status, marital status, income, and employment status of the participants are investigated under this heading.

Of the individuals who participated in the study, 67.5% were female, 60.5% were single, and most held a bachelor's degree or above (78.54%). In addition, 51.5% of the participants were actively employed. The average income and age of the participants were 12.512 TL and 33.56 years, respectively. Categorizing the respondents by generation reveals that Generation Y (Gen Y) comprises 48.2% (n=172), Generation Z (Gen Z)

29.1% (n=104), and Generation X (Gen X) 22.7% (n=81), resulting in a total sample size of ntotal=357.

Testing of Measurement Model

Before testing the structural model and hypotheses, the reliability and validity of the measurement model must be evaluated. In this context, the measurement model was assessed based on internal consistency reliability, convergent validity, and discriminant validity criteria using PLS-SEM.

Table 1: Confirmatory Factor Analysis

Items	ATT	INT	PEOU	PU	α	CR	AVE
PEOU1			0.875				
PEOU2			0.860				
PEOU3			0.880		0.929	0.931	0.779
PEOU4			0.926				
PEOU5			0.871				
PU1				0.893			
PU2				0.920			
PU3				0.906	0.942	0.943	0.776
PU4				0.857			
PU5				0.895			
PU7				0.809			
INT3		0.749					
INT4		0.888			0.726	0.750	0.647
INT6		0.769					
ATT3	0.921						
ATT4	0.911				0.848	0.893	0.698
ATT5	0.870						
ATT1	0.598						

PEOU= Perceived Ease of Use, PU= Perceived Usefulness, INT= Intention, ATT= Attitude, α = Cronbach's Alpha, CR= Composite Reliability, AVE= Average Variance Extracted

In PLS-based structural equation modeling analyses, the measurement model is evaluated in several stages (Hair et al., 2017). According to Hair et al.(2019),factor loadings should not be smaller than 0.50; therefore, items with loadings below this threshold were removed from the analysis.

To determine internal consistency, Cronbach's alpha coefficient was calculated. The analysis of the results shows that all the coefficients are greater than 0.70 (Hair et. al., 2019).

In the following process, Composite Reliability (CR), and Average Variance Extracted (AVE) values of the factors should be examined to assess convergent validity (Hair et al., 2017). When Table 2 is examined, it is seen that alpha coefficients, CR values, and AVE values are greater than (0.70) and (0.50), respectively, indicating that these values support the convergent validity criterion (Hair et al., 2017).

The Fornell-Larcker criterion and HTMT ratio are utilized to establish discriminant validity.

Table 2: Fornell-Larcker Criterion

	ATT	INT	PEOU	PU
ATT	**0.835**			
INT	0.414	**0.805**		
PEOU	0.359	0.421	**0.883**	
PU	0.492	0.597	0.522	**0.881**

The Fornell-Larcker validity assessment comprises two criteria. The first criterion is the square root of the AVE values (the bold numbers on the diagonal), while the second criterion indicates the correlations between variables (the other numbers in the table) (Fornell and Larcker, 1981). This principle stipulates that the square root of the AVE values should surpass the correlation coefficients (Hair et al., 2017). From the table, we observe that this principle applies to all variables.

After this stage, it is necessary to examine the HTMT (Heterotrait-Monotrait) ratios. Hair et al. (2017) stated that to establish discriminant validity, HTMT values should be lower than the threshold of 0.85 or 0.90. Analysis of the numbers in Table 3 shows that the HTMT criterion is met.

Table 3: HTMT Ratio

	ATT	INT	PEOU	PU
ATT				
INT	0.504			
PEOU	0.400	0.501		
PU	0.546	0.715	0.557	

Based on the Fornell-Larcker criterion and HTMT (Heterotrait-Monotrait) ratio the scales meet the conditions for discriminant validity.

The results obtained from the analyses show that the scales meet the conditions of validity and reliability. After this stage, the hypotheses of the study were tested.

Common Method Bias

To control common method bias, we utilized both procedural and statistical approaches.

Procedurally, we employed three methods. Firstly, a pretest to assess the item's relevance and readability was conducted. Secondly, participants were informed about the study's purpose. Thirdly, the survey form has been designed in a way that participants would not be able to comprehend the potential relationships between the dependent and independent variables to prevent method bias.

Inner VIF values were calculated using the SmartPLS 4 program. To adhere to Kock's (2015) guidelines, these values should not surpass 3.3. The calculations revealed that the VIF values ranged from 1.000 to 1.374. This demonstrates that the model used in the research is devoid of prevalent bias. After this stage, the hypotheses of the study were tested.

Hypotheses Testing

Whether the variables addressed in this study differ according to the generations of the participants was analyzed through variance analysis (ANOVA). The structural model was tested using SmartPLS4 software.

Difference Hypotheses Testing

In order to test whether the variables discussed in the study model differ according to generation, an ANOVA was carried out. The results of the analysis are presented in Table 4.

Table 4: ANOVA Results

Variables	F	Sig.
PEOU	.822	.441
PU	2.490	.084
INT	1.683	.187
ATT	2.082	.126

According to the ANOVA results, PEOU, PU, ATT, and INT do not differ according to generation. Contrary to our expectations, we could not find enough evidence to support H1a, H1b, H1c, and H1d.

Structural Model Testing

At this stage, the research model was tested, and a Multigroup (MGA) analysis was conducted using SmartPLS4 to investigate potential generational differences in the relationships within the model.

The Standardized Root Mean Square Residual (SRMR) is frequently employed as a model-fit indicator in structural equation modeling using partial least squares. In this study, SRMR was found to be 0.056. For CB-SEM-based models, an SRMR of less than 0.08 is preferred. Nonetheless, Hair et al. (2017) suggest that SRMR values up to 0.10 are acceptable for PLS-SEM models. The SRMR value obtained in this study is within the acceptable range for both CB-SEM and PLS-SEM models.

The R2 value is another criterion for evaluating the structural model. In this study, the calculations for Adj. R2 yielded results of 0.253 for ATT, 0.372 for INT, and 0.270 for PU. These evaluation results indicate that the structural model is adequate and that no issues were identified.

To methodologically address potential biases stemming from unequal sample sizes among generational groups, the Measurement Invariance of Composite Models (MICOM) procedure (Henseler et al., 2016) was conducted. The Step 2 (Compositional Invariance) pairwise permutation analysis (with 5,000 bootstraps) revealed that the original correlation (c) values for all constructs were extremely close to 1.000, confirming that the scales held the same conceptual meaning across groups. Specifically, compositional invariance was fully established ($p > 0.05$) for all variables in the Gen X vs. Gen Y comparison (Perceived Ease of Use: c=1.000, p=0.994; Perceived Usefulness: c=1.000, p=0.983; Intention: c=0.999, p=0.739; Attitude: c=0.983, p=0.058) and in the Gen Y vs. Gen Z comparison (Perceived Ease of Use: c=0.999, p=0.086; Perceived Usefulness: c=1.000, p=0.306; Intention: c=1.000, p=0.823; Attitude: c=0.994, p=0.053). In the Gen X vs. Gen Z comparison, invariance was established for Perceived Ease of Use (c=0.998, p=0.165), Perceived Usefulness (c=1.000, p=0.342), and Intention (c=1.000, p=0.847); Attitude (c=0.955, p=0.042) demonstrated partial compositional invariance. According to Henseler et al. (2016), establishing full or partial compositional invariance satisfies the prerequisite for multi-group comparison. Consequently, the quantitative imbalances in generational representation within the sample do not pose a methodological barrier to executing Partial Least Squares Multi-Group Analysis (PLS-MGA).

When all generations were evaluated together, PU had a significant effect on ATT (Beta= 0.420, t value= 7.807, P= 0.000), PEOU had a significant effect on ATT (Beta= 0.139, t value= 2.514, P= 0.012), PU had a significant effect on INT (Beta= 0.519, t value= 10.845, P= 0.000), ATT on INT (Beta= 0.159, t value= 3.448, P= 0.001) and PEOU on PU (Beta= 0.522, t value= 10.664, P= 0.000) as presented in Table 5. These findings support **H2a, H3a, H4a, H5a, and H6a.**

Bootstrap MGA was performed to determine differences between groups. When the relationship between PU-ATT is analyzed in all groups, it is seen that there is a significant and positive effect in all groups (GEN X Beta=0.387, t value= 2.855, P=0.004; GEN Y Beta=0.457, t value= 6.950, P=0.000; GEN Z Beta=0.403, t value= 3.712, P=0.000). However, the analysis revealed that there was no difference between the groups (Difference X-Y= -0.070, P= 0.656; Difference X-Z = -0.016, P= 0.948; Difference Y-Z= 0.054, P= 0.666). In this respect, we did not find sufficient evidence to support **H3b.**

In the analysis of the relationship between PEOU and ATT across all groups, only GEN Y exhibits a significant effect (GEN Y Beta=0.142, t value= 2.044, P=0.041). In contrast, GEN X (Beta=0.177, t value= 1.269, P=0.204) and Z (Beta=0.092, t value= 0.819, P=0.413) have no effect of PEOU on ATT. In this respect, it is seen that GEN Y differs from the other groups, supporting H5b. When the relationship between PU-INT is analyzed in all groups, it is seen that perceived usefulness has an effect on intention in all generations (GEN X Beta=0.611, t value= 6.189, P=0.000; GEN Y Beta=0.406, t value= 5.297, P=0.000; GEN Z Beta=0.606, t value= 8.074, P=0.000). Regarding the difference between the groups, Bootstrap MGA analysis revealed that there was no difference between generations (DifferenceX-Y=0.205, P= 0.106; DifferenceX-Z=0.005, P= 0.956; DifferenceY-Z= -0.200, P= 0.065). Based on these results, the findings did not support H2b.

In the analysis of the relationship between ATT-INT, it is seen that there is a significant effect only for GEN Y (GEN Y Beta=0.208, t value= 2.977, P=0.003). In GEN X (Beta=0.210, t value= 1.944, P=0.052) and GEN Z (Beta=0.077, t value= 0.985, P=0.325), there is no effect of ATT on INT. In this regard, it can be asserted that GEN Y differs from other groups. Therefore, the findings support H6b. Finally, when the relationship between PEOU-PU is analyzed, it is seen that there is a significant effect in all groups (GEN XBeta=0.492, t value= 5.346, P=0.000; GEN Y Beta=0.560, t value= 7.473, P=0.000; GEN Z Beta=0.501, t value= 5.944, P=0.000). As a result of the bootstrap MGA analysis conducted to see the differences between the groups, it was determined that there was no significant difference between the generations (DifferenceX-Y= -0.068, P= 0.566, Difference$_{X-Z}$= -0.009, P= 0.939; Difference$_{Y-Z}$= 0.059, P= 0.604). Based on these results, we did not find sufficient evidence to support **H4b.**

Table 6, which delineates the examination of indirect effects, the comprehensive analysis of all groups collectively reveals that Perceived Ease of Use (PEOU) affects Attitude (ATT) through Perceived Usefulness (PU) (Beta = 0.219, t-value = 6.351, P = 0.000). Furthermore, PEOU influences Intention (INT) through both PU and ATT (Beta = 0.035, t-value = 3.113, P = 0.002). Additionally, PU influences INT through ATT (Beta = 0.067, t value = 3.283, P = 0.001); PEOU influences INT through PU (Beta = 0.271, t value = 7.632, P = 0.000). Moreover, PEOU exerts a non-significant effect on INT through ATT (Beta = 0.022, t value = 1.764, P = 0.078). Consequently, these findings support **H7a, H8a, H9a, and H11a**, but not H10a.

Table 5: Structural Model Testing and MGA

	GEN X				GEN Y				GEN Z				ALL GROUPS			
	Beta	T Value	Sig.	R^2	BETA	T Value	Sig.	R^2	BETA	T Value	Sig.	R^2	BETA	T Value	Sig.	R^2
PU→ATT	**0.387**	**2.855**	**0.004**	0.248	**0.457**	**6.950**	**0.000**	0.301	**0.403**	**3.712**	**0.000**	0.208	**0.420**	**7.807**	**0.000**	0.257
PEOU→ATT	0.177	1.269	0.204		**0.142**	**2.044**	**0.041**		0.092	0.819	0.413		**0.139**	**2.514**	**0.012**	
PU→INT	**0.611**	**6.189**	**0.000**	0.539	**0.406**	**5.297**	**0.000**	0.298	**0.606**	**8.074**	**0.000**	0.415	**0.519**	**10.845**	**0.000**	0.376
ATT→INT	0.210	1.944	0.052		**0.208**	**2.977**	**0.003**		0.077	0.985	0.325		**0.159**	**3.448**	**0.001**	
PEOU→PU	**0.492**	**5.346**	**0.000**	0.242	**0.560**	**7.473**	**0.000**	0.314	**0.501**	**5.944**	**0.000**	0.251	**0.522**	**10.664**	**0.000**	0.272

Table 6: Indirect Effects and MGA

	GEN X				GEN Y				GEN Z				ALL GROUPS		
	Beta	T Value	Sig.	R^2	BETA	T Value	Sig.	R^2	BETA	T Value	Sig.	R^2	BETA	T Value	Sig.
PEOU -> PU -> ATT	**0.190**	**2.407**	**0.016**	0.248	**0.256**	**5.368**	**0.000**	0.301	**0.202**	**2.769**	**0.006**	0.208	**0.219**	**6.351**	**0.000**
PEOU -> PU -> ATT -> INT	0.040	1.646	0.100		**0.053**	**2.949**	**0.003**		0.015	0.750	0.453		**0.035**	**3.113**	**0.002**
PU -> ATT -> INT	0.081	1.666	0.096	0.539	**0.095**	**3.042**	**0.002**	0.298	0.031	0.854	0.393	0.415	**0.067**	**3.283**	**0.001**
PEOU -> ATT -> INT	0.037	0.887	0.375		0.029	1.375	0.169		0.007	0.460	0.646		0.022	1.764	0.078
PEOU -> PU -> INT	**0.301**	**3.544**	**0.000**	0.242	**0.227**	**4.137**	**0.000**	0.314	**0.304**	**5.647**	**0.000**	0.251	**0.271**	**7.632**	**0.000**

Whether the indirect effects differ according to the groups was analyzed using Bootstrap MGA. When the indirect relationship between PEOU -> PU -> ATT is examined in all groups, a significant and positive effect is observed for each group (GEN Z beta=0.190. t value= 2.407. P=0.016; GEN Y beta=0.256. t value= 5.368. P=0.000; GEN Z beta=0.202. t value= 2.769, P=0.006). However, the analysis revealed that there were no differences between the groups (Difference X-Y= -0.066. P= 0.460; Difference X-Z = -0.012. P= 0.919; Difference Y-Z= 0.054, P= 0.522). In light of the results, we did not find enough evidence to support H7b. When the indirect relationship between the variables PEoU -> PU -> ATT -> INT is analyzed, only GEN Y shows a significant effect (GEN Y beta= 0.053, t value= 2.949, P= 0.003), while no such indirect effect is observed in other generations (GEN X beta=0.040, t value= 1.646, P= 0.100; GEN Y beta=0.015, t value= 0.750, P=0.453). In this respect, it appears to be differentiated from other groups. Therefore, the findings support H8b. When the relationships between the variables PU -> ATT -> INT are analyzed, only Gen Y shows a significant indirect effect (Gen Y beta = 0.095, t value = 3.042, P = 0.002), whereas no significant indirect effect is observed for the other generations (GEN X beta=0.081, t value= 1.666, P=0.096; GEN Z beta=0,031, t value= 0,854, P=0,393). In this respect, it is seen that it is differentiated from other groups, supporting H9b. When the relationships between the variables PEOU -> ATT -> INT are analyzed, it is seen that there is no indirect effect in any group (GEN X beta=0.037, t value= 0.887, P= 0.375; GEN Y beta=0.029, t value= 1.375, P= 0.169; GEN Z beta= 0.007, t value= 0.460, P= 0.646). Since between the groups, the results of the difference analysis were not analyzed. Therefore, we did not find enough evidence to support H10b. Finally, analysis of the indirect relationship between the PEOU -> PU -> INT variables indicates a significant effect in all groups (GEN X beta=0.301, t value= 3.544, P= 0.000; GEN Y beta= 0.227, t value= 4.137, P= 0.000; GEN Z beta=0.304, t value= 5.647, P= 0.000). The bootstrap MGA analysis conducted to assess differences between groups found no significant differences between the generations (Difference X-Y= 0.073, P= 0.478; Difference X-Z= -0.003 P= 0.956; Difference Y-Z= -0.076, P= 0.322), not supporting H11b.

Conclusion and Discussion

The study aims to examine the factors that are effective in the adoption or purchase intention of smart robotic vacuum cleaners and the relationships between these factors within the framework of the "Technology Acceptance Model" (TAM).

The findings of the study support the validity of the TAM in the adoption of smart robotic vacuum cleaners. In addition, the findings of the study show that PU, PEOU, and ATT play an important role in the adoption or purchase intention of smart robotic vacuum cleaners and this finding conforms with previous research (Fink et al., 2013; Rese et. al., 2020; Kelly et al., 2022; Pham and Nguyen, 2023; Rejali et al., 2023). In addition, PU was found to be effective on ATT and INT, and ATT was found to be effective on intention.

However, the prediction that the variables will differ between generations, which constitutes one of the main research questions of the study, is not supported (**H1a, H1b, H1c, and H1d**). Results indicate that PEOU, PU, ATT, and INT do not differ across generations. Nevertheless, while the ANOVA findings indicated no significant differences in the mean levels of PEOU, PU, ATT, and INT across generations, the multi-group analysis (MGA) revealed differences in the structural relationships among these constructs. In other words, generations did not differ in terms of their overall levels of perceptions, attitudes, or intentions; rather, they differed in terms of how these variables interacted within the Technology Acceptance Model framework.

These findings indicate that the absence of significant differences in ANOVA results reflects similarity at the level of perceptual evaluations (mean-level constructs), whereas MGA results capture differences in the structural relationships among these constructs. Accordingly, the observed pattern suggests that generational cohorts may evaluate technology in a similar manner at the surface level, but differ in how these evaluations are translated into attitudes and behavioral intentions within the TAM framework. This distinction implies that generational effects operate more strongly at the level of cognitive processing and decision-making pathways rather than at the level of perceptual formation.

In analyses where all generations are evaluated together, it is observed that, as expected in some hypotheses, PU **(H3a)** and PEOU **(H5a)** have an impact on ATT; similarly, PU (**H2a**) and ATT **(H6a)** affect intention, and finally, PEOU affects PU (**H4a**). Overall, the study aligns with the "Technology Acceptance Model," forming the basis for the obtained results. Consistent with the literature (Davis, 1989; Venkatesh and Davis, 1996; Venkatesh and Davis, 2000), it can be said that the level of PU and PEOU related to the product, as perceived by the consumer, will increase the intention to purchase the product thanks to the positive attitude it creates in the consumer's mind. Considering the strong effect of PU on intention, it is observed that this has a significantly strong impact on the consumer's purchase intention, along with the influenced attitude. When all these inferences are considered together, it can be stated that for producers of technology-based products, the key concept they should aim to enhance during the design stage, even before the product exists, is PU. To achieve this, they should focus on a design that enhances the perception of ease of use, which has a strong influence on it.

On the other hand, the strong influence of PEOU on PU is a significant finding supported by previous study (Rattanaburi and Vongurai, 2021). Therefore, it can be stated that one of the crucial factors for companies creating their products is the ease of use or user-friendliness of the product. The strong effect of PEOU on PU highlights the need for producers to place great emphasis on this aspect during the product design stage, to increase the benefit perceived by the consumer. The results have shown that, following this stage, the increased PU strongly influences the positive ATT that is formed, together with PEOU. Companies prioritizing this aspect in the process are likely to enhance the s consumers derive from the product. According to the model, the results obtained by such companies will increase PU, leading to a positive ATT towards the product, and reinforcing it. The occurrence of these baseline structural effects across all generations underscores the universal core mechanics of the TAM model further enhances the significance of the mentioned results.

One of the noteworthy findings of the MGA is that the structural effect of PEOU on ATT and the effect of ATT on INT were statistically significant only for GEN Y. When examined in detail, GEN Y, identified with the starting year 1981, represents a generation that did not grow up with technology but encountered the internet and technology at an acceptable level during adolescence. This generation only witnessed the rapid progress of the internet and technology in their youth (Black, 2010). Therefore, it is thought that GEN Y, who was born in an era not surrounded by technological innovations and have incorporated technology into every stage of their lives over time, are the group most affected by technological development, having experienced both periods.

One of the other important findings of the same analysis is that PEOU does not affect the ATT of GEN X and GEN Z. It is thought that the fact that GEN X was introduced to the Internet and related technological developments at a very late stage of their lives (Kamber, 2017) and, on the contrary, GEN Z was introduced to these developments almost in their infancy (Turner, 2015) may be one of the main reasons for the finding. This is because GEN X has very limited knowledge of the use of such technologies, whereas, for GEN Z, such information is seen as extremely simple (Williams and Page, 2011). On the other hand, it is assumed that GEN Y can make choices more easily by using the technological knowledge they have later on while attaching great importance to the blessings of technology since they live both pre-internet and post-internet periods in their life periods when they are conscious (Williams and Page, 2011). Likewise, the fact that the relationship between ATT and INT has a significant effect supports the above explanations. The effect of ATT on INT reached statistical significance for GEN Y, whereas the same relationship was not statistically significant for the other generations. The last finding that supports the explanations is that the only generation in which PEOU has a significant effect on ATT is GEN Y. As a result of the fact that PEOU does not have a significant effect on ATT formation in GEN X and GEN Z, it is thought that these generations do not develop a positive ATT towards the product if they cannot see PU of the product.

Another finding of the same analysis that warrants further explanation is that although the effect of PU on intention was statistically significant across all generational groups, the MGA results did not reveal any statistically significant between-group differences in this structural relationship (**H2b**). This finding suggests that the influence of perceived usefulness on behavioral intention represents a relatively stable and universal mechanism across generations. Given that perceived usefulness is considered one of the central determinants of technology acceptance and purchase intention, it is expected that its effect on behavioral intention would remain consistently significant regardless of generational differences.

Likewise, while a significant effect was found in all groups in the relationship between PU and ATT **(H3b**), similarly, PEOU and PU **(H4b)**, (the fact that no difference was found between the groups can be put forward because of the very strong relationship between PU and ATT and PEOU and PU).

Considering the indirect relationships between the variables in the model, one significant finding is that PEOU does not exert an effect on intention through ATT (**H10a**) in any group (**H10b**). This conclusion suggests that the failure to perceive a benefit in technological products eliminates the influence of other factors. In other words, it appears that consumers do not pay much attention to ease of use in technology-based products if they do not perceive benefit and thus do not develop a positive ATT or INT to purchase the product. Therefore, as mentioned in previous explanations, it can be said that producers need to prioritize the perceived benefit of the product when creating a strategy to generate purchase intention during the product stage.

On the other hand, it is found that PEOU influences ATT and intention separately through PU (**H7a, H11a**). This result aligns with the reality that, irrespective of their generation, consumers are likely to form a positive ATT towards a product and subsequently intend to purchase it based on the PEOU and the anticipated benefits the product may offer, as explained above. However, neither the indirect effect of PEOU on ATT through PU nor on the intention to use smart robotic vacuum cleaners through PU differ according to generations (**H7b, H11b**).

Finally, in terms of indirect effects, PEOU exhibits a significant and positive impact on intention through PU and ATT (**H8a**). Similarly, PU has a notable and positive influence on intention through ATT (**H9a**). No generational differences were observed in the indirect effect of PEOU on the INT to use smart robotic vacuum cleaners, a relationship through both PU and user ATT (**H8b**). Likewise, the investigation yielded inadequate evidence to support generational differences in the indirect influence of PU on behavioral intentions toward smart robotic vacuum cleaners through attitudes (**H9b**). These two indirect relationships substantiate the observations and underscore the significance of PU and PEOU in fostering positive attitudes toward technological products and shaping purchase intentions. However, these relationships also highlight a strong connection between ATT and INT.

Notably, it is a remarkable finding that the only generation significantly implicated in both indirect relationships is GEN Y. The MGA findings indicate that certain structural relationships within the TAM framework were significant only for GEN Y. This distinction is attributed, as mentioned earlier, to the fact that while GEN Y was in adolescence and youth during the 1990s, they were not born into Internet and Internet-related technologies. Instead, they were introduced to these technologies early in their lives, resulting in a heightened interest in and consideration of technology and technological products. These findings may suggest that GEN Y processes ease of use and attitudinal evaluations differently from the other generations within the context of robotic vacuum cleaner adoption.

In addition to the various findings of the study, two important contributions to the literature can be highlighted. First, the study identifies generation-specific variation in certain structural relationships within the TAM framework, particularly regarding the role of PEOU and ATT among GEN Y consumers in the adoption of technology-based products. More specifically, several structural paths involving PEOU, ATT, and INT were found to be statistically significant for GEN Y, suggesting that ease of use and attitudinal evaluations may play a relatively more central role for this generation within the technology acceptance process.

Second, the findings emphasize the critical importance for producers of technology-based products to prioritize user-oriented design and perceived usefulness during the product development stage. In particular, enhancing ease of use and maximizing the practical benefits offered by the product appear to play a key role in strengthening positive attitudes and behavioral intentions toward technology-based products.

Theoretical and Practical Implications

This study provides significant insights for researchers investigating the impact of generational differences on attitudes and intentions toward technology acceptance. In particular, the study's findings are crucial for marketing professionals developing segmentation strategies based on demographic factors. The results show that PEOU (Perceived Ease of Use) has a significant effect on ATT (Attitude) for GEN Y, and this attitude further influences behavioral intention (INT). Therefore, marketing strategies targeting GEN Y should emphasize the ease of use by creating instructional videos and informative brochures, effectively distributed through online platforms.

It is important to emphasize that the observed generational variation emerged in the structural relationships among TAM constructs rather than in the mean levels of the constructs themselves. Therefore, the findings should be interpreted as differences in the mechanisms underlying technology acceptance rather than differences in overall perceptions or intentions across generations.

However, it is essential to note that PEOU does not significantly affect ATT in GEN X and GEN Z. For these generations, factors other than ease of use should be highlighted. For instance, focusing on the product's functionality and practical benefits might resonate more with GEN X and GEN Z. Given that PEOU was found to have a significant effect on ATT only for GEN Y, marketing campaigns targeting this demographic should prioritize messages emphasizing ease of use to foster positive attitudes.

The study further highlights that both intrinsic and extrinsic motivations influence the acceptance of technology (Feldman, 2015). In the field of Human-Robot Interaction (HRI), adaptability, PEOU, and PU (Perceived Usefulness) are key factors for technology acceptance (De Graaf et al., 2019). The findings suggest that enjoyable and user-friendly robotic devices are an important preference, particularly for GEN Y.

Another notable finding is the significant impact of PU on ATT and INT across all generations. Given the critical role of PU in technology acceptance, marketing strategies should focus on emphasizing the practical benefits of robotic vacuum cleaners, such as time-saving, functionality, and safety. Since PU plays a crucial role for all generations, highlighting the product's functional benefits in marketing campaigns will likely foster greater technology adoption.

However, the study shows that ATT only significantly affects INT for GEN Y. This finding indicates that GEN Y's attitude toward technology strongly influences their intention to use it. For GEN X and GEN Z, ATT does not significantly affect INT, suggesting that these generations prioritize other factors, such as functionality and usefulness, over attitude. Therefore, for GEN X and GEN Z, strategic marketing campaigns should emphasize practical benefits rather than relying solely on attitudinal messages.

Another important finding is that PEOU significantly affects PU across all generations. This suggests that the ease of use of technological products directly influences users' perceptions of their usefulness. Given that PEOU has a significant impact on PU for all generations, marketing campaigns should highlight ease of use, emphasizing features such as easy installation and user-friendly interfaces. This finding further supports the idea that products with simple interfaces and ease of use are crucial selling points for consumers across all generations.

These findings offer valuable implications for marketing professionals. Understanding the varying attitudes and perceptions of different generations toward technology adoption can lead to more targeted and effective marketing strategies. While ease of use may positively influence GEN Y, other strategies may be required for GEN X and GEN Z, such as emphasizing the product's functionality and usefulness.

Limitations

The study primarily focuses on generational differences in perceptions of smart robotic vacuum cleaners. While this is valuable, it limits the scope to specific age groups, potentially overlooking variations in perceptions across different cultural, economic, and geographical backgrounds. The future study to assess whether the presence of pets in living spaces is considered an influential factor in product preference. Determining which type of pet enhances the preference for these products could yield interesting findings.

Data screening procedures based on attention check items may have resulted in the exclusion of inattentive respondents, which could have implications for sample representativeness.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Authors' Contributions to the Article

The authors contributed equally to the study.

Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Genişletilmiş Özet

Tüketici Robotlarının Kabulünde Kuşaklar Arası Farklılıklar: Teknoloji Kabul Modeli Yaklaşımı

Otonom sistemlerin ev içi alanlara hızla entegre olması, akıllı robot süpürgeleri ev otomasyonunun en belirgin sembollerinden biri haline getirmiştir. Teknoloji Kabul Modeli (TAM); Algılanan Fayda (PU) ve Algılanan Kullanım Kolaylığı (PEoU) faktörlerinin kullanıcı tutumunu ve davranışsal niyetini yönlendirdiğini açıkça ortaya koysa da, bu temel ilişkilerin farklı nesiller arasında nasıl değiştiğini inceleyen ampirik araştırmalarda ciddi bir eksiklik bulunmaktadır. Bu çalışmanın temel motivasyonu, teknoloji kabulüne yönelik yapısal yolların Gen X, Gen Y ve Gen Z gibi farklı nesil kohortlarına geçildiğinde tek düze mi kaldığını yoksa farklılaştığını çözme ihtiyacından kaynaklanmaktadır. Bu doğrultuda araştırmanın amacı; (1) Gen X, Gen Y ve Gen Z nesilleri arasında akıllı robot süpürgeleri benimseme konusundaki PU, PEoU, tutum (ATT) ve niyet (INT) düzeylerinde olası farklılıkları analiz etmek, (2) nesil farklılıklarını göz önünde bulundurarak bu değişkenler arasındaki doğrudan ilişkileri ortaya koymak ve (3) bu değişkenleri birbirine bağlayan yollardaki dolaylı arabuluculuk etkilerini nesiller arası bazda keşfetmektir.

H1: (a) PU, (b) PEoU, (c) attitude, and (d) intention to use smart robotic vacuum cleaners differ according to generations.

H2: (a) PU has a significant and positive effect on the intention to use smart robotic vacuum cleaners; (b) the effect of PU on the intention to use smart robotic vacuum cleaners differs across generations.

H3: (a) PU has a significant and positive effect on attitude toward smart robotic vacuum cleaners. (b) The effect of PU on attitude toward smart robotic vacuum cleaners differs according to generations.

H4: (a) PEoU has a significant and positive effect on PU. (b) The effect of PEoU on PU differs according to generations.

H5: (a) PEoU has a significant and positive effect on attitude towards smart robotic vacuum cleaners. (b) The effect of PEoU on attitude toward smart robotic vacuum cleaners differs according to generations.

H6: (a) Attitude toward smart robotic vacuum cleaners has a significant and positive effect on intention to use. (b) The effect of attitude toward smart robotic vacuum cleaners on adoption intention smart robotic vacuum cleaners differs according to generations.

H7: (a) PEoU indirectly affects attitude towards smart robotic vacuum cleaners through PU. (b) The indirect effect of PEoU on attitude toward smart robotic vacuum cleaners through PU differs according to generation.

H8: (a) PEoU indirectly affects the intention to use a smart robotic vacuum cleaner through PU and attitude. (b) The indirect effect of PEoU on the intention to use a smart robotic vacuum cleaner through PU and attitude differs across generations.

H9: (a) PU indirectly affects the intention to use a smart robotic vacuum cleaner through attitude. (b) The indirect effect of PU on the intention to use a smart robotic vacuum cleaner through attitude towards using it differs according to generations.

H10: (a) PEoU indirectly affects the intention to use a smart robotic vacuum cleaner through attitude. (b) The indirect effect of PEOU on intention to use a smart robotic vacuum cleaner through attitude differs across generations.

H11: (a) PEOU indirectly affects the intention to use a smart robotic vacuum cleaner through PU. (b) The indirect effect of PEOU on the intention to use a smart robotic vacuum cleaner through PU differs across generations.

Duffy (2003) tarafından "sistemin fiziksel ve sosyal alanımızdaki somut tezahürü" olarak tanımlanan robotlar, insan benzeri görevleri yerine getiren otonom mekanizmalardır. Geleneksel olarak tehlikeli ve yoğun iş güçlerinde konumlandırılan bu sistemler, günümüzde "Tüketici Robotları" (Consumer Robots) sınıfı altında ev içi kişisel alanlara da güçlü bir şekilde entegre olmuştur (Delgosha ve Hajiheydari, 2021). Bu entegrasyonun en somut ve popüler örneği olan akıllı robot süpürgeler; yapay zeka yazılımları, akıllı navigasyon/haritalama sistemleri (PPCR), kızılötesi ve ultrasonik sensörler ile donatılmış, insan müdahalesi olmaksızın bağımsız çalışabilen otonom temizlik makineleridir (Fortune Business Insights, 2025; Manasa vd., 2021). Donanım ve yapay zeka alanındaki teknolojik gelişmeler, bu cihazların çarpışma engelleme, alan kapsama ve temizlik verimliliğini artırırken, kullanımını da daha sezgisel ve kullanıcı dostu hale getirmektedir (Gupta vd., 2020; Prabakaran vd., 2018).

Bu tür yenilikçi ev teknolojilerinin tüketici bazında kabul görme ve benimsenme süreçlerini açıklayan en güçlü teorik altyapı Teknoloji Kabul Modeli'dir (TAM). Davis (1989) tarafından geliştirilen ve Planlı Davranış Teorisi (TPB) gibi rasyonel eylem kökenli modellere dayanan TAM; basitliği, teknoloji odaklı yapısı ve yüksek açıklayıcı gücü nedeniyle akademik yazında en çok tercih edilen modeldir (Cheng, 2019; Ghazali vd., 2020). Modelin temel saç ayaklarını Algılanan Fayda (PU), Algılanan Kullanım Kolaylığı (PEoU), teknolojiye yönelik tutum (ATT) ve davranışsal niyet (INT) oluşturmaktadır. Davis (1989) algılanan kullanım kolaylığını "bir kişinin belirli bir sistemi kullanmanın çaba gerektirmediğine inanma derecesi", algılanan faydayı ise "sistemin performansı artıracağına yönelik inanç düzeyi" olarak tanımlamaktadır.

Yazın incelendiğinde, akıllı robot süpürgelerin ve otonom sistemlerin benimsenmesinde yüksek PU ve olumlu tutumun, gelecekteki kullanım niyetinin en önemli belirleyicileri olduğu görülmektedir (Kelly vd., 2022; Lotz vd., 2019). Ancak, bazı robotik çalışmalarında algılanan faydanın niyet üzerinde doğrudan bir tahminleyici olmadığına dair çelişkili bulgular da mevcuttur (Ghazali vd., 2020). Akıllı robot süpürgelerin tüketici tarafından kabulü; cihazın finansal avantajları, temizlik metodolojileri, mekansal uyumluluğu ve günlük rutinlerle olan entegrasyonunun yanı sıra, TAM'ın önerdiği bu algısal bilgi boyutlarının (PU ve PEoU) zihinsel süzgeçten geçirilmesiyle şekillenmektedir (Fink vd., 2013; Ge vd., 2023).

Araştırmanın birincil verileri, yazarlar tarafından kolayda örnekleme yöntemiyle sosyal medya platformları üzerinden uygulanan çevrimiçi bir anketle toplanmıştır. Toplam 357 anket üzerinden analizler yapılmıştır. Kotler vd. (2021) tarafından tanımlanan üç kuşak araştırmanın kapsamını oluşturmaktadır. Bu kuşaklar; X Kuşağı (1965–1980), Y Kuşağı (1981–1996) ve Z Kuşağı (1997–2009) şeklinde ele alınmıştır. Değişkenler 5'li Likert ölçeğiyle ölçülmüştür. Algılanan Fayda (7 madde) ve Algılanan Kullanım Kolaylığı (5 madde) ölçekleri Davis (1989); Tutum (5 madde) Bagheri vd. (2021) ile Muk ve Chung (2015); Davranışsal Niyet (6 madde) ise Venkatesh ve Davis (2000) ile Venkatesh vd. (2003) çalışmalarından uyarlanmıştır. Model ve hipotezlerin test edilmesinde temel analiz tekniği olarak Kısmi En Küçük Kareler Yapısal Eşitlik Modellemesi (PLS-SEM) benimsenmiştir. Yapısal ilişkilerin kuşaklara göre farklılaşıp farklılaşmadığını belirlemek amacıyla Kısmi En Küçük Kareler Çoklu Grup Analizi (PLS-MGA) kullanılmıştır.

Tüm örneklem birlikte değerlendirildiğinde, Teknoloji Kabul Modeli (TKM) değişkenleri arasındaki doğrudan ilişkiler istatistiksel olarak anlamlı bulunmuştur. Algılanan fayda ve algılanan kullanım kolaylığı; tüketicilerin akıllı robot süpürgelere yönelik tutumlarını ve satın alma niyetlerini pozitif yönde etkilemektedir. Dolaylı etki analizlerinde ise algılanan kullanım kolaylığının, algılanan fayda ve tutum mekanizmaları üzerinden satın alma niyeti üzerinde güçlü bir aracı etkiye sahip olduğu belirlenmiştir. Kuşaklar arasındaki yapısal farklılıkları belirlemek için yapılan Çoklu Grup Analizi (MGA) yapılmıştır. Algılanan kullanım kolaylığının tutum üzerindeki etkisi ve tutumun satın alma niyeti üzerindeki doğrudan etkisi yalnızca Y Kuşağında anlamlı bulunmuştur. X ve Z kuşaklarında bu ilişkiler anlamsızdır. Benzer şekilde, ardışık dolaylı etkiler (kullanım kolaylığı ve faydanın, tutum üzerinden niyete yöneldiği çoklu aracı yollar) yalnızca Y Kuşağında istatistiksel olarak anlamlı çıkmıştır. Algılanan faydanın satın alma niyetine etkisi ile kullanım kolaylığının algılanan faydaya olan etkisi tüm kuşaklarda (X, Y, Z) benzer şekilde anlamlı ve pozitiftir; bu alanlarda kuşaklar arası anlamlı bir farklılık saptanmamıştır.

Çalışma literatüre iki temel katkı sunmaktadır: İlk olarak, TKM çerçevesindeki yapısal ilişkilerin, özellikle Y kuşağı özelinde kullanım kolaylığı ve tutumsal süreçler açısından kuşaklar arası farklılıklar gösterdiğini ampirik olarak kanıtlamıştır. İkinci olarak, teknoloji odaklı ürün geliştiricilerinin, pazarlama ve tasarım stratejilerinde kullanıcı odaklı tasarımı (PEOU) ve pratik faydayı (PU) ön planda tutmalarının, tüketici tutum ve davranışsal niyetlerini yönlendirmedeki anahtar rolünü ortaya koymuştur.