Digital Servitization in Practice: Understanding Consumer Adoption of Smart Home Appliances

Esra Öztürk[1]

[1]School of Administrative and Social Sciences, Ankara Medipol University, Ankara, Türkiye, ORCID: 0000-0001-7463-088X

* Corresponding author: Esra Öztürk (esra.ozturk@ankaramedipol.edu.tr)

Received: 07 November 2025, Accepted: 18 December 2025, Published: 19 December 2025

Abstract: Digital servitization has transformed traditional product–consumer relationships by embedding digital services, connectivity, and continuous value creation into physical products. As smart home technologies become more widespread, understanding what drives consumer adoption is critical for manufacturers seeking to create sustainable and service-based revenue models**.** This study aims to investigate the factors influencing consumers' behavioral intention to adopt digitally servitized smart home appliances and white goods within the framework of the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2). A quantitative research design was employed, and data were collected through a structured questionnaire consisting of 35 items measuring UTAUT2 constructs. Using convenience sampling, valid responses were obtained from 250 participants residing in Turkey. Structural Equation Modeling (SEM) was used to test the proposed model and examine the effects of each construct on usage intention. Results from the structural model analysis revealed that price value ($\beta = 0.564$) and habit ($\beta = 0.559$) had the strongest positive effects on usage intention. Effort expectancy (β=0.342), performance expectancy (β=0.329), hedonic motivation (β=0.260), and social influence (β=0.208) were also found to have significant positive effects. However, the effect of facilitating conditions (β=-0.028) was found to be insignificant. The model demonstrated a very high predictive power, explaining 96.8% of the variance in usage intention ($R^2 = 0.968$). The findings indicate that consumers' adoption decisions are primarily driven by rational value assessment (price value) and behavioral tendencies (habit), rather than by external support or technical assistance. The non-significant influence of facilitating conditions may be linked to the sample's high education and technological literacy. Overall, the results highlight that emphasizing value-for-money, creating repetitive usage cycles, and enhancing user engagement through digital touchpoints strengthen adoption. The study contributes to the literature by providing empirical evidence on digital servitization in the consumer goods context and offers managerial insights that help firms design strategies centered on value communication and habit formation.

Keywords: Digital Servitization, Smart Home Appliances, UTAUT2, Technology Adoption, Consumer Behavior

1. Introduction

In today's highly competitive environment, where product and service differentiation has become increasingly difficult and many firms offer similar value to consumers, the pursuit of adding additional value to products has gained importance across various industries. The concept of servitization, which refers to the transition from a product-oriented business model to a service-oriented one to improve user experience, has emerged as one of the key strategies for creating customer value.

Baines et al. (2009), who laid the foundations of the servitization concept, define it as an interconnected process in which manufacturers move beyond merely selling products and develop the capability to offer integrated product–service systems. The authors highlight that servitization affects firm performance and represents not only a change in the business model but also a strategic transformation. Servitization enables firms to enrich their product portfolios to respond more effectively to customer needs (Jat et al., 2022) and to complement product-based revenues with service-based earnings (López et al., 2023). Although the demand for a strong theoretical foundation in servitization research has increased, its widespread adoption among practitioners remains limited (Baines et al., 2017).

In today's world, where digitalization is accelerating, the concept of servitization has become even more significant, particularly through the integration of digital technologies. The use of digital technologies has reshaped companies' value-creation processes (Kryvinska & Bickel, 2020) and enhanced customer experience (Pizzichini et al., 2023). Pezzotta et al. (2022) note that many manufacturing firms are restructuring their value propositions to include service-oriented solutions, and that this shift is becoming increasingly widespread in line with Industry 4.0 principles. This digital transformation encourages the development of new services and the improvement of existing ones through advanced digital capabilities, leading to new revenue streams and increased customer satisfaction (Pezzotta et al., 2023). Companies can pursue digital servitization in three fundamental ways: (1) industrial servitization, (2) commercial servitization, and (3) value servitization—thereby offering additional value to their customers (Coreynen et al., 2017). Each of these approaches leverages digital technologies differently to enhance service offerings and customer interaction. Existing literature emphasizes the interaction between servitization and digitalization, suggesting that servitization is critical, while digitalization acts as a key enabler of this transition (Lei et al., 2021).

Therefore, digital servitization represents a significant evolution in both manufacturing and service sectors, driven by the integration of digital technologies into service offerings. The advancement of digital technologies is transforming traditional manufacturing industries from being solely product-oriented into service-focused structures. One prominent example of this transformation is the digital servitization process observed in the smart home appliances and white goods sector. Consumers' interactions with smart appliances and digital services shape not only product usage but also the overall service experience. The development of smart home appliances is based on the integration of IoT (Internet of Things) technologies to make users' daily lives more efficient and convenient. The integration of new technologies such as IoT has expanded the functionality of smart appliances and enabled the delivery of various innovative services (Hoyer et al., 2020). Kong et al. (2016) developed device selection methods in smart home applications based on location and activity information and showed how context-based selection improves user experience. Khan et al. (2016) demonstrated that energy efficiency and smart control systems in smart homes have the potential to increase user comfort. The digital servitization process is built upon the transformation of the consumer experience by digital services integrated into the product; this transformation naturally triggers the psychological and behavioral factors that determine usage intention. Digital services (remote control, automatic updates, predictive maintenance, etc.) increase the consumer's perceived value from the product and transform its use into a continuous and repetitive experience. In this context, the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) (Venkatesh et al., 2003) model provides a suitable theoretical framework to explain how the digital servitization process translates into consumer behavioral intention. The functionality offered by digital services strengthens performance expectations, ease of use strengthens effort expectations, in-app interaction strengthens hedonic motivation, and continuous usage habits. Thus, a relationship emerges: Digital servitization enhances perceived value and usage experience, thereby strengthening the UTAUT2 constructs that determine usage intention. In this context, UTAUT2 enables us to measure the impact of digital servitization on consumer behavior at the behavioral intention level.

Many existing studies address the UTAUT2 model in the context of healthcare applications, mobile payment systems, or e-commerce; however, studies on digitally servitized physical products, particularly smart home appliances and white goods, are limited. In this context, understanding consumers' usage behavior regarding smart home appliances and white goods is critical for firms seeking to gain a competitive advantage. The lack of empirical studies measuring the impact of the product and digital service combination on user behavior presents this area with a clear research opportunity. Therefore, this study aims to fill a significant gap in existing literature by examining the factors influencing consumers' intention to use smart home appliances and white goods, based on the UTAUT2 model, which is widely used to explain consumer behavior. The study empirically demonstrates the impact of the product and digital service combination on consumer usage intention, rather than solely digital platforms or software-based services. Furthermore, by demonstrating that behavioral factors such as price value and habit are the dominant determinants of usage intention during the digital servitization process, it offers new insight into how models explaining technology acceptance apply to physical products.

Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain individuals' technology adoption and usage behaviors. According to this model, four core factors influence technology acceptance: facilitating conditions, social influence, performance expectancy, and effort expectancy. Later, Venkatesh, Thong, and Xu (2012) expanded the model by adding three additional factors—price value, habit, and hedonic motivation—thus forming UTAUT2. The UTAUT2 model provides a framework for understanding consumer technology acceptance and consists of seven main factors that influence users' intention to adopt technology.

Performance Expectancy refers to users' perception of the functional benefits provided by a product. In the context of smart home appliances, users consider the extent to which these devices can simplify their daily lives. Research shows that performance expectancy strongly influences users' behavioral intentions (Tamilmani et al., 2020; Plohl & Babič, 2024). Users are inclined toward such technologies by considering the advantages offered by smart home systems (Kułak et al., 2019).

Effort Expectancy refers to users' assessment of how easy or difficult it will be to use technology. Smart home devices with user-friendly interfaces can positively influence adoption intentions. Research indicates that effort expectancy has a significant impact on consumer behavior (Plohl & Babič, 2024; Hidayah & Putri, 2021). User-friendly and simple designs are particularly important for users with limited technological experience (Raman & Thannimalai, 2021).

Social Influence refers to how the tendencies and opinions of people around users affect their own decision to adopt technology. Smart home appliances can be supported by information and encouragement from the social environment. Users may prefer products that they observe in their social circles, which increases the likelihood of adoption (Plohl & Babič, 2024; Breil et al., 2022).

Facilitating Conditions encompass the physical and social infrastructure that supports technology use. Internet access, technical support, and ease of installation are influential factors in the adoption of smart home products. Research shows that when these conditions are favorable, users' intention to adopt increases (Plohl & Babič, 2024; Çiftçi et al., 2023).

Habit refers to an individual's automatic responses toward a certain behavior. As users frequently interact with smart home appliances, this usage becomes habitual, strengthening their attitude toward technology. Habit has been identified as a significant determinant in many studies on the subject (Tamilmani et al., 2018). Habit is of particular importance in this context because it creates a continuous cycle of use of digital services.

Hedonic Motivation refers to the pleasure and enjoyment users experience while using technology. Smart home appliances attract users by offering convenience and enjoyment. Elements that enhance the user experience positively affect hedonic motivation (Plohl & Babič, 2024; Tamilmani et al., 2017).

Price Value refers to users' evaluation of the balance between the price of a product and the benefits it provides. Although smart home appliances may require a high initial investment, they should demonstrate that the savings and benefits they offer in the long term make the investment worthwhile. Affordable smart devices can appeal to a wider range of users (Kułak et al., 2019; Tamilmani et al., 2017). Price value captures the cost-benefit balance of the "product + service" package in the eyes of the consumer, which is critical in digital servitization.

Digital servitization in smart home technologies redefines the relationship between the consumer and the product; the device is transformed from a mere object to a platform that provides continuous interaction and service experiences. Usage decisions are no longer solely based on technical performance, but rather on how well the device integrates into daily life, how effortless its use is, whether the value provided by the product is balanced by its price, and whether users routinize this interaction over time. Furthermore, data sharing and privacy concerns in smart home devices are frequently emphasized in literature, making user acceptance decisions more sensitive to psychological and social factors. Therefore, a model explaining technology acceptance is not sufficient to focus solely on technical benefits; it must address perception, experience, and behavioral intentions together. For this very reason, UTAUT2 provides a suitable framework for examining how digital servitization translates into user behavior. The factors evaluated within the UTAUT2 framework play a critical role in determining consumers' intention to use smart home appliances and other technological products. By considering these elements, users make decisions that increase technology acceptance and adoption. Hassan et al. (2022) found that consumers' decisions to adopt smart home technologies are influenced by emotional and behavioral factors such as hedonic motivation and habit. Tsai (2021) showed that psychological factors—such as social influence, effort expectancy, and facilitating conditions—are significant determinants of consumers' intentions to use mobile payments. These findings highlight the strength of the UTAUT2 model as a framework for explaining consumers' technology adoption and usage behaviors in the context of smart home appliances and white goods. Based on this framework, the main hypotheses of the research are presented below:

H1: Performance expectancy has a positive effect on usage intention.
H2: Effort expectancy has a positive effect on usage intention.
H3: Social influence has a positive effect on usage intention.
H4: Facilitating conditions have a positive effect on usage intention.
H5: Hedonic motivation has a positive effect on usage intention.
H6: Price value has a positive effect on usage intention.
H7: Habit has a positive effect on usage intention.

2. Methodology

2.1. Research Model and Variables

This study adopts a quantitative research design to examine consumers' adoption and usage behavior regarding digitally servitized smart home appliances and white goods. Data were collected using a survey method, and a structural model based on the UTAUT2 framework was tested. The research model is grounded in the UTAUT2 (Extended Unified Theory of Acceptance and Use of Technology) developed by Venkatesh et al. (2012). According to the model, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit are included as independent variables. The effects of these variables on the dependent variable, Usage Intention, are examined.

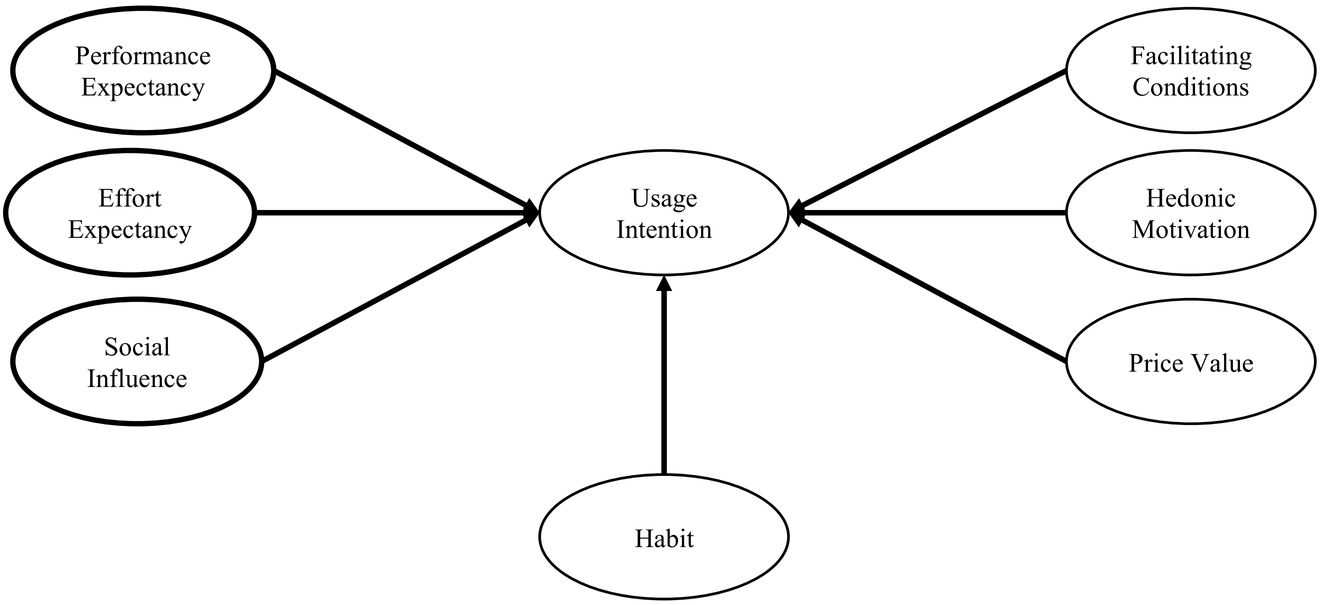

Figure 1. Research Model

2.2. Population and Sample

The population of the study consists of consumers in Türkiye who use, or have the potential to use, smart home appliances and/or digital service-integrated white goods. A convenience sampling method was used to reach the sample. During data collection, responses were obtained from the target audience through online survey platforms and social media channels. A total of 250 valid responses were collected. This sample size is considered sufficient for analyses conducted with structural equation modeling (SEM).

2.3. Data Collection Instruments

The research data were collected through a questionnaire adapted from widely used scales developed to measure the constructs in the UTAUT2 model. The questionnaire consists of three sections:

1) General Usage Questions: Items regarding which smart home appliances and white goods the participants use.
2) UTAUT2 Constructs: A total of 35 items measuring the seven independent variables and usage intention/behavior. All items were adapted from the study of Venkatesh et al. (2012). The items were rated on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).
3) Demographic Information: Questions measuring participants' age, gender, and education level.

The scale items used in the study were adapted from the original scales found in the literature. During the adaptation process, the items were first translated from English into Turkish, and then a back-translation procedure was applied to ensure semantic equivalence. Subsequently, the scale was reviewed for content validity by two subject-matter experts, and revisions were made based on their suggestions. A pilot test (n = 30) conducted before the main study confirmed the clarity of the items, and the reliability coefficients were found to be within acceptable limits.

2.4. Data Analysis

Statistical software packages (SPSS 26.0 and AMOS 24.0) were used to analyze the collected data. The analysis process consisted of the following steps:

1) Descriptive Statistics: Used to summarize participants' demographic profiles and provide mean, standard deviation, and normality values for the scale variables.
2) Confirmatory Factor Analysis (CFA): Applied to test the validity and reliability of the measurement model (the scale structures). Convergent and discriminant validity values were examined.
3) Structural Equation Modeling (SEM): After confirming the measurement model, path analysis was used to test the causal relationships proposed in the hypotheses.

3. Results

3.1 Descriptive Statistics

The study sample consists of 250 participants (n = 250). Examination of the demographic characteristics shows a relatively balanced gender distribution: 52.4% men (n = 131) and 47.6% women (n = 119). In terms of education level, the group exhibits a high level of education. Of the participants, 46.8% (n = 117) hold a bachelor's degree and 34.4% (n = 86) hold a graduate degree, indicating that more than four-fifths (81.2%) are at least university graduates. The proportions of associate degree and high school graduates are 9.2% (n = 23) and 9.6% (n = 24), respectively, and no participant reported having only primary education. Thus, the findings of this study are based on a sample predominantly composed of individuals with higher education.

Table 1. Participants' Characteristics

Gender	Frequency	%
Female	119	%47.6
Male	131	%52.4
Education	**F**	**%**
Primary School	0	%0
High School	24	%9.6
Associate	23	%9.2
Bachelor	117	%46.8
Graduate	86	%34.4
	n=250	

When examining the smart home appliances owned by the participants, the most commonly used products are smart TVs (67.2%; n = 168) and smart robot vacuums (60.4%; n = 151). These are followed by smart washing machines (38.8%; n = 97). Smart ovens/stoves/air fryers (34.8%; n = 87) and smart refrigerators (32.4%; n = 81) are reported at similar levels. Smart dishwashers (29.2%; n = 73) and smart air conditioners/thermostats/air purifiers (24.0%; n = 60) show relatively lower usage rates. Smart curtain/blind systems (5.2%; n = 13) are the least common smart home product among participants.
These findings indicate that entertainment- and cleaning-oriented smart devices have a high adoption rate, whereas home automation systems appeal to a more niche user segment. The widespread use of smart TVs and robot vacuum cleaners suggests that usage intention is influenced not only by functionality but also by experiential benefits. Smart TVs stimulate hedonic motivation through entertainment and enjoyment, while robot vacuum cleaners emphasize functional utility by saving time. This distribution supports that consumers consider both rational factors—such as ease of use and efficiency—and experiential factors—such as comfort and satisfaction—when adopting smart home technologies.

Table 2. Categories of Smart Home Appliances and White Goods Used

Categories	Frequency	%
Smart television	168	67.2
Smart robot vacuum cleaner	151	60.4
Smart washing machine	97	38.8
Smart oven/stove/air fryer	87	34.8
Smart refrigerator	81	32.4
Smart dishwasher	73	29.2
Smart air conditioner/thermostat/air purifier	60	24.0
Smart curtain/blinds system	13	5.2
Total	**250**	**100**

To test whether the data obtained from the scales used in the study showed a normal distribution, a normality test was conducted. For a dataset to be considered normally distributed, skewness and kurtosis values should fall between −1.5 and +1.5 (Tabachnick & Fidell, 2013). As shown in Table 3, the skewness and kurtosis values meet the normality criterion, except for the kurtosis values of facilitating conditions and hedonic motivation. Given the large sample size (n = 250), the Central Limit Theorem (Field, 2017; Lumley et al., 2002) and the robustness of parametric tests against deviations from normality (Tabachnick & Fidell, 2019) allow some flexibility as long as values are not extreme. Therefore, these results indicate that parametric statistical methods can be used in the analysis.

Table 3. Normality Test

Scales	N	Mean	Std. Dev.	Skewness	Kurtosis
Performance expectancy (P)	250	4.0173	0.04935	-1.082	1.369
Effort expectancy (E)	250	3.9830	0.05187	-0.982	1.021
Social influence (S)	250	3.7973	0.05296	-0.285	-0.886
Facilitating conditions (F)	250	3.8560	0.04195	-1.150	2.689
Hedonic motivation (HM)	250	4.0827	0.04347	-1.074	2.424
Price value (P)	250	3.7493	0.04957	-0.381	-0.065
Habit (H)	250	3.8827	0.05406	-0.807	0.566
Usage intention (UI)	250	3.9040	0.04969	-0.630	1.094

3.2 Validity and Reliability of the Measurement Model

The measurement model is a structural equation model that identifies the indicators for each construct and enables the assessment of construct validity (Hair et al., 2010). Therefore, beyond determining the validity and reliability of each variable individually, the validity and reliability of the scales included in the measurement model were also examined. To test the construct validity of the research scales, confirmatory factor analysis (CFA) was performed using SPSS AMOS 22.
To achieve acceptable fit indices, error terms of certain items were correlated, and necessary modifications were applied. Factor loadings obtained from the analyses ranged between 0.598 and 0.915 and were statistically significant. Factor loadings above 0.50 are generally considered acceptable (Hair et al., 2010). Having factor loadings above this threshold indicates adequate construct validity.
The goodness-of-fit statistics for the measurement and research models are presented in Table 4. The unidimensional structure of the variables was confirmed, and the research model demonstrated acceptable fit (χ^2/df = 4.818).

Table 4. Goodnes-of-fit indices

Goodness-of-Fit Indices	x2/df	GFI	CFI	NFI	RMSEA
Measurement model	4.818	0.624	0.641	0.594	0.129
Good fit*	≤3	≥ 0.95	≥ 0.95	≥ 0.95	≤ 0.05
Acceptable fit*	≤ 5	≥ 0.90	≥ 0.90	≥ 0.90	≤ 0.08

Resource: Hair et al. (2010)

To accept the construct validity of the research variables, both convergent and discriminant validity must be ensured. Convergent validity refers to the high correlation among the indicators that form each construct (Bülbül & Demirer, 2008). According to Fornell and Larcker (1981), convergent validity is achieved when AVE values are greater than 0.50 and CR values are greater than 0.70. The values testing convergent validity of the measurement model are presented in Table 5. The AVE values of the variables range between 0.5205 and 0.7402, while the CR values range between 0.7592 and 0.911. These results indicate that convergent validity is established.

Table 5. Convergent validity and reliability analysis

Factors	Items	Loadings (λ)*	AVE	CR	Cronbach's Alpha
Performance Expectancy (P)	P1	0.798	0.5767	0.8019	0.794
	P2	0.650			
	P3	0.819			
Effort Expectancy (E)	E1	0.801	0.6819	0.8939	0.876
	E2	0.650			
	E3	0.909			
	E4	0.915			
Social influences (S)	S1	0.669	0.5476	0.7827	0.777
	S2	0.828			
	S3	0.714			
Facilitating Conditions (F)	F1	0.716	0.5460	0.8278	0.813
	F2	0.738			
	F3	0.750			
	F4	0.751			
Hedonic Motivation (HM)	HM1	0.847	0.6626	0.8548	0.853
	HM2	0.800			
	HM3	0.794			
Price value (P)	P1	0.889	0.5205	0.7592	0.746
	P2	0.643			
	P3	0.598			
Habit (H)	H1	0.802	0.5703	0.7986	0.840
	H2	0.689			
	H3	0.770			
Usage Intention (UI)	UI1	0.865	0.7402	0.8953	0.911
	UI2	0.862			
	UI3	0.854			

**All standardized factor loadings are significant at the 0.001 level.*

To establish construct validity, discriminant validity must also be ensured. Discriminant validity indicates the extent to which the factors in the model are distinct from one another. According to Fornell and Larcker (1981), discriminant validity is achieved when the square root of the AVE value for each construct is greater than the correlations among the constructs. As shown in Table 6, the square roots of the AVE values are higher than the correlation coefficients among the constructs. However, the high correlation between Habit (HB) and Usage Intention (UI) (0.843), which exceeds the √AVE value of Habit (0.7551), indicates that these two constructs are not sufficiently distinct. This finding suggests that

Habit and Usage Intention are conceptually very close and represent a limitation regarding discriminant validity.

Table 6. Correlations among variables and discriminant validity

Factors	*P*	*E*	*S*	*F*	*HM*	*P*	*H*	*UI*	*√AVE*
Performance expectancy (P)	-	0.704	0.374	0.600	0.680	0.559	0.736	0.739	0.7594
Effort expectancy (E)	0.704	-	0.305	0.684	0.701	0.492	0.717	0.718	0.8257
Social influences (S)	0.374	0.305	-	0.535	0.374	0.587	0.473	0.419	0.7400
Facilitating conditions (F)	0.600	0.684	0.535	-	0.564	0.567	0.702	0.581	0.7389
Hedonic motivation (HM)	0.680	0.701	0.374	0.564	-	0.543	0.779	0.728	0.8140
Price value (P)	0.559	0.492	0.587	0.567	0.543	-	0.694	0.561	0.7214
Habit (H)	0.736	0.717	0.473	0.702	0.779	0.694	-	0.843	0.7551
Usage intention (UI)	0.739	0.718	0.419	0.581	0.728	0.561	0.843	-	0.8603

* $p<0.001$

In addition to construct validity, examining reliability is also essential. Reliability refers to the likelihood of obtaining consistent results when the same measurements are applied to different samples drawn from the same population (Şencan, 2005). To assess reliability, Cronbach's alpha coefficients are used to determine the internal consistency of the items, and these coefficients should generally be above 0.70 (Pallant, 2017). The reliability analysis results of the scales used in the study are shown in Table 5. All Cronbach's alpha values exceed 0.70, indicating that the scales are reliable.

3.3. Structural Equation Model

To test the research hypotheses, a structural equation modeling (SEM) analysis was conducted using AMOS. The results of the path analysis are presented in Table 7.

Table 7. Path coefficients and model statistics

Paths	*Path coefficients (β)*	*Standard error (SE)*	*t-value (CR)*	*p-value*	*R^2 (Explained variance)*
P→ UI	0,329	0,046	3,969	0,000	
E→ UI	0,342	0,033	4,346	0,000	
S→ UI	0,208	0,041	2,596	0,009	
F→ UI	-0,028	0,051	-0,338	0,735	0,968
HM→ UI	0,260	0,056	2,829	0,005	
P→ UI	0,564	0,050	5,818	0,000	
H→ UI	0,559	0,038	6,239	0,000	

According to the analysis results, the strongest effects on usage intention come from price value (β = 0.564, $p < 0.001$) and habit (β = 0.559, $p < 0.001$). In addition, effort expectancy (β = 0.342, $p < 0.001$), performance expectancy (β = 0.329, $p < 0.001$), hedonic motivation (β = 0.260, $p < 0.01$), and social influence ($\beta = 0.208$, $p < 0.01$) have significant and positive effects on usage intention. In contrast, facilitating conditions ($\beta = -0.028$, $p = 0.735$) have no significant effect on usage intentions. These findings indicate that usage intention is primarily shaped by price value and habit, while the other variables provide supportive contributions. Furthermore, the R^2 value shows that 96.8% of the variance in usage intention is explained by the constructs in the model, indicating a strong explanatory power.

4. Discussion and Conclusion

The purpose of this study is to examine the factors influencing consumers' adoption of digitally servitized smart home appliances and white goods within the UTAUT2 theoretical framework. The findings show that while some factors are highly effective in shaping consumers' usage intentions, others do not produce the expected impact.

According to the results, price value ($\beta = 0.564$, $p < 0.001$) and habit ($\beta = 0.559$, $p < 0.001$) emerge as the strongest predictors of usage intention. This indicates that the perceived value of the product relative to its cost plays a critical role in consumers' purchase decisions. Likewise, habits formed through prior use strongly drive behavioral intention. This finding aligns with earlier studies such as Tamilmani et al. (2018) and Hassan et al. (2022), emphasizing the importance of emotional and behavioral factors in technology adoption.

Effort expectancy ($\beta = 0.342$, $p < 0.001$) and performance expectancy ($\beta = 0.329$, $p < 0.001$) also exhibited significant and strong positive effects on usage intention. These results reflect the importance users place on ease of use and functional utility and are consistent with the findings of Kułak et al. (2019) and Plohl and Babič (2024). Hedonic motivation ($\beta = 0.260$, $p < 0.01$) and social influence ($\beta = 0.208$, $p < 0.01$) were also significant, though their effect sizes were comparatively smaller. This suggests that while enjoyment and social environment play a role, more rational factors (such as price value and performance) weigh more heavily in decision-making.

Contrary to expectations, facilitating conditions ($\beta = -0.028$, $p = 0.735$) did not have a statistically significant effect on usage intention. This unexpected outcome can be explained by the demographic profile of the sample. With the majority of participants (81.2%) being higher education graduates, their level of technological literacy is presumably high. As a result, factors such as internet access or technical support may already be perceived as prerequisites, reducing the distinct role of facilitating conditions in shaping intentions. This finding suggests that the influence of facilitating conditions may be limited in certain contexts and among specific target groups.

The R^2 value of 0.968 indicates that 96.8% of the variance in usage intention is explained by the independent variables in the model, demonstrating that the UTAUT2 framework is a highly powerful predictor of smart home technology adoption. The level of explanatory power is notably high. While this reflects a strong predictive capacity, it also raises the possibility of overfitting. Including multiple variables simultaneously, especially constructs that are conceptually or statistically correlated, may cause the model to fit the sample data excessively well. Therefore, when interpreting the results, model complexity and the likelihood that some variables represent overlapping behavioral constructs should be considered.

Like all scientific research, this study has several limitations. The primary limitation concerns the characteristics of the sample. More than 80% of the participants are higher-education graduates, forming a group with high technological literacy and strong adoption tendencies. This creates a relatively homogeneous sample and limits the external validity of the findings. For consumers with lower education levels or limited experience with technology, the influence of certain factors, particularly facilitating conditions, may be more pronounced. Therefore, the results of this research are most applicable to highly educated consumer groups with similar characteristics. Future studies should aim to include more diverse and representative samples in terms of education, age, income, and technological literacy. Including more heterogeneous groups will strengthen the generalizability and validity of the findings. In addition, using qualitative methods can provide deeper insights into the motivations underlying consumers' decision-making processes.

There are also methodological limitations. The high correlation between habit and usage intention and the lack of discriminant validity indicate that these two constructs should be reconsidered in future research. The strong correlation between habit and usage intention ($r = 0.843$) suggests not only a statistical multicollinearity concern but also theoretical overlap. In the UTAUT2 model, habit is defined as an automated behavioral tendency shaped by past experiences, whereas usage intention is a cognitive plan regarding future behavior. However, such a high correlation may imply that the measurement instruments do not empirically distinguish between the two constructs. This shows that although differentiating “habit” and “intention” is theoretically necessary, it may be empirically challenging in technology adoption research. Future studies could benefit from developing measurement items that more clearly distinguish between these constructs or by integrating them into a combined structure within the model.

Another methodological limitation concerns the goodness-of-fit indices of the measurement model. Confirmatory factor analysis indicated that some indices, such as CFI (0.641) and NFI (0.594), fell below the recommended thresholds (≥ 0.90), while RMSEA (0.129) exceeded acceptable limits. This suggests that the constructs do not fully align with the measurement model and that the model's fit to the data is not ideal. Future research could achieve stronger fitness by revising scale items or testing alternative measurement models.

Despite its limitations, this study contributes to the literature by testing the UTAUT2 model in the context of digitally servitized consumer products. The findings indicate that facilitating conditions, traditionally considered important, may not be a decisive factor for a highly educated, technologically proficient consumer group, emphasizing the contextual boundaries of the model. From a practical perspective, the results offer strategic implications for smart home appliance manufacturers and marketers. Clearly highlighting the price–value ratio in marketing communications and designing user-friendly, continuous usage experiences that help consumers form habits are critical. In addition, emphasizing product performance and ease of use can positively influence consumers' usage intentions Another strategic implication is the importance of creating usage cycles that encourage repeated interaction with the product. Digital touchpoints such as trial periods, in-app guidance, and usage reminders can increase product interaction and support habit formation. Subscription-based service bundles, including maintenance, software updates, and additional services, can strengthen the digital servitization revenue model. This not only ensures ongoing engagement with the product but also creates a recurring revenue stream for the brand.

Practically, firms should move from a one-time sales approach to a service ecosystem that enables continuous interaction with the consumer. During the initial usage phase, onboarding flows, in-app instructions, and personalized recommendations can help integrate the product into users' daily routines. During usage, feedback mechanisms that reflect outcomes such as energy savings, time efficiency, or convenience reinforce continued behavior. Furthermore, offering maintenance, remote diagnostics, software updates, and predictive service features within subscription packages can enhance the servitization model. This sustains customer engagement and encourages habit formation. In marketing communication, it is essential to emphasize the real value delivered to the consumer (such as comfort, time savings, and cost benefits) rather than focusing solely on technical features. Transparent communication on data security can also reduce privacy concerns and accelerate adoption among new users.

In conclusion, the study shows that rational factors (price value, performance expectancy) and behavioral factors (habit) strongly determine the adoption of digitally servitized products. As the smart home technologies market continues to grow, research that deepens our understanding of consumer behavior will provide valuable guidance for both academics and practitioners.

Acknowledgments

ChatGPT was used to edit and revise the language of the article. Specifically, the researchers seek suggestions on synonyms, antonyms, lexical diversity, transitions, and conjunctions from this tool to ensure the readability of the article.

This study was presented at the 12th International Conference on Management Information Systems (ICMIS 2025), held at Ankara Medipol University, Ankara, Türkiye, between October 23–25, 2025.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

References

Baines, T., Lightfoot, H., Peppard, J., Johnson, M., Tiwari, A., Shehab, E., & Swink, M. (2009). Towards an operations strategy for product-centric servitization. *International Journal of Operations & Production Management, 29*(5), 494-519.

Baines, T., Ziaee Bigdeli, A., Bustinza, O. F., Shi, V. G., Baldwin, J., & Ridgway, K. (2017). Servitization: revisiting the state-of-the-art and research priorities. *International Journal of Operations & Production Management, 37*(2), 256-278.

Breil, B., Salewski, C., & Apolinário-Hagen, J. (2022). Comparing the acceptance of mobile hypertension apps for disease management among patients versus clinical use among physicians: cross-sectional survey. *JMIR Cardio, 6*(1), e31617.

Bülbül, H. & Demirer, Ö. (2008). Hizmet kalitesi ölçüm modelleri SERVQUAL ve SERVPERF'in karşılaştırmalı analizi. *Selçuk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 20,* 181-198.

Coreynen, W., Matthyssens, P., & Bockhaven, W. (2017). Boosting servitization through digitization: pathways and dynamic resource configurations for manufacturers. *Industrial Marketing Management, 60,* 42-53.

Çiftçi, Ş., Gök, R., & Karadağ, E. (2023). Acceptance and use of the distance education systems of Turkish medical educators during covid-19 pandemic: an analysis of contextual factors with the UTAUT2. *BMC Medical Education, 23*(1).

Field, A. (2017). *Discovering Statistics Using IBM SPSS Statistics* (5th ed.). Sage Publications.

Fornell, C. & Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Gürbüz, S. & Şahin, F. (2017). *Sosyal bilimlerde araştırma yöntemleri, felsefe-yöntem-analiz* (Gözden Geçirilmiş ve Güncellenmiş 4. Baskı). Ankara: Seçkin Yayıncılık.

Hair, J. F., & Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson.

Hassan, I., Murad, M., El-Shekeil, I., & Liu, J. (2022). Extending the UTAUT2 model with a privacy calculus model to enhance the adoption of a health information application in Malaysia. *Informatics, 9*(2), 31.

Hidayah, S. & Putri, C. (2021). Factors affecting interest in utilization and use of online shop (study on shopee customers*). Journal of Soft Computing Exploration, 2*(2).

Hoyer, W., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Interactive Marketing, 51*(1), 57-71.

Jat, M., Jajja, M., Shah, S., & Farooq, S. (2022). Manufacturer's servitization level and financial performance: the role of risk management. *Journal of Manufacturing Technology Management, 34*(1), 122-146.

Khan, M., Silva, B., & Han, K. (2016). Internet of things based energy aware smart home control system. *IEEE Access, 4*, 7556-7566.

Kong, Q., Maekawa, T., Miyanishi, T., & Suyama, T. (2016, September). Selecting home appliances with smart glass based on contextual information. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (pp. 97-108).

Kryvinska, N. & Bickel, L. (2020). Scenario-based analysis of it enterprises servitization as a part of digital transformation of modern economy. *Applied Sciences, 10*(3), 1076.

Kułak, J., Trojanowski, M., & Barmentloo, E. (2019). A literature review of the partial unified theory of acceptance and use of technology 2 (UTAUT2) model. *Annales Universitatis Mariae Curie Skłodowska Sectio H Oeconomia, 53*(4), 101.

Lei, S., Sun, C., & Ali, M. (2021). Role of servitization, digitalization, and innovation performance in manufacturing enterprises. *Sustainability, 13*(17), 9878.

Li, C., Li, D., Liang, Y., & Wang, Z. (2024). Underdog entrepreneurship in the digital era: the effect of digital servitization on household entrepreneurship in China. *Heliyon, 10*(2), e24154.

López, J., Peña, M., Garrido, E., & Magro, C. (2023). The moderating role of technological collaboration in the relationship between absorptive capacity and servitization: an open innovation approach in high-tech industries. *Journal of Manufacturing Technology Management, 35*(2), 314-335.

Lumley, T., Diehr, P., Emerson, S., & Chen, L. (2002). The Importance of the Normality Assumption in Large Public Health Data Sets. *Annual Review of Public Health, 23,* 151–169.

Pallant, J. (2017). *SPSS kullanma klavuzu: SPSS ile adım adım veri analizi* (2. Baskı) (S. Balcı & B. Ahi, Çev.). Ankara: Anı.

Peña, M., López, J., & Garrido, E. (2019). Servitization and digitalization in manufacturing: the influence on firm performance. *Journal of Business and Industrial Marketing, 35*(3), 564-574.

Pezzotta, G., Arioli, V., Adrodegari, F., Rapaccini, M., Saccani, N., Rakic, S., ... & Gaiardelli, P. (2022, September). Digital servitization in the manufacturing sector: survey preliminary results. In *IFIP International Conference on Advances in Production Management Systems* (pp. 310-320). Cham: Springer Nature Switzerland.

Pezzotta, G., Arioli, V., Adrodegari, F., Rapaccini, M., Saccani, N., Rakic, S., ... & Gaiardelli, P. (2023, September). The digital servitization of manufacturing sector: evidence from a worldwide digital servitization survey. In *IFIP International Conference on Advances in Production Management Systems* (pp. 165-180). Cham: Springer Nature Switzerland.

Pizzichini, L., Temperini, V., Caboni, F., & Papa, A. (2023). The role of digital knowledge servitization in supply chain management. *International Journal of Physical Distribution & Logistics Management, 53*(5/6), 589-611.

Plohl, N. & Babič, N. (2024). Using the UTAUT2 components and trust to predict consumer acceptance of smart home technology: a systematic review. *Human Technology, 20*(1), 93-113.

Raman, A. & Thannimalai, R. (2021). Factors impacting the behavioural intention to use e- learning at higher education amid the covid-19 pandemic: UTAUT2 model. *Psychological Science and Education, 26*(3), 82-93.

Şencan, H. (2005). *Sosyal ve davranışsal ölçümlerde güvenilirlik ve geçerlilik*. Ankara: Seçkin Yayıncılık.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using Multivariate Statistics* (7th ed.). Pearson.

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2017). A systematic review of citations of UTAUT2 article and its usage trends. In *Conference on e-Business, e-Services and e-Society* (pp. 38-49). Springer, Cham.

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2018, June). Use of 'habit'is not a habit in understanding individual technology adoption: a review of UTAUT2 based empirical studies. In *International working conference on transfer and diffusion of IT* (pp. 277-294). Cham: Springer International Publishing.

Tamilmani, K., Rana, N., & Dwivedi, Y. (2020). Consumer acceptance and use of information technology: a meta-analytic evaluation of UTAUT2. *Information Systems Frontiers, 23*(4), 987-1005.

Tsai, L. (2021). Evaluating the effects of facilitating conditions and usage experience on mobile payment. *International Journal of Information Systems in the Service Sector, 13*(4), 88-106.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use