Chapter 7:

Perceived Functional and Emotional Value as Drivers of Technological Innovativeness in Technology-Intensive Products

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Abstract

More advanced products do not automatically make users more willing to try new technologies. This study looks at how perceived functional value and perceived emotional value relate to the propensity for technological innovation among users of technology-intensive products. Survey data were collected from 604 graduate students who actively used smartphones. Two cases with missing values were dropped, and the remaining 602 responses were analysed with multiple linear regression. Both value dimensions had positive, significant effects on users' propensity for technological innovation, although together they explained a modest share of the variance ($R^2 = .087$). The results suggest that openness to new technology depends on what users get out of a product as well as on what the product can technically do. Treating perceived value as an antecedent of future adoption, rather than of a single adoption decision, moves the Technology and Innovation Management literature a step past the usual acceptance-and-use models.

Keywords: technology and innovation management, technology-intensive products, perceived functional value, perceived emotional value, technological innovativeness

1. Introduction

Each new generation of technology-intensive products comes with faster hardware, more capable software and more digital functions than the last. Does this make users more willing to adopt new technologies? Not necessarily. Technically superior products often fail to produce a stronger propensity for technological innovation, and the reasons for this gap deserve more attention in Technology and Innovation Management research. Digital products succeed when users notice what a technology offers, judge it worthwhile and fit it into their daily routines, engineering quality is only part of that story (Adner, 2006, 2017; Nambisan et al., 2017; Yoo et al., 2010).

Most earlier studies have examined technology acceptance, usage intention, user satisfaction or continued use. Much less is known about how the value users see in a technology shapes their wider readiness to take up innovations. This matters because firms in technology-intensive markets need customers who will move on to the next product and the next update, beyond the one they already own (Jiang et al., 2022; Santos-Vijande et al., 2022).

Perceived value offers a useful point of departure here. Functional value reflects the way users assess a product's performance and its practical usefulness. Emotional value, in turn, concerns the experiential and psychological bonds that users develop with a technology. Considering these two aspects side by side helps to explain why some users embrace technological innovation more readily than others (Beaudry & Pinsonneault, 2010; Sheth et al., 1991; Woodruff, 1997).

Taking smartphones as its empirical setting, this study examines the extent to which perceived functional value and perceived emotional value affect users' propensity for technological innovation. Perceived value is seen here as more than a predictor of present use; it is also treated as something that shapes how willing users are to accept innovations in the future. Previous research on value-based adoption has generally concentrated on a single, specific technology or service (a new platform,

an application, a type of service) at a given moment. This study, by contrast, understands the propensity for technological innovation as a relatively stable, future-oriented disposition: a willingness to keep taking part in an ongoing flow of change, such as new devices, new features and updates. The distinction suits smartphones particularly well. Unlike many settings that involve just one technology, the smartphone belongs to an ecosystem that never stops changing, so users are repeatedly confronted with adoption decisions.

2. Conceptual Framework

2.1. Technology-Intensive Products from a Technology and Innovation Management Perspective

From a Technology and Innovation Management (TIM) perspective, a smartphone is better understood as a technology-intensive digital system than as an ordinary consumer product. Its hardware, software, connectivity and data are bound up with a much larger innovation ecosystem, one that includes platform owners, app developers, component suppliers and network operators, along with a steady flow of software updates. How a smartphone performs in the market therefore has as much to do with its place in this ecosystem as with the quality of its engineering. Studies of digital innovation describe such products as modular and layered, not as self-contained artifacts. Their commercial success depends on many interdependent actors working in step, and in the end on whether users are able to see and use the value that this ecosystem produces (Adner, 2006, 2017; Nambisan et al., 2017; Porter & Heppelmann, 2014; Yoo et al., 2010).

The smartphone is a particularly clear case. It is never finished: new chipsets, sensors, interfaces and AI features arrive regularly, and operating system updates keep changing what an existing device can do. A good part of its value, moreover, comes from outside the device, from the services and software people use on it. Adoption also involves a trade-off between

the new and the familiar. Even a technically superior feature may be resisted if it feels unfamiliar to users or lacks adequate software support. For manufacturers, this means that better specifications alone will not carry an innovation. Users have to see it as useful and worth the effort of adopting (Lu et al., 2026; Wang et al., 2022; Zhang et al., 2026).

This study therefore treats perceived value as the link between what a technology can do and whether it is actually adopted, rather than simply as an outcome of marketing. Innovation management research has long recognized that technical superiority on its own seldom secures market acceptance. A firm can build technological potential, but that potential turns into adoption only when users see real value in it and decide to explore, adopt and use the new technology in everyday life. Functional and emotional value are examined in this light, as two routes through which a smartphone's innovative potential can either encourage or hold back users' technological innovativeness (Wang et al., 2022; Woodruff, 1997; Zeithaml, 1988; Zheng et al., 2025).

2.2. Perceived Functional Value

For technology-intensive products, perceived functional value means more than a simple judgement of usefulness. It reflects how well, in the user's eyes, a product's technical architecture delivers performance, reliability, ease of use and efficiency. Classical value theories describe value as a trade-off between benefits and costs. Technology adoption research adds that perceived usefulness and perceived ease of use are the main mechanisms through which technical features become behavioral intentions. The functional value of a smartphone is therefore not a matter of how many functions it has. What matters, then, is whether users feel that these functions help them get things done. A good interface and reliable performance are part of this, as is a phone that fits into daily routines without making technology feel more complicated than it needs to be (Davis, 1989; Sheth et al., 1991; Venkatesh et al., 2003, 2012; Woodruff, 1997; Zeithaml, 1988).

For innovation management the point is significant, because firms frequently bring out innovations faster than users can take them in. Building a new function solves only part of the problem; people still have to understand it, learn how to use it and make it part of their habits. Recent research on digital devices shows that innovations are rated more favourably when new technology is paired with familiar design principles and software that is intuitive to use. Research on mobile usability leads to a similar conclusion. Complexity can feel like a benefit or like a burden, and which of the two it becomes depends mostly on how effective, operable and easy to understand users find an application. Performance, interface quality, system stability and smooth integration thus sit at the heart of a smartphone's functional value and influence how users evaluate technological innovation (Huang & Benyoucef, 2026; Lu et al., 2026; Zhang et al., 2026).

The influence of functional value is not limited to the moment of first use. In digital services and mobile applications, it supports people's immediate intention to use a technology and gradually adds to the value they get from it over a longer period. Studies report that perceived value mediates the relationship between discoverability and adoption. They also show that functional value raises engagement and continued use, because it makes the experience more enjoyable and more rewarding in social terms. Functional value should therefore be regarded as more than a utilitarian attribute. Technological solutions create value partly through it, since it provides users with operational reliability and reduces the uncertainty they face when adopting something new (Blut et al., 2024; Jiang et al., 2022; Santos-Vijande et al., 2022; Sweeney & Soutar, 2001).

2.3. Perceived Emotional Value

Where functional value concerns what a technology allows users to do, emotional value concerns how it makes them feel and what kind of person it lets them be. This distinction is important in Technology and Innovation Management. Digital products compete on technical performance, but they also compete through the meanings attached to them, the experiences they provide and the identities users express

through them. A smartphone stays with its owner for most of the day. Its value therefore goes beyond efficiency: people enjoy using it, it gives them a sense of control, they appreciate how it looks, and it becomes a means of symbolic self-expression and an object of emotional attachment. None of this is a secondary or irrational add-on to technological utility. It is a large part of how people experience digital innovation and make sense of it (Hirschman & Holbrook, 1982; Holbrook, 1999; Wang et al., 2022).

Research on hedonic information systems and user experience makes clear that accepting a technology involves feelings as well as cognitive judgement. If using a technology is enjoyable, engaging, attractive or personally meaningful, people tend to explore its new functions, stay with it and work it into their routines. Studies of emotions in information technology adoption reach a similar conclusion, showing that emotional responses accompany use and also shape it. In technology-intensive settings, emotional value reduces the psychological distance between user and innovation. The technology no longer feels external or complicated; it becomes part of ordinary experience (Beaudry & Pinsonneault, 2010; Hassenzahl & Tractinsky, 2006; van der Heijden, 2004).

Studies of emotional attachment to mobile devices, smartphones especially, support this argument. Early work showed how the mobile phone turned into a tool for staying permanently in touch. Its emotional value came from a feeling of closeness to others, from the anxiety people felt when separated from it and from the symbolic role it played in their social relationships. More recent research goes as far as calling the smartphone a "significant other" and connects attachment to the device with interpersonal dependency and attachment patterns. Product attachment research adds that functionality and appearance both strengthen the emotional bond between user and product, which means the technical and the emotional cannot really be separated. In the case of smartphones, emotional value develops out of enjoyment and attachment, and out of the symbolic meaning the device carries and its role in how users construct their identity (Gritti et al., 2023; Mugge et al., 2010; Vincent, 2006).

Recent studies of digital technologies and augmented reality (AR) point in the same direction. Emotionally engaging experiences, including telepresence, flow, immersion and rich customer experiences, encourage continued use and greater openness to innovative applications. Read alongside research on product meaning in digital innovation, these findings suggest that emotional value is how digital products come to matter personally. Once a technology means something to users, adoption barriers are easier to overcome, because users see it as part of their own technological experience and not as a bundle of technical features (Santos-Vijande et al., 2022; Song et al., 2025; Wang et al., 2022).

2.4. Technological Innovativeness

In this study, technological innovativeness is defined as users' innovative orientation toward new technological solutions, rather than in terms of traditional consumer behavior. It refers to a relatively stable tendency to notice, evaluate, try, adopt and integrate technological innovations into one's own practices. From the standpoint of diffusion of innovations theory, this tendency is a micro-level precondition for diffusion: new solutions move from technical feasibility to wide use only if some users adopt them early. Technological innovativeness is therefore broader than wanting the latest device. It includes experimenting, learning, coping with uncertainty and accepting technological change (Agarwal & Prasad, 1998; Venkatesh et al., 2012).

This is especially true of smartphones, which go through continuous incremental and architectural innovation. Users do not make one adoption decision. They make a long series of small ones: trying a new application, moving to a new device, testing artificial intelligence features, changing how they interact with a platform, installing an update. Openness to technological innovation can thus be read as a willingness to move along with a product's technological path. The concept is closely related to personal innovativeness in the domain of information technology, technology readiness and motivated consumer innovativeness. Each of these describes a user's inner tendency to take part in technological change

actively instead of receiving it passively (Parasuraman, 2000; Parasuraman & Colby, 2015).

Openness to innovation cannot be taken for granted, however. Passive innovation resistance and barriers specific to a given innovation can weaken both adoption intentions and actual innovative behavior. Studies of smartphone users show that people may reject innovative digital solutions even when they have access to the technology, because of a mix of functional barriers, perceived utility, perceived hedonism, complexity and a general tendency to resist innovation. The propensity for technological innovation is best seen as the result of a tension between value drivers and resistance barriers. Perceived value matters strategically within this tension, since it can make an innovation feel meaningful and useful or leave it looking like an uncertain risk (Heidenreich & Kraemer, 2015).

2.5. Developing a Hypothesis on the Effect of Perceived Functional Value

The expectation is that perceived functional value will increase the propensity for technological innovation, since it makes the practical benefits of an innovation easier for users to see. Newness or technical sophistication rarely wins users over on its own. People turn to a technology when it proves useful, is easy to learn and helps with problems they really have. Research based on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and perceived value supports this view. It shows that perceived usefulness and ease of use reduce cognitive uncertainty, and that performance expectancy and value perceptions have the same effect; together, they make users more confident about adopting new technologies (Davis, 1989; Venkatesh et al., 2003, 2012; Zeithaml, 1988).

The smartphone is a good example. Recent research on digital devices finds that users react more positively to an innovation when it mixes the new with the familiar, and when software support lets new functions blend into the experience users already have. Mobile usability

studies trace favorable evaluations of mobile technologies back to perceived ease of use and effectiveness. Work on digital services and mobile applications adds that perceived value encourages adoption and that functional value later strengthens engagement. A phone with high perceived functional value therefore offers its user more than technical superiority. Once users notice how innovations improve their interactions in digital settings, they tend to conclude that adopting technological innovations in general is worthwhile (Huang & Benyoucef, 2026; Jiang et al., 2022; Lu et al., 2026; Santos-Vijande et al., 2022; Zhang et al., 2026).

A broader argument in innovation management points in the same direction, namely that technological opportunities produce value only when users can recognize them and put them to use. Users who consistently find their smartphone reliable, useful, well made and technically advantageous are more inclined to treat the next innovation as an improvement. It makes little difference whether that innovation is a new device, a software update, a digital service or an extra function. In each case, it is less likely to be resisted as a threat to familiar routines. Perceived functional value raises the propensity for technological innovation precisely because it changes how technological change is perceived, making it appear as a visible improvement in the user experience rather than a source of uncertainty (Blut et al., 2024; Corrocher & Paganuzzi, 2025; Zheng et al., 2025).

On this basis, the following hypothesis is proposed:

H_1: Perceived functional value has a positive effect on the propensity for technological innovation.

2.6. Developing a Hypothesis on the Effect of Perceived Emotional Value

A similar effect is expected from perceived emotional value, though it operates differently. Where functional value reduces uncertainty by showing users what an innovation can practically do for them, emotional value acts through engagement, personal meaning and the feeling of being close to a technology. Users who take pleasure in their smartphones, or

who see them as meaningful and as part of the way they present themselves to others, generally show more willingness to explore new functions. For them, a new feature is less a technical change than a continuation of an experience they already value (Hirschman & Holbrook, 1982; Holbrook, 1999; van der Heijden, 2004).

This reasoning finds support in research on emotions and user experience in information technology. Emotions shape technology use in direct as well as indirect ways. Pleasant interactions and hedonic qualities encourage people to keep using a technology, and they also make people more open to trying out new features. Studies of smartphone attachment show that the device can become an important relational object for its owner. Users who are more strongly attached to it interact with it more and are keener to maintain the relationship. Recent work on digital product innovation makes an additional observation: the meanings people assign to digital products are part of the innovation process itself, and do not simply result from marketing communication. In this light, emotional value can be treated as a strategic resource that helps users accept new technologies and build them into their identities and everyday lives (Beaudry & Pinsonneault, 2010; Gritti et al., 2023; Mugge et al., 2010; Vincent, 2006; Wang et al., 2022).

Evidence from augmented reality and mobile application research strengthens the argument. Emotionally engaging digital experiences have been found to improve user retention, and individual innovativeness increases the positive effects of immersive technologies. For this study, the implication is that emotional value adds to functional value instead of substituting for it. Because it stimulates curiosity, exploratory behavior and intrinsic motivation, emotional value makes users actively want technological innovation instead of merely putting up with it. The smartphone market changes continuously, and in such a setting perceived emotional value can be expected to act as an important antecedent of the propensity for technological innovation. It helps users keep pace with the changes that keep coming (Santos-Vijande et al., 2022; Song et al., 2025).

On this basis, the following hypothesis is proposed:

H_2: Perceived emotional value has a positive effect on the propensity for technological innovation.

3. Methodology

3.1. Research Design

The study used a quantitative, explanatory, cross-sectional design. A quantitative approach made it possible to measure the relationships between the model's variables with numerical data and to test the hypotheses statistically. The design is explanatory because it examines the effects of perceived functional and emotional value on consumers' propensity for technological innovation, and cross-sectional because all data were collected at one point in time. The hypotheses were tested with survey data, and the research model was analysed using multiple linear regression.

3.2. Research Model

The conceptual model draws on theoretical work in Technology and Innovation Management that explains how perceived value influences consumer behavior. Perceived functional value and perceived emotional value are the independent variables, and the propensity for technological innovation is the dependent variable. The model is designed to examine how the two value dimensions influence consumers' propensity for technological innovation in the context of technology-intensive products. Figure 1 shows the proposed relationships.

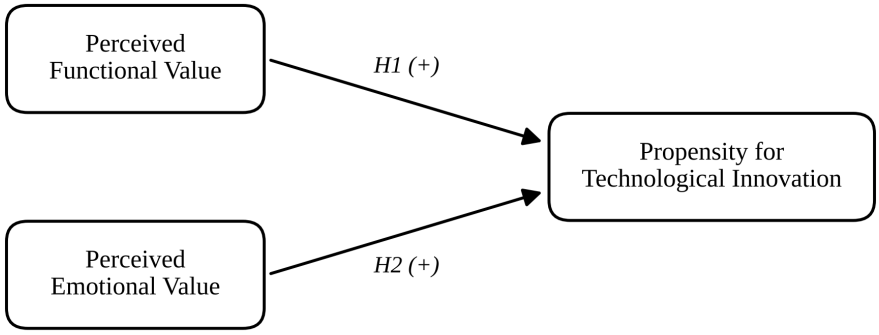


Figure 1. Research Model

3.3. Research Hypotheses

Following the model in Figure 1, the study tests the two hypotheses developed in Section 2 (H_1 and H_2) on the effects of perceived functional and emotional value on the propensity for technological innovation.

3.4. Population and Sample

The target population was graduate students at Istanbul Beykent University. The required sample size was calculated with the formula below, assuming a 95% confidence level and a ±4% margin of error (Yükselen, 2017):

$$n = p \times q \times (Z/e)^2$$

where $p = .50$, $q = .50$, $Z = 1.96$, and $e = \pm.04$.

$$n = .50 \times .50 \times (1.96/.04)^2 \approx 600 \text{ participants}$$

With these parameters ($p = .50$, $q = .50$, $Z = 1.96$, $e = \pm.04$), the minimum sample size came to 600 participants. Data collection produced 604 valid questionnaires. Two items had one missing response each (KAL5 and DUYDER2), and the two cases concerned were removed by listwise deletion. The exploratory factor analysis (EFA), reliability analysis, confirmatory factor analysis (CFA), correlation analysis and multiple

regression analysis were therefore all run on $n = 602$, which still meets the calculated minimum.

Participants were reached through convenience sampling. Graduate students were chosen because they use smartphones heavily for study, work, communication and everyday tasks and have enough experience to compare different technological options. They can judge both the functional features of their phones and the emotional benefits of using them, which makes them a suitable group for studying perceived functional value, perceived emotional value and the propensity for technological innovation. Students were drawn from several graduate programs to increase variety in educational background, occupation and user experience. Only responses from active smartphone users were included in the final analysis.

3.5. Data Collection Process and Measurement Instruments

The data come from a structured questionnaire. Before taking part, respondents were informed about the aim of the study, and participation was entirely voluntary. The questionnaire was given only to active smartphone users, and forms that were incomplete or filled in incorrectly were not used. Screening left 604 valid questionnaires. Two of these had a missing response on a scale item and were dropped, so the analyses that follow are based on 602 cases.

To measure perceived value, the scale developed by Tümen (2011) was adapted. Of its dimensions, we kept perceived functional value and perceived emotional value, each measured with five items; monetary value was not included, as it had no direct bearing on the research question. The propensity for technological innovation was measured with a scale adapted from Suh and Yi (2006), which originally contained three items. In the exploratory factor analysis (EFA), one of these items loaded on more than one factor, so it was removed and two items were retained. Responses to all items were given on a five-point Likert scale, with 1 meaning “Strongly disagree” and 5 meaning “Strongly agree”.

Because the scales were used in a new sample, their validity and reliability were checked again. This involved an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA), as well as the calculation of Cronbach's alpha, composite reliability (CR), average variance extracted (AVE) and the heterotrait–monotrait ratio (HTMT). These results are presented in the Findings section.

The survey was conducted in 2016, some years before the present manuscript was prepared, and this gap may be regarded as a limitation. Perceived functional value, perceived emotional value and technological innovativeness are, however, fairly stable psychological and behavioral tendencies. They do not depend on a particular generation of devices or a specific software version, which is why the findings can still be considered relevant. The conceptual framework, the literature review, the hypotheses and the analytical approach have all been revised in light of recent research in Technology and Innovation Management so that the study reflects the current state of the field.

3.6. Data Analysis

All analyses were carried out in Python. The dataset was first checked for missing values, data entry errors and outliers. The two cases with missing responses on scale items were removed listwise, and every analysis was run on $n = 602$. Frequencies, percentages, means and standard deviations were used to describe the participants' demographic characteristics and the research variables.

Exploratory factor analysis (EFA) was used first to assess construct validity. Sampling adequacy was checked with the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. Once the factor structure was established, internal consistency was assessed with Cronbach's alpha.

The structure from the EFA was then tested with confirmatory factor analysis (CFA). Convergent validity was evaluated with composite reliability (CR) and average variance extracted (AVE), and discriminant validity with the heterotrait–monotrait ratio (HTMT). Pearson correlations were computed to describe the linear relationships among the

variables, and the hypotheses were tested with multiple linear regression. The main regression assumptions (normality of residuals, homoscedasticity, independence of errors, multicollinearity and influential observations) were also checked. Because the homoscedasticity tests gave mixed results, the coefficients were re-estimated with heteroscedasticity-consistent (HC3) standard errors (Long & Ervin, 2000). The significance level was set at $p < .05$. Since all constructs came from the same self-report questionnaire administered at one time, Harman's single-factor test was used to look for possible common method bias.

4. Findings

4.1. Demographic Characteristics of the Participants

Table 1 summarises the participants' demographic characteristics. Of the 602 respondents in the analytic sample, 54.5% were female (n = 328) and 45.5% male (n = 274). By age, 34.9% were 20–25, 30.1% were 26–30, 22.4% were 31–35, and 12.6% were 36 or older. The sample thus covers users of technology-intensive products from several age groups and both genders.

Table 1. Demographic characteristics of the participants (n = 602)

Variable	Category	*n*	%
Gender	Male	274	45.5
	Female	328	54.5
Age	20–25	210	34.9
	26–30	181	30.1
	31–35	135	22.4
	36 or older	76	12.6

4.2. Exploratory Factor Analysis

Exploratory factor analysis (EFA) was used to assess the construct validity of the scales. The analysis was run in Python with the factor_analyzer library, using minimum residual (minres) extraction and Varimax orthogonal rotation. Before the analysis, the suitability of the data

was checked with the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity.

All 13 items were entered at first. Item IMAJ3 loaded at similar levels on two factors (.425 and .409). Because cross-loading items weaken construct validity, it was dropped and the EFA was repeated with the remaining 12 items.

The final analysis used data from the 602 participants without missing values, the same sample used in all later analyses. The KMO value was .890, and Bartlett's test was significant ($\chi^2(66) = 5493.87$, $p < .001$), so the data were suitable for factor analysis.

After Varimax rotation, a three-factor structure emerged that matched the theoretical model. Loadings ranged from .751 to .852 for perceived emotional value, from .702 to .826 for perceived functional value and from .735 to .985 for the propensity for technological innovation. The three factors together explained 72.6% of the total variance. With all loadings above the recommended threshold and a satisfactory level of explained variance, the three-dimensional structure supports the theoretical model and shows adequate construct validity.

Table 2. Final exploratory factor analysis results (n = 602, minres, varimax)

Item	Perceived Emotional Value	Perceived Functional Value	Propensity for Technological Innovation
DUYDER1	.783		
DUYDER2	.852		
DUYDER3	.820		
DUYDER4	.827		
DUYDER5	.751		
KAL1		.758	
KAL2		.826	
KAL3		.702	
KAL4		.807	
KAL5		.765	

CTILG8	.985
CTILG9	.735

Note: KMO measure of sampling adequacy = .890, Bartlett's test of sphericity: $\chi^2(66) = 5493.87$, $p < .001$, total variance explained = 72.6%. Loadings below .40 are not shown.

4.3. Reliability Analysis

Cronbach's alpha was then calculated to assess internal consistency. Values of .70 or higher are generally taken to indicate acceptable reliability (Hair et al., 2019; Kline, 2023).

Alpha was .913 for perceived functional value, .934 for perceived emotional value and .860 for the propensity for technological innovation. All three exceed the threshold, so the scales show high internal consistency. Table 3 reports the results.

Table 3. Reliability analysis results (n = 602)

Dimension	Number of Items	Cronbach's Alpha
Perceived Functional Value	5	.913
Perceived Emotional Value	5	.934
Propensity for Technological Innovation	2	.860

4.4. Confirmatory Factor Analysis

A confirmatory factor analysis (CFA) was then run on the 602 observations to test the measurement model. It was estimated in Python with the *semopy* library using maximum likelihood. Standardized loadings ranged from .768 to .898, and every item represented its latent variable adequately (see Table 5). The propensity for technological innovation construct was left with two items after the cross-loading item was removed at the EFA stage. Both items still loaded strongly (.851–.886), and the construct reached satisfactory composite reliability (CR = .860) and average variance extracted (AVE = .755), so the shorter item set appears to measure the construct adequately.

Model fit was judged on several types of indices rather than on any single one (Hu & Bentler, 1999; Kline, 2023). The values were: $\chi^2(51) = 318.01$, $p < .001$, $\chi^2/df = 6.24$, CFI = .951, TLI = .937, GFI = .943, AGFI = .926, NFI = .943, RMSEA = .093 (90% CI [.084, .103]), SRMR = .035. SRMR is well under the ≤ .08 cut-off for good fit, and CFI is above the ≥ .95 cut-off (Hu & Bentler, 1999). TLI, GFI, AGFI and NFI meet the ≥ .90 criterion for acceptable fit (Schermelleh-Engel et al., 2003). The χ^2/df ratio of 6.24, on the other hand, is above both the ≤ 3 criterion (Schermelleh-Engel et al., 2003) and the more lenient ≤ 5 limit used by some authors (Marsh & Hocevar, 1985). The chi-square statistic is sensitive to sample size and tends to inflate this ratio in large samples (Kline, 2023), but the value should still be read as a sign of poor fit. RMSEA (.093) falls in the "mediocre" range (.08–.10) in MacCallum et al.'s (1996) classification, and the upper limit of its confidence interval (.103) is slightly above .10. In short, fit is acceptable on the incremental and residual-based indices but only mediocre on χ^2/df and RMSEA. No error covariances were added, since there was no theoretical reason for them and adding them would only have fitted the model to this sample. The issue is taken up again in the limitations. Table 4 lists the fit indices.

Standardized loadings ranged from .768 to .878 for perceived functional value, from .821 to .898 for perceived emotional value and from .851 to .886 for the propensity for technological innovation. All loadings exceed the recommended threshold, so the observed variables represent their latent constructs adequately. The factor structure supports the theoretical model, but the overall fit of the measurement model should be interpreted cautiously given the limitations noted above.

Table 4. Confirmatory factor analysis fit indices (n = 602)

Index	Value	Criterion (source)	Result
χ^2/df	6.24	≤ 2 good, ≤ 3 acceptable (Schermelleh-Engel et al., 2003), lenient criterion ≤ 5 (Marsh & Hocevar, 1985)	Above thresholds
CFI	.951	≥ .95 good, ≥ .90 acceptable (Hu & Bentler, 1999)	Good fit
TLI	.937	≥ .95 good, ≥ .90 acceptable (Hu & Bentler, 1999)	Acceptable
GFI	.943	≥ .95 good, ≥ .90 acceptable (Schermelleh-Engel et al., 2003)	Acceptable
AGFI	.926	≥ .90 good, ≥ .85 acceptable (Schermelleh-Engel et al., 2003)	Good fit
NFI	.943	≥ .95 good, ≥ .90 acceptable (Schermelleh-Engel et al., 2003)	Acceptable
RMSEA [90% CI]	.093 [.084, .103]	≤ .05 good, .05–.08 acceptable, .08–.10 mediocre, > .10 poor (MacCallum et al., 1996)	Mediocre
SRMR	.035	≤ .08 good (Hu & Bentler, 1999)	Good fit

Note: $\chi^2(51) = 318.01$, $p < .001$. CI = confidence interval.

Table 5. Standardized factor loadings from the confirmatory factor analysis

Dimension	Item	Standardized Factor Loading
Perceived Functional Value	KAL1	.810
	KAL2	.878
	KAL3	.768
	KAL4	.831
	KAL5	.834
Perceived Emotional Value	DUYDER1	.841
	DUYDER2	.898
	DUYDER3	.869
	DUYDER4	.870
	DUYDER5	.821
Propensity for Technological Innovation	CTILG8	.886
	CTILG9	.851

Note: All loadings are significant at $p < .001$.

4.5. Convergent and Discriminant Validity

Convergent and discriminant validity were assessed next. For convergent validity, composite reliability (CR) and average variance extracted (AVE) were used, CR above .70 and AVE above .50 are the usual benchmarks (Fornell & Larcker, 1981; Hair et al., 2019).

Perceived functional value had CR = .914 and AVE = .681, perceived emotional value had CR = .934 and AVE = .740, and the propensity for technological innovation had CR = .860 and AVE = .755. All values exceed the benchmarks, so convergent validity is supported.

Discriminant validity was assessed with the heterotrait–monotrait ratio (HTMT). Values below .85 (strict criterion) or .90 (lenient criterion) indicate that constructs are sufficiently distinct (Henseler et al., 2015). The HTMT values ranged from .287 to .631, all below both thresholds. Convergent and discriminant validity are therefore both supported. Table 6 presents the results.

Table 6. Convergent and discriminant validity results

Panel A. Reliability and Convergent Validity			
Construct	**Cronbach's Alpha**	**CR**	**AVE**
Perceived Functional Value	.913	.914	.681
Perceived Emotional Value	.934	.934	.740
Propensity for Technological Innovation	.860	.860	.755

Panel B. HTMT Values			
Constructs	**Functional**	**Emotional**	**Technological Innovation**
Functional	—		
Emotional	.631	—	
Technological Innovation	.301	.287	—

Note: The results of Harman's single-factor test for common method bias are reported separately in Section 4.9.

4.6. Descriptive Statistics and Correlation Analysis

Table 7 gives the descriptive statistics and Pearson correlations. Mean scores were 3.838 (SD = 0.937) for perceived functional value, 3.815 (SD = 1.007) for perceived emotional value and 3.320 (SD = 1.299) for the propensity for technological innovation.

Perceived functional value and perceived emotional value were moderately and positively correlated (r = .582, p < .001). The propensity for technological innovation was positively and significantly correlated with perceived functional value (r = .267, p < .001) and with perceived emotional value (r = .257, p < .001).

All correlations run in the expected direction, which provides a sound basis for the regression analysis.

Table 7. Descriptive statistics and correlation analysis (n = 602)

Variable	*M*	*SD*	1	2	3
1. Perceived Functional Value	3.838	0.937	—		
2. Perceived Emotional Value	3.815	1.007	.582***	—	
3. Propensity for Technological Innovation	3.320	1.299	.267***	.257***	—

***p < .001.

4.7. Hypothesis Testing

The hypotheses were tested with multiple linear regression. The model as a whole was significant (F(2, 599) = 28.48, p < .001) and explained 8.7% of the variance in the propensity for technological innovation (R^2 = .087, adjusted R^2 = .084).

Perceived functional value had a positive and significant effect on the propensity for technological innovation (B = 0.245, SE = 0.067, β = .177, t = 3.68, p < .001), so H_1 is supported.

Perceived emotional value also had a positive and significant effect (B = 0.199, SE = 0.062, β = .155, t = 3.22, p = .001), so H_2 is supported as well. Both effects stayed significant with heteroscedasticity-consistent (HC3) standard errors (functional value: t = 3.41, p < .001, emotional value: t = 2.94, p = .003). The standardized coefficients show that the two effects are small and of similar size. Full results are given in Table 8.

Table 8. Regression analysis results for hypothesis testing (n = 602)

Independent Variable	*B*	*SE*	β	*t*	*p*	95% CI (*B*)
Constant	1.620	0.231	—	7.01	< .001	[1.167, 2.074]
Perceived Functional Value	0.245	0.067	.177	3.68	< .001	[0.114, 0.375]
Perceived Emotional Value	0.199	0.062	.155	3.22	.001	[0.078, 0.321]

Note: Dependent variable: Propensity for Technological Innovation. B = unstandardized coefficient, SE = standard error, β = standardized coefficient, CI = confidence interval. R^2 = .087, adjusted R^2 = .084, $F(2, 599) = 28.48$, p < .001. H_1 and H_2 are supported.

4.8. Testing the Assumptions of the Regression Model and Diagnostics

The main assumptions of multiple linear regression were checked through residual analysis and diagnostic statistics (Hair et al., 2019).

Multicollinearity: The variance inflation factor (VIF) was 1.51 and tolerance was .66 for both perceived functional value and perceived emotional value. These values meet the usual criteria (VIF < 10, tolerance > .10) (Hair et al., 2019), so multicollinearity is not a concern.

Normality of residuals: Residual skewness (−0.38) and kurtosis (−0.76) were within ±1. The Shapiro–Wilk test did indicate a significant departure from normality (W = .966, p < .001), but this test is known to flag even small deviations in large samples. With n = 602, the departure is unlikely to affect the coefficient estimates in any meaningful way (Hair et al., 2019).

Homoscedasticity: The Breusch–Pagan test found no heteroscedasticity ($\chi^2(2) = 1.03$, $p = .598$), whereas the more general White test was marginally significant ($\chi^2(5) = 12.20$, $p = .032$). The model was therefore re-estimated with HC3 heteroscedasticity-consistent standard errors (Long & Ervin, 2000), and both coefficients remained significant (Section 4.7).

Independence of errors: The Durbin–Watson statistic was 1.62, inside the commonly accepted range of 1.5 to 2.5.

Linearity and influential observations: The Ramsey RESET test was marginally significant ($F(1, 598) = 4.19$, $p = .041$). The added nonlinear term explained only about 0.6% more variance, however, so the linear model was kept. No standardized residual lay outside ±3, and the largest Cook's distance was .035 (< 1), so no single observation had an undue influence on the results.

Overall, the diagnostics suggest that the regression estimates can be relied on. The small departures from normality and homoscedasticity did not change the results once robust estimates were used.

4.9. Common Method Bias

All constructs were measured with the same self-report questionnaire at a single point in time, so common method bias (CMB) is a possible concern (Podsakoff et al., 2003). Harman's single-factor test was used to assess it: the 12 items of the final measurement model were entered into an unrotated principal component analysis. The first component (eigenvalue = 6.28) accounted for 52.3% of the total variance. This is above the 50% level often used as a warning sign, so common method variance may have influenced the observed relationships to some degree, and the result should be read with caution. Harman's test is also a blunt instrument. Its sensitivity is limited, and on its own it can neither confirm nor rule out common method bias (Fuller et al., 2016; Podsakoff et al., 2003).

The HTMT results in Section 4.5 address a separate question. Because all HTMT values (.287–.631) are below .85, the three constructs can be told apart empirically, which establishes discriminant validity (Henseler et al., 2015). HTMT does not, however, measure common method bias directly, and good discriminant validity should not be taken as evidence that such bias is absent.

Given the single-source, cross-sectional design, the possibility of common method variance cannot be excluded, and the strength of the reported relationships should be interpreted with this in mind. The Conclusion returns to this limitation and to the need for designs that separate the measurement of predictor and criterion variables in time or by procedure.

5. Discussion

The overall picture is consistent. For technology-intensive products, both perceived functional value and perceived emotional value are positively related to users' propensity for technological innovation. This is easy to miss in a market that competes on specification sheets and feature lists: technical superiority does not guarantee that users will take up what a product offers. The value users actually experience when they use the technology seems to matter more. The result agrees broadly with earlier work on perceived value and technology acceptance (Davis, 1989; Sheth et al., 1991; Venkatesh et al., 2003; Venkatesh et al., 2012) and with more recent studies (Kowalczuk & Hof, 2025; Lee & Yoon, 2025). What this study adds is a step further in the same logic. Perceived value is shown to explain whether a person adopts one particular technology and, beyond that, how willing they are to keep up with future technological change.

The size of the effects needs to be stated plainly. The two value dimensions explained only 8.7% of the variance in the propensity for technological innovation ($R^2 = .087$), and the standardized coefficients ($\beta = .177$ and $\beta = .155$) point to small effects. Much of what drives users' openness to innovation clearly lies outside this model. Perceived social value, technology readiness and individual innovativeness are obvious

candidates for future studies. On the other hand, the sample was large (n = 602), the effects held up with robust standard errors and their direction matched theoretical expectations. Taking into account the possibility of common method variance and the mediocre fit of the measurement model (Sections 4.4 and 4.9), the findings are best seen as one meaningful piece of a larger picture, to be interpreted with some caution.

The positive effect of perceived functional value suggests that users judge new technologies first in practical terms: what will this actually do for me? This matches the perceived usefulness construct of the Technology Acceptance Model (Davis, 1989) and performance expectancy in UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2012). It also fits more recent work that puts performance, ease of use and functional utility at the center of how users evaluate technology (Lee & Yoon, 2025; Shen et al., 2026; Wang et al., 2022). Earlier studies mostly stopped at acceptance, purchase intention or continued use. Here, functional value is also linked to users' general openness to innovation. It seems to do more than switch technology use on, it helps make people willing to adopt whatever comes next.

Perceived emotional value adds a complementary explanation. Its positive, significant effect shows that technology use is seldom a purely rational weighing of costs and benefits. The feelings and personal meanings people attach to their devices matter as well. This is consistent with the emotional value dimension of the Theory of Consumption Values (Sheth et al., 1991), with the PERVAL model (Sweeney & Soutar, 2001) and, more broadly, with research on user experience and hedonic motivation (Beaudry & Pinsonneault, 2010; Hassenzahl & Tractinsky, 2006). Recent studies of emotional attachment to smart devices point the same way (Kowalczuk & Hof, 2025; Shen et al., 2026). The pattern is not the same for every technology, though. In their study of AI-based digital humans, Tang and Son (2025) found that functional value counted for relatively little and that cognitive and emotional value did most of the work. The relative weight of functional and emotional value probably depends on the kind of technology involved. With something as

embedded in daily life as a smartphone, the two seem to work side by side, while for more experience-driven technologies emotional value may weigh more heavily. Either way, the present findings suggest that emotional value affects how open people stay to future technologies, and not just how they use technology now.

More generally, the results cannot be explained by technical features alone. Whether a technological innovation succeeds seems to depend less on its raw potential than on the value users get from it. This fits the digital innovation literature, which sees innovation as emerging from the interaction of technology, users and value creation (Nambisan et al., 2017; Yoo et al., 2010). Recent work on technology-intensive markets also observes that competitive advantage increasingly comes from value created through user experience (Ferreira et al., 2025; Ray et al., 2026), and the present results are in line with that view.

The study makes three contributions. It brings perceived functional value and perceived emotional value into one model as antecedents of technological innovativeness instead of examining them separately. It shows that the reach of perceived value extends past acceptance and use to users' wider openness to future innovations. And it offers a more integrated view of Technology and Innovation Management, in which lasting success depends on turning advanced technologies into products users find meaningful, useful and emotionally engaging, as well as on building those technologies in the first place.

6. Conclusion

Users' propensity for technological innovation in technology-intensive products depends, significantly but modestly, on the value they perceive in those technologies. Both perceived functional value and perceived emotional value had positive, significant effects on users' openness to innovation. Technical superiority alone is not enough to secure adoption, what counts is whether users find a technology useful and meaningful and believe it can give them a good experience.

For the Technology and Innovation Management literature, the study shows that perceived value helps explain users' underlying propensity to adopt future innovations, in addition to acceptance and use. For managers of technology-intensive products, the practical message is that technological performance is not decisive on its own. Investment in the experiences and product attributes that create functional and emotional value is just as justified. In these markets, helping users recognize and feel that value appears to matter as much as building more advanced technology.

The study has several limitations. The data were collected in 2016, at a single point in time, from a convenience sample of graduate students at one university, which limits both generalisability and causal inference. All constructs were measured with the same self-report questionnaire, and the first factor in Harman's single-factor test accounted for 52.3% of the total variance, common method variance may therefore have influenced the observed relationships to some extent (Podsakoff et al., 2003). Future studies should separate the measurement of predictor and criterion variables in time or by procedure, include a marker variable or model a latent method factor. The measurement model fitted only moderately well on χ^2/df and RMSEA, and the propensity for technological innovation was measured with only two items, so the measurement results call for caution. Lastly, the model was deliberately restricted to perceived functional and emotional value as antecedents of technological innovativeness. Future research could test the same relationships for other technology-intensive product categories and in other cultural settings, ideally with longitudinal designs. The model could also be widened to include perceived social value, epistemic value, technology readiness or individual innovativeness, which would give a fuller account of what drives users' propensity for technological innovation.

Declarations

Ethics Committee Approval: The data for this study were collected in 2016 as part of the author's doctoral dissertation research. In Türkiye, the requirement for survey-based social science research to obtain institutional

ethics committee approval became binding for higher education institutions only from 2020 onwards. Because no such requirement existed at the time of data collection, no application for ethics committee approval was made for this study. Nevertheless, the study was conducted in accordance with the ethical principles of the Declaration of Helsinki: participation was voluntary, respondents were informed of the purpose of the study before participating, and all responses were collected anonymously.

Use of Artificial Intelligence: In this chapter, artificial intelligence tools were utilized for translation purposes. The author retains full responsibility for the content of the chapter.

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References

Adner, R. (2006). Match your innovation strategy to your innovation ecosystem. *Harvard Business Review, 84*(4), 98-107.

Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. *Journal of Management, 43*(1), 39-58. https://doi.org/10.1177/0149206316678451

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research, 9*(2), 204-215. https://doi.org/10.1287/isre.9.2.204

Beaudry, A., & Pinsonneault, A. (2010). The other side of acceptance: Studying the direct and indirect effects of emotions on information technology use. *MIS Quarterly, 34*(4), 689-710. https://doi.org/10.2307/25750701

Blut, M., Chaney, D., Lunardo, R., Mencarelli, R., & Grewal, D. (2024). Customer perceived value: A comprehensive meta-analysis. *Journal of Service Research, 27*(4), 501-524. https://doi.org/10.1177/10946705231222295

Corrocher, N., & Paganuzzi, S. (2025). Planned obsolescence and smartphone replacement: Empirical evidence on the Italian market. *Telecommunications Policy, 49*(8), 103022. https://doi.org/10.1016/j.telpol.2025.103022

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Ferreira, C., Lind, F., Pedersen, A.-C., & Eriksson, V. (2025). Value creation from combining digital and non-digital resources: The case of "smart products." *Industrial Marketing Management, 125*, 60-70. https://doi.org/10.1016/j.indmarman.2024.12.013

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research, 69*(8), 3192-3198. https://doi.org/10.1016/j.jbusres.2015.12.008

Gritti, E. S., Bornstein, R. F., & Barbot, B. (2023). The smartphone as a "significant other": Interpersonal dependency and attachment in maladaptive smartphone and social networks use. *BMC Psychology, 11*, 296. https://doi.org/10.1186/s40359-023-01339-4

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hassenzahl, M., & Tractinsky, N. (2006). User experience—A research agenda. *Behaviour & Information Technology, 25*(2), 91-97. https://doi.org/10.1080/01449290500330331

Heidenreich, S., & Kraemer, T. (2015). Passive innovation resistance: The curse of innovation? Investigating consequences for innovative consumer behavior. *Journal of Economic Psychology, 51*, 134-151. https://doi.org/10.1016/j.joep.2015.09.003

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic consumption: Emerging concepts, methods and propositions. *Journal of Marketing, 46*(3), 92-101. https://doi.org/10.1177/002224298204600314

Holbrook, M. B. (Ed.). (1999). *Consumer value: A framework for analysis and research*. Routledge.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Huang, Z., & Benyoucef, M. (2026). User perception of mobile application usability: Do individual differences matter? *Cognitive Systems Research, 97*, 101459. https://doi.org/10.1016/j.cogsys.2026.101459

Jiang, L., Zhou, W., Ren, Z., & Yang, Z. (2022). Make the apps stand out: Discoverability and perceived value are vital for adoption. *Journal of Research in Interactive Marketing, 16*(4), 494-513. https://doi.org/10.1108/JRIM-03-2021-0076

Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). The Guilford Press.

Kowalczuk, P., & Hof, N. (2025). The customer's perceived value-in-use of voice-assisted smart products and its impact on continuance intention: A trade-off between benefits and costs. *Journal of Product & Brand Management, 34*(5), 690-706. https://doi.org/10.1108/JPBM-08-2023-4670

Lee, J., & Yoon, S.-J. (2025). Exploring consumers' innovative products adoption process: Based on technology readiness and value-based adoption. *The International Review of Retail, Distribution and Consumer Research, 35*(4), 405-422. https://doi.org/10.1080/09593969.2024.2414086

Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity consistent standard errors in the linear regression model. *The American Statistician, 54*(3), 217-224. https://doi.org/10.1080/00031305.2000.10474549

Lu, Z., Dou, Y., Wu, D. J. J., & Chen, J. (2026). Leveraging network effects for connected products: Strategies and implications for the value chain. *MIS Quarterly, 50*(2), 641-672. https://doi.org/10.25300/MISQ/2025/18441

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130-149. https://doi.org/10.1037/1082-989X.1.2.130

Marsh, H. W., & Hocevar, D. (1985). Application of confirmatory factor analysis to the study of self-concept: First- and higher order factor models and their invariance across groups. *Psychological Bulletin, 97*(3), 562-582. https://doi.org/10.1037/0033-2909.97.3.562

Mugge, R., Schifferstein, H. N. J., & Schoormans, J. P. L. (2010). Product attachment and satisfaction: Understanding consumers' post-purchase behavior. *Journal of Consumer Marketing, 27*(3), 271-282. https://doi.org/10.1108/07363761011038347

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly, 41*(1), 223-238. https://doi.org/10.25300/MISQ/2017/41:1.03

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307-320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research, 18*(1), 59-74. https://doi.org/10.1177/1094670514539730

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review, 92*(11), 64-88.

Ray, R. K., Singh, A., & Dash, D. P. (2026). Quantifying consumer perceptions in smartwatch markets: Integrating aspect-based sentiment analysis with panel data modelling. *Journal of Enterprise Information Management*. https://doi.org/10.1108/JEIM-05-2025-0403

Santos-Vijande, M. L., Gómez-Rico, M., Molina-Collado, A., & Davison, R. M. (2022). Building user engagement to mHealth apps from a learning perspective: Relationships among functional, emotional and social drivers of user value. *Journal of Retailing and Consumer Services, 66*, 102956. https://doi.org/10.1016/j.jretconser.2022.102956

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online, 8*(2), 23-74.

Shen, J., Li, H., Phantumabamrung, P., Qiu, Y., Sun, W., Xiong, S., & Wang, Y. (2026). Beyond functionality: How perceived value shapes purchase intention for smart wearable fitness devices?. *International Journal of Sports Marketing and Sponsorship*. https://doi.org/10.1108/IJSMS-07-2025-0306

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. *Journal of Business Research, 22*(2), 159-170. https://doi.org/10.1016/0148-2963(91)90050-8

Song, J., Wang, Q., & Yi, H.-T. (2025). The impact of AR app characteristics on telepresence, customer experience, and continued app usage intention: The moderating effect of consumer innovativeness. *Journal of Retailing and Consumer Services, 87*, 104385. https://doi.org/10.1016/j.jretconser.2025.104385

Suh, J. C., & Yi, Y. (2006). When brand attitudes affect the customer satisfaction-loyalty relation: The moderating role of product involvement. *Journal of Consumer Psychology, 16*(2), 145-155. https://doi.org/10.1207/s15327663jcp1602_5

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing, 77*(2), 203-220. https://doi.org/10.1016/S0022-4359(01)00041-0

Tang, Y., & Son, H. (2025). How perceived value drives usage intention of AI digital human advisors in digital finance. *Systems, 13*(11), 973. https://doi.org/10.3390/systems13110973

Tümen, G. (2011). *Tüketicilerin tercih ettiği cep telefonu markasına ilişkin algılanan değer farklılıklarının belirlenmesine yönelik bir pilot araştırma* [Yüksek lisans tezi]. İstanbul Üniversitesi.

van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly, 28*(4), 695-704. https://doi.org/10.2307/25148660

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. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Vincent, J. (2006). Emotional attachment and mobile phones. *Knowledge, Technology & Policy, 19*(1), 39-44. https://doi.org/10.1007/s12130-006-1013-7

Wang, G., Henfridsson, O., Nandhakumar, J., & Yoo, Y. (2022). Product meaning in digital product innovation. *MIS Quarterly, 46*(2), 947-976. https://doi.org/10.25300/MISQ/2022/15252

Woodruff, R. B. (1997). Customer value: The next source for competitive advantage. *Journal of the Academy of Marketing Science, 25*(2), 139-153. https://doi.org/10.1007/BF02894350

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research, 21*(4), 724-735. https://doi.org/10.1287/isre.1100.0322

Yükselen, C. (2017). *Pazarlama araştırmaları* (7. baskı). Detay Yayıncılık.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing, 52*(3), 2-22. https://doi.org/10.1177/002224298805200302

Zhang, N., Boh, W. F., & Lee, G. (2026). Consumer evaluation of digital device innovations: Disentangling effects of novelty and familiarity. *MIS Quarterly, 50*(2), 557-588. https://doi.org/10.25300/MISQ/2025/18750

Zheng, J., Zhang, J. Z., Kamal, M. M., Wang, H., Yang, Y., Dey, B., & Apostolidis, C. (2025). Empowering radical innovation: How digital technologies drive knowledge transfer and co-creation in innovation ecosystems. *R&D Management, 55*(5), 1444-1458. https://doi.org/10.1111/radm.12764