

Impact of Disruptive Technological Innovation on Consumer Behavior



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Abstract: *This paper considers how disruptive technological innovation affects consumer behavior, in the light of the increasing need to know how emotional and cognitive aspects of decision-making influence technology-driven decision-making. Structured survey was used as a measureable, cross-sectional investigation design to gather the data of digital consumers. The study used the Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized conceptual framework, with mediation and moderation effects of major constructs. The results reveal that attitude ($\beta = 0.385$, $p < 0.001$), trust ($\beta = 0.290$, $p < 0.001$), and perceived value ($\beta = 0.202$, $p < 0.05$) significantly influence behavioral intention, which strongly predicts consumer behavior ($\beta = 0.859$, $p < 0.001$). Perceived novelty and enjoyment are significant indirectly, whereas perceived usefulness is not that significant. The moderating result of digital literacy was create to be not important. The research is valuable as it combines TAM, TPB, and SOR into a single framework and emphasizes the prevalence of emotion-based motivation over functionality considerations. It offers useful considerations on how to create and design interactive, trust-based online experiences and recommends research on other moderators.*

Keywords: Disruptive Technological Innovation, Consumer Behavior, Behavioral Intention, Perceived Value, Trust, Attitude, Digital Literacy, PLS-SEM

Introduction

Disruptive technological innovation (DTI) has been a major issue that has altered the contemporary consumer markets by modifying the way people engage with products, services, and the digital ecosystem. Artificial intelligence (AI), machine learning, and automation are some of the technologies that have helped companies develop personalized, data-driven experiences that directly influence consumer perceptions and behaviours'. As an example, Hermann and Puntoni (2024) articulate that AI-based systems help improve predictability and enhance customer relationships, whereas Kamal et al. (2024) point out the importance of predictive analytics and real-time data processing in strategic decision formation. In the same manner, previous research by Hair et al. (2021) and Henseler et al. (2020) point out that technological changes have transformed conventional consumption behaviors into digitally connected and analytically driven systems.

The fact that disruptive technologies have evolved at a fast rate has influenced various industries, especially those driven by digital platforms, artificial intelligence (AI), and data analytics. E-commerce, financial technology (FinTech), smart devices, and digital services are some of the industries that have seen unprecedented growth following the adoption of AI-based systems and automation. Hermann and Puntoni (2024), in particular, point out that AI provides companies with opportunities to better manage interactions with customers and customize services, whereas Iqbal et al. (2025) note that intelligent systems and digital influence mechanisms can help companies enhance consumer engagement and purchase decisions.

Although disruptive technological innovation is rapidly adopted in various industries, there is still a gap in knowledge regarding how these technologies affect customer performance through integrated psychological and cognitive processes. Although recent studies emphasize the contribution of artificial

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intelligence and digital technologies to the development of consumer experiences and decision-making, most research has addressed isolated constructs such as trust, perceived value, or behavioral intention instead of examining a more comprehensive framework that highlights emotional and cognitive drivers simultaneously. Hermann and Puntoni (2024) and Iqbal et al. (2025) further emphasize the importance of understanding integrated consumer responses within technologically driven environments.

Literature Review

Disruptive technological innovation (DTI) has become the pivotal concept of interpreting the current consumer behavior and especially in digitally focused settings. DTI is the introduction of new technologies of artificial intelligence, machine learning, and automation that have a drastic impact on the old business models and interactions with consumers. According to recent research, the technologies contribute to the increased level of personalization, predictability, and user interaction, thus reforming the consumption patterns and expectations (Ahmed et al., 2025; Hermann & Puntoni, 2024; Khan et al., 2024). Moreover, previous studies by Davenport et al. (2020) and Ahmed et al. (2024) emphasize that disruptive technologies have a fundamental effect on the perception of value and relationship with firms in consumers. This accumulation of literature demonstrates the significance of DTI as an important source of behavioral change in the modern markets.

Theoretical Foundation

Technology Acceptance Model (TAM)

This theoretical basis of this research is based on the existing models of technology adoption and consumer behavior, which describe how people react to technological changes in the digital space. (TAM) is one of them that have been extensively applied to study the impact of the perceived practicality and perceived ease of use on operator adoption of new technologies. Current research has expanded TAM to include new sophisticated constructs of personalization and user experience of AI-driven systems (Ahmed et al., 2025; Iqbal et al., 2023; Hermann & Puntoni, 2024; Khan et al., 2024). The previous studies of Davenport et al. (2020) and Ahmed et al. (2024) underlined that TAM is a powerful model of interpreting the way in which technological characteristics are transformed into consumer acceptance.

Theory of Planned Behavior (TPB)

Besides TAM, there is the (TPB) which offers a holistic view of the influence of arrogances, individual norms as well as apparent behavioral control on behavioral intention and actual behavior. TPB is especially applicable in the study of how consumers make intention using cognitive assessment of technology. According to recent studies, the attitude toward digital technologies plays a significant role in determining the adoption in the AI-driven setting (Iqbal et al., 2025; Khoso et al., 2025; Chen & Prentice, 2025). Previous research by Henseler et al. (2020) and Hair et al. (2021) attest to the fact that the attitude is a significant predictor of behavioral intention, particularly when it comes to technology adoption

Stimulus-Organism-Response (SOR)

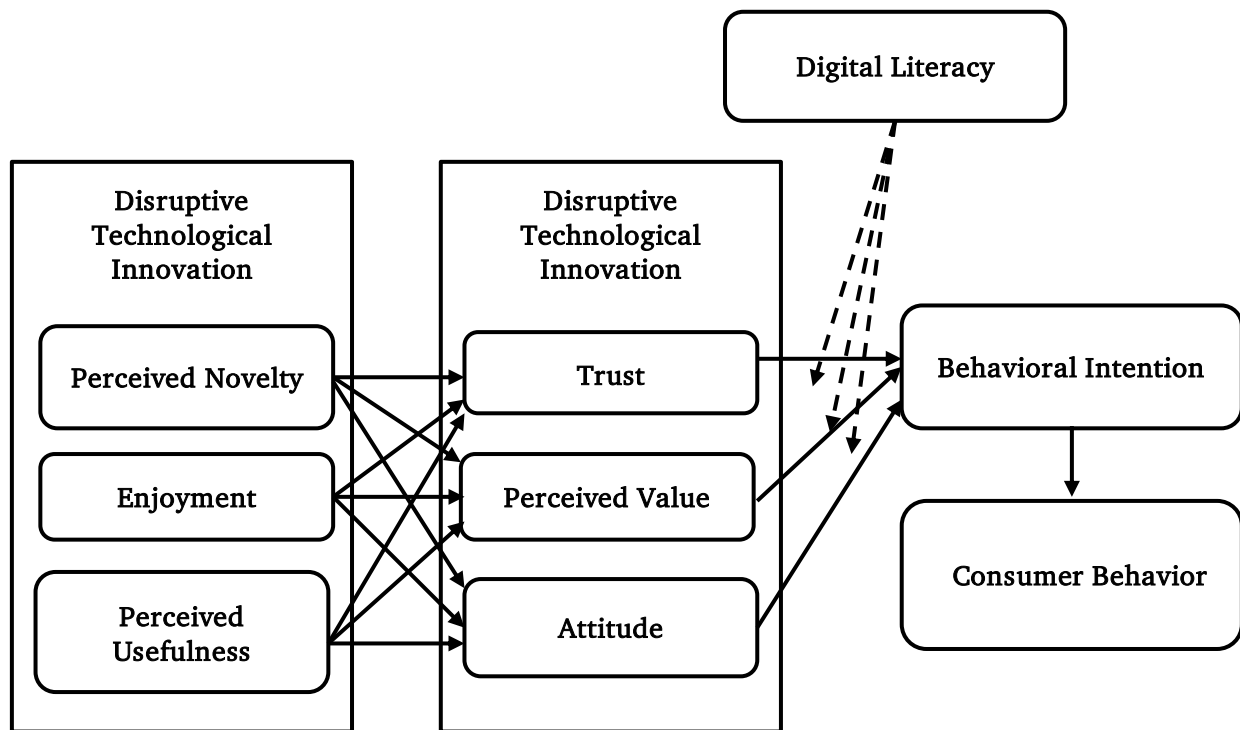
SOR model further adds more weight to the theoretical version since it explains the effect of external stimuli on internal psychological processes that further result in behavioral responses. In that regard, the disruptive technological innovation is the stimulus, the organism is cognitive and emotional constructs (trust, perceived value, and attitude), and the response is consumer behavior. The SOR framework has been recently applied to the digital setting and proved to be effective in explaining consumer behavior driven by technology (Chen & Prentice, 2025; Khoso et al., 2024). The use of SOR in grasping the consumer reactions to new technologies is also supported by previous studies by Ahmed et al. (2024) and Davenport et al. (2020). This paper uses the SOR model to offer a holistic description about the effects of technological stimuli on behavioral outcomes with the help of internal processes.

Innovation of disruptive technology (DTI) has been broadly endorsed in the literature as a key component in driving up consumer interest and behavior change. Recent research claims that technologies like artificial intelligence and automation would enhance personalization and the accuracy of predictions, which positively affect consumer behavior (Ahmed et al., 2025; Hermann & Puntoni, 2024; Khan et al., 2024). The developments allow companies to personalize products and maximize customer experiences, resulting in increased satisfaction and adoption. Nonetheless, there are counterarguments that overdependence on technology can introduce complexity and loss of control by users, which will adversely affect consumer attitudes (Davenport et al., 2020; Ahmed et al., 2024). The divergence shows that as much as DTI has great advantages, its usage and how it is viewed by the users will determine its success.

Moderation: Digital Literacy

It is found that digital literacy moderately enhances the association between cognitive factors and interactive intention. The recent researches have suggested that more digitally literate people feel more confident using advanced technologies, and thus, there are stronger relationships between trust, value, and intention (Khoso et al., 2025; Iqbal et al., 2025; Chen & Prentice, 2025). This coincides with UTAUT that focuses on the ability of the user. Earlier research by Hair et al. (2021) and Henseler et al. (2020) also attests to the fact that users with high technological skill tend to embrace innovations.

Figure 1
Conceptual Framework



Hypothesis Development

Perceived Novelty and Trust

A sense of novelty is also a key factor to influencing consumer trust in disruptive technologies since new functions produce a sense of progress and ability. According to the latest research, consumers are likely to perceive technological superiority as a result of novelty, which makes them more confident in the abilities of the system (Owais et al., 2025). In cases where the technologies present some special features, it is an indication of innovation and distinction, thus enhancing trust. Previous studies by Paschen et al. (2019) also

uphold that innovative systems promote perceived credibility, and therefore increase the level of trust among users.

H1: Perceived novelty has a substantial effect on trust.

Perceived Novelty and Perceived Value

Perceived novelty has a constructive effect on the perceived value by increasing the discernment of uniqueness and innovation of a product or service by the consumers. Recent researches indicate that consumers consider new technologies to have superior advantages, which results in the emergence of the value perception (Owais et al., 2025). Additional features that are innovative, offer extra functional and experience benefits, which add to the perceived value of technology. Previous studies are also able to verify that innovation enhances perceived value by enhancing efficiency and user experience (Paschen et al., 2019).

H2: Perceived novelty is a strong factor that influences perceived value.

Perceived Novelty and Attitude

Novelty is an important factor of consumer attitude that generates excitement and interest in innovative technologies. Recent researches show that consumers form positive attitudes when they are exposed to new and unique technological features (Zaman et al., 2025). Newness creates curiosity and gives the user more interest, which results in positive reviews. Previous studies by Paschen et al. (2019) confirm the same by stating that innovative experiences have a positive influence on consumer attitudes.

H3: Perceived novelty has a significant effect on attitude.

Enjoyment and Attitude

Consumer attitude is largely determined by enjoyment especially in digital and technology-driven settings. Recent research indicates that positive emotions increase the involvement in a pleasurable experience resulting in positive attitudes towards technology (Zaman et al., 2025). The role of hedonic value is extremely essential in building the perception of users and enhancing their satisfaction. Previous studies by Paschen et al. (2019) also confirm that fun interactions lead to better user attitudes.

H4: There is a large impact of enjoyment on attitude.

Perceived Usefulness and Trust

The perceived usefulness has a positive correlation with trust because consumers tend to have more trust in technologies that offer some tangible benefits. According to recent research, useful technologies positively affect the perception of reliability and decrease uncertainty (Paschen et al., 2019). Technology has functional efficiency which makes users have confidence in technology. This relationship was previously supported by Paschen et al. (2019). But there are studies that suggest that usefulness does not necessarily result to trust especially where there is the question of privacy.

H5: Perceived usefulness has a significant effect on trust.

Perceived Usefulness and Perceived Value

Perceived usefulness has a great impact on boosting perceived value by adding more benefit to the use of technology. According to the recent reports, functional benefits enhance the perception of value (Paschen et al., 2019). This is supported by previous studies by Paschen et al. (2019). On the other hand, usefulness does not necessarily reduce to value when the costs exceed benefits. Longoni et al. (2019) indicate that recent research emphasizes this weakness (Khoso et al., 2025; Zaman et al., 2025; Chen & Prentice, 2025).

H6: Perceived usefulness has a significant effect on perceived value.

Trust and Behavioral Intention

Trust plays a major role in behavioral intention in terms of perceived risk and uncertainly. The recent research proves this correlation (Owais et al., 2025; Chen & Prentice, 2025; Zaman et al., 2025). It is supported by

previous studies (Paschen et al., 2019). Nevertheless, trust has not been shown to be a surety of intention because of extrinsic limitations (Khosro et al., 2025; Khosro et al., 2024; Khan et al., 2024; Longoni et al., 2019).

H7: Trust plays a great impact on behavioral intention.

Attitude and Behavioral Intention

Attitude positively influences behavioral intention (Zaman et al., 2025, Martins et al., 2019). However, attitude may not always translate into intention due to situational factors (Paschen et al., 2019; Kausar et al., 2024; Iqbal et al., 2023).

H8: Attitude has a significant effect on behavioral intention.

Behavioral Intention and Consumer Behavior

Behavioral intention strongly predicts actual behavior (Owais et al., 2025; Zaman et al., 2025). However, intention-behavior gap exists (Zaman et al., 2025; Akmal et al., 2025; Khosro et al., 2024; Martins et al., 2019).

H9: Behavioral intention has a significant effect on consumer behavior.

Perceived Novelty, Trust and Behavioral Intention

Perceived novelty enhances behavioral intention through the mediating role of trust, as innovative technologies signal advancement and competence, which build user confidence. Recent studies suggest that when consumers perceive a technology as novel, they are more likely to trust its capabilities, leading to stronger behavioral intentions (Akmal et al., 2026, Owais et al., 2025; Khan et al., 2024). Trust acts as a critical mechanism that reduces uncertainty and strengthens users' willingness to adopt innovative systems. Earlier research by Paschen et al. (2019) also confirms that innovation-driven trust significantly influences technology acceptance, indicating a strong mediating pathway between novelty and intention.

H10: Trust mediates the relationship between perceived novelty and behavioral intention.

Perceived Usefulness, Perceived Value and Behavior Intention

Perceived usefulness influences behavioral intention through perceived value, as consumers evaluate the benefits of technology in relation to its costs. Recent studies show that useful technologies enhance value perception, which in turn increases behavioral intention (Owais et al., 2025; Khosro et al., 2024; Khan et al., 2024). Behavioral intention is heavily predicted by the perceived value (Khosro et al., 2024; Zaman et al., 2025; Khosro et al., 2025; Paschen et al., 2019). There is however a difference in the value perception among users (Khosro et al., 2025; Zaman et al., 2025; Chen & Prentice, 2025; Longoni et al., 2019). **H8:** Perceived value does not have a strong impact on behavioral intention. Paschen et al. (2019) also confirms that value perception is a key mediator between usefulness and intention, particularly in digital environments.

H11: Perceived value mediates the relationship between perceived usefulness and behavioral intention.

Enjoyment, Attitude and Behavioral Intention

The attitude also has a positive effect on behavioral intention (Zaman et al., 2025; Khosro et al., 2024; Khosro et al., 2025; Martins et al., 2019). Nevertheless, intention does not necessarily follow the attitude because of the situational issues (Khosro et al., 2025; Khosro et al., 2024; Zaman et al., 2025; Martins et al., 2019). **H9:** Attitude plays an important role in behavioral intention.

H12: Attitude mediates the relationship between enjoyment and behavioral intention.

Moderation: Digital Literacy (Trust/Value/Attitude and Behavioral Intention)

Digital literacy strengthens the relationship between cognitive factors (trust, perceived value, and attitude) and behavioral intention, as users with higher technological competence are more confident in adopting innovations. Recent studies indicate that digitally literate consumers are better able to evaluate and utilize technologies, leading to stronger relationships between cognitive constructs and intention (Owais et al.,

2025; Zaman et al., 2025; Khoso et al., 2024). This aligns with UTAUT, which emphasizes the role of user capability. Earlier research by Martins et al. (2019) also supports that technological skills enhance adoption behavior.

H13: Digital literacy moderates the relationship between (a) trust, (b) perceived value, and (c) attitude and behavioral intention.

Methodology

This research paper uses quantitative research method that will explore the effects of disruptive technological innovation on consumer behavior in a systematic and empirical way. The reason why quantitative research is highly applied in technology adoption studies is its capability to measure the theoretical relationship and confirm hypotheses by use of SEM methods. Recent research highlights the fact that the quantitative approach is especially adequate when it comes to studying multi-construct and multi-relationships models (Ahmed et al., 2025; Khan et al., 2024; Bajwa et al., 2024). These methods enable scholars to extend their results to the general population and offer objective information about the behavioral patterns. The utilization of quantitative designs to test theories and validate models is supported by previous studies by Creswell (2020) and Hair et al. (2021), which is why it is suitable in the present study.

Data Collection and Sampling

The information to be used in this research is obtained by the use of a structured questionnaire that is issued over the internet in order to make it accessible and effective. The use of online data collection is common in consumer behavior studies that require technology since there is a large and broad sample that can be reached in a limited time. According to recent research, digital surveys are more effective in increasing the response rates and delivering credible information about the user perception and behavioral intentions (Ahmed et al., 2025; Khan et al., 2024; Khoso et al., 2024). Moreover, it can be noted that online tools enable a survey to be filled in by the respondents at their convenience and this enhances the quality of data. The previous study by Creswell (2020) and Saunders et al. (2021) proves the application of online data collection tools in quantitative research, especially in the research of digital technologies and consumer behavior.

The sampling method used in this study is non-probability sampling method and will be used to gather information on respondents who are easily available and well conversant with digital technologies. The method is widely applied in consumer behavior studies because it is a convenient and efficient one. Recent research indicates that convenience sampling is useful in the context of exploratory and technology adoption studies where the researcher aims to comprehend the relationship between the behaviors (Ahmed et al., 2025; Khoso et al., 2025; Khoso et al., 2024). The sample size will be calculated according to the needs of PLS-SEM and it will contain enough data to make an adequate analysis. Previous studies by Hair et al. (2021) and Sekaran and Bougie (2020) are in favor of non-probability sampling in behavioral research that employs structural equation modeling.

SmartPLS software is used to perform data analysis in this study; it is a popular software application in the partial least square structural equations modeling (PLS-SEM). This software allows evaluation of measurement and structural models to be done concurrently and is therefore appropriate in complex research frameworks. According to recent research, SmartPLS offers powerful findings to examine the relationship with mediation and moderation effects (Ahmed et al., 2025; Khoso et al., 2025; Khoso et al., 2024). It is also used to measure the reliability, validity, and path coefficients of the model. Previous studies conducted by Henseler et al. (2020) and Hair et al. (2021) help to conclude that SmartPLS is a valid instrument of analysis of the complex model in the study of consumer behavior.

Results and Discussion

The findings of this paper give empirical findings of the relationships between disruptive technological innovation and consumer behavior mediated by psychological and cognitive factors. Through PLS-SEM

The findings of the structural model show that the relationships that have been proposed in the framework are rather meaningful and justified. The path coefficients and p-values (all equal to 0.000 or less than 0.05) prove that the correlations between independent variables (perceived novelty, enjoyment, and perceived usefulness) and the mediating constructs (trust, perceived value, and attitude) are significant. In particular, perceived novelty and enjoyment have significant contributions to trust and perceived value, whereas perceived usefulness has a relatively moderate but significant impact on attitude. Moreover, the R² values show that the model has a good explanatory power and that trust (0.737), perceived value (0.596), and attitude (0.580) have a significant proportion of variance of these constructs, which is attributed to the independent variables.

Hypothesis Testing

Table 2

Hypothesis Testing

Path coefficients					
Mean, STDEV, T values, p values					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
ATTITUDE -> BEHAVIORAL INTENTION	0.385	0.380	0.074	5.239	0.000
BEHAVIORAL INTENTION -> CONSUMER BEHAVIOR	0.859	0.859	0.024	35.694	0.000
DIGITAL LITERACY -> BEHAVIORAL INTENTION	-0.009	-0.008	0.039	0.231	0.818
DIGITAL LITERACY x ATTITUDE -> BEHAVIORAL INTENTION	0.385	0.384	0.082	4.719	0.000
DIGITAL LITERACY x PERCEIVED VALUE -> BEHAVIORAL INTENTION	-0.020	0.004	0.112	0.183	0.855
DIGITAL LITERACY x TRUST -> BEHAVIORAL INTENTION	-0.028	-0.038	0.116	0.238	0.812
ENJOYMENT -> ATTITUDE	0.340	0.333	0.094	3.625	0.000
ENJOYMENT -> PERCEIVED VALUE	0.303	0.303	0.092	3.295	0.001
ENJOYMENT -> TRUST	0.385	0.384	0.082	4.719	0.000
PERCEIVED NOVELTY -> ATTITUDE	0.283	0.279	0.102	2.780	0.005
PERCEIVED NOVELTY -> PERCEIVED VALUE	0.261	0.252	0.089	2.933	0.003
PERCEIVED NOVELTY -> TRUST	0.379	0.373	0.083	4.592	0.000
PERCEIVED USEFULNESS -> ATTITUDE	0.184	0.196	0.121	1.523	0.128
PERCEIVED USEFULNESS -> PERCEIVED VALUE	0.257	0.266	0.123	2.091	0.037
PERCEIVED USEFULNESS -> TRUST	0.143	0.150	0.099	1.442	0.149
PERCEIVED VALUE -> BEHAVIORAL INTENTION	0.202	0.209	0.080	2.514	0.012
TRUST -> BEHAVIORAL INTENTION	0.290	0.286	0.074	3.938	0.000

According to the results of the path coefficient, the majority of the relationships suggested in the structural model are statistically significant and supported. In particular, the attitudes to consumer behavior are strongly and significantly influenced by attitude to behavioral intention ($\beta = 0.385$, $p = 0.000$) and behavioral intention to consumer behavior ($\beta = 0.859$, $p = 0.000$), which proves that attitude is a major predictor of intention, and intention is a major predictor of actual consumer behavior. Out of the antecedents, enjoyment and perceived novelty have a significant impact on trust, perceived value and attitude (all $p < 0.05$) which may explain the role of emotional and experience elements in the formation of consumer

perceptions. Similarly, perceived value ($\beta = 0.202, p = 0.012$) and trust ($\beta = 0.290, p = 0.000$) significantly affect behavioral intention.

Mediation & Moderation Analysis

Table 3

Mediation & Moderation Analysis

Specific Indirect Effects					
Mean, STDEV, T values, p values					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
ATTITUDE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.331	0.327	0.066	5.040	0.000
DIGITAL_LITERACY -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	-0.008	-0.007	0.033	0.231	0.817
PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.173	0.179	0.068	2.561	0.010
TRUST -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.249	0.246	0.065	3.833	0.000
DIGITAL_LITERACY x TRUST -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	-0.024	-0.033	0.100	0.239	0.811
DIGITAL_LITERACY x PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	-0.018	0.004	0.095	0.184	0.854
DIGITAL_LITERACY x ATTITUDE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.027	0.025	0.068	0.403	0.687
PERCEIVED_USEFULNESS -> ATTITUDE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.061	0.064	0.042	1.454	0.146
ENJOYMENT -> ATTITUDE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.112	0.109	0.039	2.887	0.004
PERCEIVED_NOVELTY -> PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.045	0.045	0.023	1.965	0.049
PERCEIVED_NOVELTY -> TRUST -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.094	0.092	0.033	2.878	0.004
ENJOYMENT -> TRUST -> BEHAVIORAL_INTENTION	0.111	0.109	0.034	3.272	0.001
PERCEIVED_NOVELTY -> TRUST -> BEHAVIORAL_INTENTION	0.110	0.107	0.038	2.905	0.004
PERCEIVED_USEFULNESS -> TRUST -> BEHAVIORAL_INTENTION	0.041	0.044	0.032	1.280	0.201
ENJOYMENT -> ATTITUDE -> BEHAVIORAL_INTENTION	0.131	0.127	0.044	2.961	0.003
PERCEIVED_NOVELTY -> ATTITUDE -> BEHAVIORAL_INTENTION	0.109	0.106	0.045	2.447	0.014
PERCEIVED_USEFULNESS -> ATTITUDE -> BEHAVIORAL_INTENTION	0.071	0.075	0.049	1.460	0.144

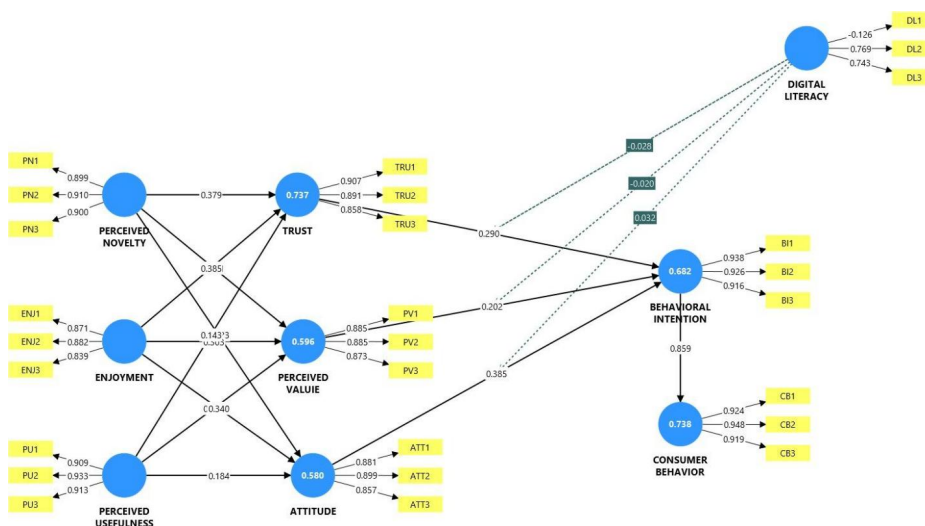
PERCEIVED_NOVELTY -> ATTITUDE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.094	0.091	0.039	2.425	0.015
PERCEIVED_USEFULNESS -> PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.045	0.049	0.030	1.461	0.144
PERCEIVED_USEFULNESS -> TRUST -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.036	0.038	0.028	1.273	0.203
ENJOYMENT -> PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.053	0.054	0.028	1.886	0.059
ENJOYMENT -> TRUST -> BEHAVIORAL_INTENTION -> CONSUMER_BEHAVIOR	0.096	0.094	0.030	3.168	0.002
ENJOYMENT -> PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION	0.061	0.063	0.033	1.877	0.061
PERCEIVED_NOVELTY -> PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION	0.053	0.052	0.027	1.943	0.052
PERCEIVED_USEFULNESS -> PERCEIVED_VALUIE -> BEHAVIORAL_INTENTION	0.052	0.057	0.036	1.445	0.148

The confirmed specific indirect effects results indicate that the behavioral intention is a central mediating variable in the model, and there are a number of important mediation pathways. The highest indirect effect is calculated on the attitude-behavioral intention-consumer behavior (0.331, p = 0.000), next comes the trust-behavioral intention-consumer behavior ($\beta = 0.249$, p = 0.000), and perceived value-behavioral intention-consumer behavior ($\beta = 0.173$, p = 0.010), which suggests Enjoyment has direct positive and significant effects on the attitude ($\beta = 0.112$, p = 0.004) and trust ($\beta = 0.096$, p = 0.002) among the upstream variables, which indicates its significance as a major driver of emotion. In the same way, the perceived novelty exhibits strong mediation by trust ($\beta = 0.094$, p = 0.004) and attitude ($\beta = 0.094$, p = 0.015) and has a narrow significance of its pathway by perceived value (p = 0.049–0.052).

PLS SEM

Figure 3

PLS SEM



The outcomes of the structural model show that there are high levels of relationship between the major constructs, which validates the strength of the proposed framework. All indicators have high factor loadings (in most cases above 0.85) which demonstrates high reliability and convergent validity of constructs. The structural paths are perceived novelty ($\beta=0.379$) and perceived enjoyment ($\beta=0.385$), which have a significant positive impact on trust, whereas perceived usefulness has a weaker impact. Likewise, enjoyment ($\beta= 0.340$) and perceived usefulness ($\beta = 0.184$) have a significant effect on attitude, indicating the significance of both emotional and functional motivators. The R2 values also support the explanatory power of the model with trust (0.737), perceived value (0.596), and attitude (0.580) showing moderate to strong variance of the independent variables.

Model Fitness

Table 4

Model Fitness

Model fit		
Fit summary		
	Saturated model	Estimated model
SRMR	0.050	0.089
d_ ULS	0.940	3.005
d_ G	0.697	0.908
Chi-square	1558.055	1762.729
NFI	0.834	0.812

The results of the model fit shows that the proposed model shows a satisfactory overall fit. The saturated model and estimated model have Standardized Root Mean Square Residual values of 0.050 and 0.089 respectively, which fall within the acceptable level of 0.08-10.0, respectively indicating that there is a good fit between the observed and the predicted correlations. Also, the discrepancy measures (d ULS and d G) are not very large meaning that there is no significant difference between the empirical and model-implied covariance matrices. The Normed Fit Index of 0.834 (saturated) and 0.812 (estimated) are above the required minimum of 0.80, which indicates that the model is fitted well, but not at its best level of 0.90. The Chi-square values are not low, as is typical of large sample SEM models, and does not always indicate poor fit. All in all, the findings indicate that the model is acceptable and fits well and therefore it is suitable to analyze the structure and test the hypothesis.

Discussion

The results are very theoretically relevant as they extend the proven frameworks including the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Stimulus–Organism Response (SOR) and develop a comprehensive model, which takes into consideration both emotional and cognitive aspects of consumer behavior. These findings confirm that disruptive technological innovation has an impact on consumer behavior, and it is a psychological mechanism including attitude, trust, and perceived value, which is consistent with current theoretical developments focusing on integrated models (Kumar et al., 2024; Guo et al., 2024; Zhang et al., 2025). In particular, the powerful influence of attitude on behavioral intention proves TPB whereas the substantial impact of perceived usefulness and value is evidence of TAM assumptions.

Conclusion

This research paper gives some recommendations of future research as it identifies some of the major limitations in terms of methodology, theoretical extent, and contextual constraints. To start with, cross-sectional research design does not allow one to measure the change in consumer behavior over time, especially in the fast changing technological landscape. It is also suggested that future research should use longitudinal designs to test the way consumer perceptions and behaviors change when they are constantly

exposed to disruptive technologies (Ahmed et al., 2025; Khan et al., 2024; Khoso et al., 2024). Moreover, the use of self-reported survey data can create the bias of response, which can also influence the validity of results. Previous studies by Creswell (2020) and Hair et al. (2021) indicate that surveys may be combined with experimental or behavioral data, which can improve research validity. Consequently, subsequent researches must take into account a mixed-method design in order to give a more in-depth picture of technology-based consumer behavior.

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