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THE INFLUENCE OF PERSONALIZED MARKETING AND DATA PRIVACY CONCERNS ON CONSUMER BEHAVIOR: THE MEDIATING ROLE OF PERCEIVED VALUE

KİŞİSELLEŞTİRİLMİŞ PAZARLAMA VE VERİ GİZLİLİĞİ KAYGILARININ TÜKETİCİ DAVRANIŞI ÜZERİNDEKİ ETKİSİ: ALGILANAN DEĞERİN ARACILIK ROLÜ

Altuğ OCAK[1]

Abstract*: This study examines the complex interplay between personalized marketing (PM), data privacy concerns (DPC), perceived value (PV) and purchase intention (PI) in a sample of online consumers. The main aim of the research is to investigate the dual influence of PM and DPC on PV and PI, focusing on the mediating role of PV. To achieve this, all the data was collected through a constructed questionnaire involving 386 online consumers who have encountered PM. The questionnaire used established scales to measure PM, DPC, PV and PI. Analytical tools such as Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were used to validate the measurement model and test the hypotheses. The outcomes show PM positively influences both PV and PI, while DPC negatively influences PV and has a weaker effect on PI. PV was found to mediate the link between PM and PI and the relationship between DPC and PI. These results suggest that marketers need to strike a better balance between personalization and sound data privacy practices to increase PV and drive consumer behavior.*

Keywords: *Personalized Marketing, Data Privacy Concerns, Perceived Value, Purchase Intention, Consumer Behavior.*

JEL*: M31, M37, D83*

Öz: Bu çalışma, kişiselleştirilmiş pazarlama, veri gizliliği endişeleri, algılanan değer ve satın alma niyeti arasındaki karmaşık ilişkiyi çevrimiçi tüketiciler bağlamında incelemektedir. Çalışmanın temel amacı, algılanan değerin aracılık rolüne odaklanarak, kişiselleştirilmiş pazarlama ve veri gizliliği endişelerinin algılanan değer ve satın alma niyeti üzerindeki ikili etkisini araştırmaktır. Bunu başarmak için veriler, daha önce kişiselleştirilmiş pazarlama deneyimi olan 386 çevrimiçi tüketiciyi kapsayan yapılandırılm-ış bir anket aracılığıyla toplanmıştır. Ankette kişiselleştirilmiş pazarlama, veri gizliliği endişeleri, algılanan değer ve satın alma niyetini ölçmek için mevcut ölçekler kullanılmıştır. Ölçüm modelini doğrulamak ve hipotezleri test etmek için Doğrulayıcı Faktör Analizi (DFA) ve Yapısal Eşitlik Modellemesi (YEM) gibi analitik teknikler uygulanmıştır. Bulgular, kişiselleştirilmiş pazarlamanın hem algılanan değeri hem de satın alma niyetini olumlu yönde desteklediğini, veri gizliliği endişelerinin ise algılanan değeri olumsuz yönde etkilediğini ve satın alma niyeti üzerinde daha zayıf bir doğrudan etkisinin olduğunu ortaya koymaktadır. Algılanan değer, kişiselleştirilmiş pazarlama ile satın alma niyeti arasındaki ve veri gizliliği endişeleri ile satın alma niyeti arasındaki etkileşime aracılık etmektedir. Bu bulgular, pazarlamacıların algılanan değeri artırmak ve tüketici davranışını yönlendirmek için kişiselleştirme ile güçlü veri gizliliği uygulamaları arasında bir denge kurması gerektiğinin altını çizmektedir.

[1] İstanbul Beykent Üniversitesi, Meslek Yüksekokulu, Seyahat - Turizm ve Eğlence Hizmetleri Bölümü; altugocak@beykent.edu.tr, ORCID: 0000-0002-8018-4158
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Anahtar Kelimeler: Kişiselleştirilmiş Pazarlama, Veri Gizliliği Endişeleri, Algılanan Değer, Satın Alma Niyeti, Tüketici Davranışı.

1. Introduction

In today's digital marketplace, businesses are increasingly using PM strategies to engage their audiences and increase conversion rates. By leveraging tools such as customized ads, tailored recommendations and targeted promotions, marketers aim to create engaging and relevant consumer interactions. The effectiveness of these strategies has increased significantly thanks to advances in artificial intelligence, data analytics and machine learning, enabling businesses to effectively use consumer data for personalization (Bleier and Eisenbeiss, 2015). The importance of PM relies on its capability to enhance customer experiences, build loyalty and increase sales.

However, as firms increasingly rely on consumer information to support these strategies, DPC are growing. It is becoming clear that people are becoming more and more conscious of how their private information is collected, stored and processed. This increased awareness has led to concerns about potential privacy breaches and misuse of data. Such concerns have emerged as critical challenges in digital marketing and have affected consumer trust and engagement in personalized efforts (Malhotra, Kim and Agarwal, 2004). These DPC have become a central issue in digital marketing as they can affect consumer trust, PV and overall engagement in PM efforts. Research has shown that DPC can deter consumers from interacting with brands, especially when they feel that the ga-ins of personalization do not largely eliminate the risks to their private data (Culnan and Armstrong, 1999; Dinev and Hart, 2006).

This research fills a gap in existing research on the joint effects of PM and DPC on consumer behavior. While numerous studies have explored the independent effects of PM and data privacy on consumer perceptions and decisions, few have examined how these factors interact to shape PV and PI. To fill this gap, this research explores the link between PM and PI, which is moderated by DPC and mediated by PV. Specifically, this study aims to uncover how PV influences buyer reactions to PM and DPC impact these reactions. Using the following research questions to guide this research, the paper focuses on the following questions:

- How do PM efforts impact PV and PI?
    - This question explores direct and indirect impacts of PM strategies on consumer perceptions and behaviors (Bleier and Eisenbeiss, 2015).
- What role do DPC play in shaping PV and PI?
    - This examines influence of privacy apprehensions on the value consumers derive from PM and their subsequent PIs (Malhotra, Kim and Agarwal, 2004; Dinev and Hart, 2006).
- Does PV mediate the interactions between PM, DPC and PI?
    - This focuses on the mediating role of PV in the dynamics of personalization and DPC (Sweeney and Soutar, 2001).

Through answering these queries, research seeks to build a deep understanding of how PM efforts are shaped by consumers' concerns about data privacy and how these factors collectively influence consumer behavior. This research has many strategic implications for how to design marketing strategies that maximize PV while minimizing DPC and ul-timately foster a more trustworthy digital marketing environment, which in turn has practical implications for marketers and policymakers.

The following sections in this article are structured as below. In the literature section, the theories and empirical studies related to PM, DPC, PV and PI are discussed. In the section on research methodology, it describes the methods of collecting data, the survey instrument and the analytical techniques used to examine the study objectives. While the results chapter provides the findings from the statistical analyses, in the discussion chapter, we interpret them in the light of available literature. Lastly, in the conclusion chapter, the contributions and limitations of the study and implications for further research are briefly summarized.

2. Literature Review

2.1. Data Privacy Concerns and Perceived Value

In an era dominated by digital transactions, consumers are increasingly prioritizing how companies handle their personal information. DPC have a profound impact on how consumers perceive value of products or services. Research shows that companies that promote transparent data management practices tend to increase consumers' perceptions of value. When firms implement clear privacy policies and provide secure platforms, trust is built, which positively affects PV (Chellappa and Shivendu, 2005). DPC can shape perceptions of both the security and ethical standards of a company and thus affect the PV of its products or services (Bansal et al., 2016). Companies effectively addressing these concerns can alleviate them and thus increase PV.

Transparent data handling, clear privacy policies and secure platforms enhance trust, transforming DPC into a positive driver of PV (Aguirre et al., 2015; Martinand Murphy, 2017). This shift occurs when consumers believe that the company uses their data responsibly, resulting in an enhanced perception of value (Tirtayani et al., 2024). Recent literature underscores that consumers are increasingly sensitive to how their personal data is handled, which directly affects their perception of a brand's value. In a 2022 study, Lin et al. highlighted that DPC reduce PV when consumers feel their personal data might be misused. However, firms that implement clear data protection measures and privacy policies can enhance PV by fostering trust (Liao et al., 2023). Addressing DPC has become a competitive advantage, as consumers reward companies that respect their privacy by perceiving more value in their offerings.

H1: Data privacy concerns have a positive effect on perceived value.

2.2. Data Privacy Concerns and Purchase Intention

Worries about misuse of personal information can deter consumers from making purchase decisions. However, when organizations prioritize data protection and communicate their efforts effectively, these concerns can diminish and lead to increased PIs. This relationship underscores the critical role of ethical data practices (Malhotra et al., 2004). However, firms that provide assurances about data security and use ethical data practices can reduce these concerns and positively influence PIs (Dinev and Hart, 2006). Companies that build trust through privacy assurances are better able to overcome consumer resistance to purchase, especially in online environments (Hoang, 2019; Quach et al., 2022).

DPC have also been shown to negatively affect PIs. A systematic review of digital privacy issues found that when consumers believe their data may be at risk, their desire to transact is significantly reduced (Bhattacharya et al., 2023). The paradox of personalization vs. privacy is a recurring theme that consumers enjoy personalized experiences but are reluctant to share too much data. However, firms that are transparent about their data practices and actively protect personal information can mitigate this negative impact and increase purchase intent (Muhammad et al., 2018).

H2: Data privacy concerns have a negative effect on purchase intention.

2.3. Perceived Value and Purchase Intention

PV is a strong determinant of CPI. If customers sense strong PV in a good or in a service, they are more likely to buy it. This is in line with previous studies linking perceived benefits and purchase behavior in various market contexts (Ajzen, 1991). Research by Sweeney and Soutar (2001) emphasizes how individuals are significantly higher likelihood to purchase products that they perceive to have high value, especially regarding quality, utility and price. Higher value perception makes consumers more probable to continue with the buying decision, especially in competitive markets with similar offers (Zeithaml, 1988).

PV is a fundamental motivator of PI, as shown in the Stimulus-Organization-Response (SOR) model. Recent studies, such as those by Ponte et al. (2021), have confirmed positive evidence such that buyers are more likely to make a purchase if they perceive a product to offer more value. PV often results from a combination of utilitarian (functional) and hedonic (emotional) benefits and social value plays an increasingly important role in e-commerce platforms such as live streaming (Wu and Huang, 2023). There is a clear connection between PV and PI that is consistent across all sectors, from e-commerce to traditional retail.

H3: Perceived value has a positive effect on purchase intention.

2.4. Personalized Marketing and Perceived Value

PM directly contributes to increased PV by aligning offers with individual consumer preferences. When done effectively, personalization improves consumer evaluations by promoting a sense of relevance and connection (Zhang et al., 2017). This is especially true in digital environments, where personalized recommendations based on user data can provide a better alignment between consumer needs and company offerings (Arora et al., 2008). However, this relationship can be nuanced, as the effectiveness of PM often depends on the actual relevance and perceived appropriateness of personalized content (Tam and Ho, 2006).

PM continues to influence PV by aligning product recommendations with consumer preferences. In a recent study, Aguirre et al. (2021) found that personalization strategies effectively increase the perceived relevance of products, leading to a higher perception of value. However, the effect is moderated by consumers' comfort with data sharing—if personalization is perceived as invasive, it can backfire, reducing the PV of the offering (Tirtayani et al., 2024). Striking the right balance between personalization and privacy is critical for maximizing PV.

H4: Personalized marketing has a positive effect on perceived value.

2.5. Personalized Marketing and Purchase Intention

Effective PM strategies significantly influence PIs by creating tailored experiences that resonate with consumers. However, the success of such strategies depends on their alignment with consumer expectations and privacy preferences (Pappas, 2016). When implemented effectively, PM can create stronger emotional bonds between consumers and brands, making them more inclined to engage in purchase behavior (Bleier and Eisenbeiss, 2015). However, while personalization often leads to positive outcomes, personalization needs to be tempered with confidentiality considerations to prevent creating discomfort among consumers (Tucker, 2014).

PM positively impacts PI by making the consumer feel understood and valued. Recent findings highlight that personalized recommendations not only enhance engagement but also boost PI, particularly in digital contexts such as e-commerce platforms (Fan et al., 2022). However, trust plays a mediating role—consumers are more likely to act on personalized recommendations when they trust the source of the personalization (Tirtayani et al., 2024). Ensuring that PM aligns with data privacy expectations can further amplify its effect on PI (Martin and Murphy).

H5: Personalized marketing has a positive effect on purchase intention

2.6. Personalized Marketing and Data Privacy Concerns

PM and DPC have a complex and intertwined relationship in the digital economy. While PM aims to provide tailored experiences to consumers, the underlying data collection practices often raise DPC (Martin and Murphy, 2017). Research highlights that consumers appreciate personalized offers when they perceive the data collection as transparent and consensual (Tirtayani et al., 2024). However, when data use appears intrusive or is conducted without clear consent, DPC intensify, leading to negative consumer responses (Dinev and Hart, 2006).

The personalization calculation model suggests when individuals consider the perceived gains of personalization versus the possible risks of personal information being misused (Culnan and Armstrong, 1999). Effective PM must balance these elements by providing data protection and transparent communication. Companies that can strike this balance can increase consumer trust and acceptance of personalized offers, while those that fail to do so may face customer backlash and regulatory scrutiny (Malhotra, Kim and Agarwal, 2004).

Research shows that confidentiality worries can reduce the efficiency of PM. When privacy safeguards such as opt-in mechanisms and clear privacy policies are in place, individuals are more likely to respond positively (Liao et al., 2023). As a result, firms should adopt proactive privacy management strategies to mitigate concerns while maximizing the PV of PM (Aguirre et al., 2015).

H6: Personalized marketing has a negative effect on data privacy concerns

2.7. Perceived Value Mediates the Relationship Between Personalized Marketing and Purchase Intention

The mediator effect of PV in the relationship between PM and PI is based on the understanding that PV acts as a critical force in the decision-making process of consumers. PV refers to the general evaluation of the benefits a consumer receives derived from a good or service relative incurred costs (Sweeney and Soutar, 2001). In the context of PM, PV reveals the extent to which consumers believe that PM efforts add value to their shopping experience and meet their individual needs.

PM, which tailors promotional content and offers to individual preferences and behaviors, has been shown to increase consumers' perceptions of relevance and value (Bleier and Eisenbeiss, 2015). Research shows that personalized interactions foster a sense of connection and relevance, leading consumers to view products or services more positively (Alkadrie, 2024). This enhanced perception of relevance can translate into higher PV as consumers feel that PM is more closely aligned with their preferences and expectations (Ding and Keh, 2016). For example, when consumers receive product recommendations that align with their past behavior or preferences, these recommendations are perceived as valuable, which may increase their PIs.

The Theory of Planned Behavior (TPB) offers a useful framework to explain the mediation role of PV. TPB suggests that attitudes shaped by consumers' cost and benefit evaluations influence their behavioral intentions (Ajzen, 1991). Applied to PM, this theory argues that PV, an attitudinal construct, acts as a mediator by transforming the positive impressions created by PM into a concrete PI (Ajzen, 1991; Sweeney and Soutar, 2001). When consumers feel that a brand's marketing efforts add value, it is more likely that consumers will form positive intentions and attitudes towards purchasing promoted products.

Previous academic studies provided evidence for the mediation effect of PV across a variety of consumer decision-making contexts. For example, Sweeney and Soutar (2001) found that PV directly influences PIs by increasing consumers' evaluation of product benefits relative to costs. Similarly, Kim, Steinhoff and Palmatier (2021) showed that PV mediated the effect of customer loyalty on PIs, suggesting that consumers are more motivated to act on their PIs when they perceive added value. PV mediates the connection with PM and PI, essentially transforming a positive effect of personalization into an actionable PI.

PM can create PIs by increasing PV. Baek and Morimoto (2012) show the effect of personalized advertising directly enhances PIs by making promotional content more engaging and relevant. However, they also argue that PV reinforces this effect, increasing the likelihood that consumers will act on their PIs when they perceive personalization as valuable. The presence of PV as a mediator highlights that PM alone may not be enough; instead, it is the perceived relevance and value created by PM that encourages consumers to take purchase actions.

This mediating role of PV provides insights for marketers: fostering PV through PM can reinforce consumers' intentions to purchase. When consumers believe they are receiving unique value tailored to their preferences, they feel more positively about the brand and are more inclined to buy (Grewal, Monroe and Krishnan, 1998). Therefore, understanding the mediating role of PV allows marketers to refine personalization strategies in ways that emphasize consumer benefit, thereby translating personalization into actual purchase behavior.

H7: Perceived value mediates the relationship between personalized marketing and purchase intention.

2.8. Perceived Value Mediates the Relationship Between Data Privacy Concerns and Purchase Intention

DPC have become an influential factor in molding public behavior, especially in online platforms where personal information is frequently collected and analyzed. The theory of confidentiality calculus proposes that individuals evaluate the costs and benefits associated with the disclosure of personal information before deciding to interact with a product or service (Culnan and Armstrong, 1999). When consumers are worried about information privacy, they can detect greater risks associated with sharing personal information, which can negatively affect their trust and willingness to transact (Malhotra, Kim and Agarwal, 2004). In the context of online shopping and PM, high DPC may lead consumers to view these marketing efforts as intrusive and ultimately reduce their PIs (Dinev and Hart, 2006).

PV is an important component in understanding consumer responses to DPC, as it reflects an individual's overall assessment of the utility and costs related to a good or service. The Theory of Planned Behavior (TPB) suggests behavioral intentions are strongly related to attitudes and PV (Ajzen, 1991). When consumers perceive value from a service, they are more likely to engage with that service, even if they have some concerns about privacy. Thus, if consumers perceive that PM provides sufficient value, this positive evaluation may mediate the adverse effect of DPC on PIs, essentially offsetting some of the concerns about data privacy risks.

Empirical evidence supports the role of PV as a mediator in scenarios involving DPC. For example, Kim, Ferrin and Rao (2008) found that consumers' trust and PV positively mediated the relation of DPC with their intention to engage in online transactions. This suggests that when consumers feel that they receive significant value, their PIs may remain strong despite DPC. This mediation effect highlights the importance of PV in shaping PIs, especially when there is a potential risk or cost associated with a transaction.

The effect of DPC on PI is complex. On the one hand, high DPC may directly discourage PIs by making consumers skeptical or hesitant to share information. On the other hand, PV can act as a cushion and mitigate the negative effects of DPC by strengthening the utility side of consumers' accounts (Culnan and Armstrong, 1999). When consumers perceive that a product or service provides strong value, they may be more willing to disregard DPC to obtain perceived benefits (Grewal, Monroe and Krishnan, 1998).

Research on privacy and value perceptions has shown that consumers make trade-offs between the perceived level of privacy risk and the amount of rewards they derive out of a good or service (Dinev and Hart, 2006). Xu et al. (2011), for instance, suggest that in personalized services, PV can significantly mediate the impact of DPC on usage intentions, as consumers are willing to accept some privacy risks if they perceive that the service provides sufficient value. This suggests that while DPC may initially deter consumers, PV can positively change attitudes and intentions if perceived benefits are significant.

H8: Perceived value mediates the relationship between data privacy concerns and purchase intention.

3. Methodology

3.1. Reseach Model

The study framework developed for this paper integrates PM and DPC as the main independent variables. PV acts as a mediator influencing PI as the dependent variable. The model reflects the complex interplay between personalization, privacy and consumer decision-making processes and provides a comprehensive framework for testing the proposed hypotheses. A cross-sectional approach was chosen as it enables the analysis of insights collected from a population at a time point within a population and gives a glimpse of the relationships between these variables in the selected population (Bryman and Bell, 2015).

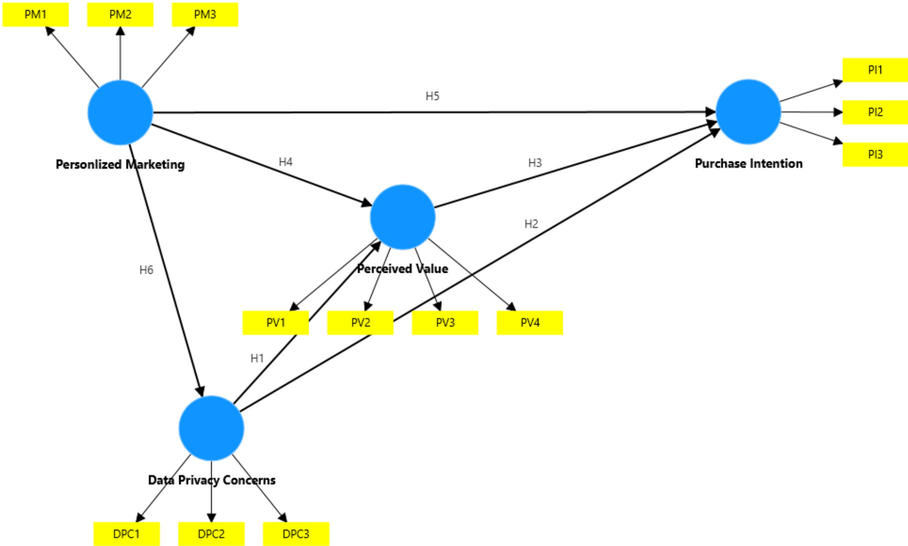

Figure 1. Research Model

Figure 1 is a visual representation of the conceptual framework showing the relationships between PM, DPC, PV (mediating variable) and PI (dependent variable). The arrows show how the independent variables influence the mediating variable and how this in turn influences the dependent variable.

3.2. Population and Sample

The intended audience for this research includes online consumers who have experienced PM efforts. For this research, convenience sampling, a nonprobability recruitment technique in which respondents are chosen according to their suitability and motivation to participate, was used. This is practical and effective to obtain a sample that reflects the diverse experiences and perspectives within the target audience.

3.3. Data Collection Methods

Information was gathered through an internet questionnaire. The questionnaire method is suitable for reaching a large audience and efficiently collecting quantitative data from a large number of respondents. Online distribution tools like social media platforms, mailing lists and other online consumer forums were used to disseminate the survey, ensuring a varied and relevant sample of the target audience (Wright, 2005). Participants were notified of the aim of the research and their approval was taken before participation.

3.4. Instrument and Scales

The survey instrument consists of structured questions designed to measure the variables of interest: PM, DPC, PV and PI. The survey constructs have been tailored from previously approved scales to guarantee reliability and validity. The PM scale was constructed with items specifically adapted from previous studies on PM and advertising (Bleier and Eisenbeiss, 2015). The data privacy concern items in the data privacy scale were derived from a scale developed by Malhotra, Kim and Agarwal (2004) that measures individuals' concerns about their online privacy. PV was assessed through questions measuring participants' evaluation of the benefits and costs of the PM they experienced. The items were adapted from Sweeney and Soutar's (2001) PERVAL scale. The PI variable was assessed with questions derived from previous research by Dodds, Monroe and Grewal (1991) that examined consumers' likelihood to purchase based on marketing stimuli. Respondents expressed the degree of agreeing statements on a Likert scale between 1 (strongly disagree) and 5 (strongly agree).

3.5. Data Analysis Plan

The data collected have been analyzed through SEM, a powerful tool that allows for the inspection of the links between observed and latent variables. SEM was used to confirm the hypothesized associations between PM, DPC, PV and PI. The analysis followed the following steps:

In order to summarize the population demographics and the distribution of questionnaire responses, exploratory descriptive data were calculated. CFA is performed to validate the scale model and to ensure the constructs' reliable and well validated. Structural model was tested and used as a PV instrument to explore the effects of PM and DPC directly and indirectly on PI. The fit of the construct was assessed using fit indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI) and Root Mean Square Error of Approximation (RMSEA).

By employing SEM, this study delivers nuanced insights into how personalized marketing and DPC interact to shape PV and PIs.

3.6. Demographic characteristics

3.6.1. Gender Distribution

The sample consists of 386 respondents, with an almost even distribution between genders. Women represent 51% (n = 197), while men make up 49% (n = 189). This balanced distribution ensures that gender-related differences, if any, can be appropriately analyzed as shown in Table 1.

Table 1. Gender Distribution

Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Women	197	51.0%	51.0%	51.0%
Men	189	49.0%	49.0%	100.0%

3.6.2. Marital Status

The majority of respondents are married 53.9% (n = 208), while 46.1% (n = 178) are single. This distribution allows for comparisons based on marital status within the analysis as seen in Table 2.

Table 2. Marital Status

Marital Status	Frequency	Percent	Valid Percent	Cumulative Percent
Married	208	53.9%	53.9%	53.9%
Single	178	46.1%	46.1%	100.0%

3.6.3. Educational Background

A significant majority of respondents, 74.6% (n = 288), hold a bachelor's degree. Doctorate holders represent 18.1% (n = 70), while high school graduates account for 7.3% (n = 28). This indicates a well-educated sample, suitable for studies requiring higher cognitive engagement as presented in Table 3.

Table 3. Educational Background

Education Level	Frequency	Percent	Valid Percent	Cumulative Percent
High School Graduate	28	7.3%	7.3%	7.3%
Bachelor's Degree	288	74.6%	74.6%	81.9%
Doctorate	70	18.1%	18.1%	100.0%

3.6.4. Age Distribution

Respondents are predominantly aged between 18–30 years (52.1%, n = 201). The age group 31–40 years accounts for 29.3% (n = 113), followed by 41–50 years at 12.7% (n = 49) and those over 51 years at 6.0% (n = 23). This distribution highlights a younger sample, which may influence the perspectives and behaviors analyzed in the study as as given in Table 4.

Table 4. Age Distribution

Age Group	Frequency	Percent	Valid Percent	Cumulative Percent
18–30	201	52.1%	52.1%	52.1%
31–40	113	29.3%	29.3%	81.3%
41–50	49	12.7%	12.7%	94.0%
Over 51	23	6.0%	6.0%	100.0%

The near-equal representation of genders supports balanced insights into gender-specific perspectives. The predominance of bachelor's and doctorate degree holders underscores the potential for more nuanced responses. The high proportion of respondents aged 18–30 suggests findings may reflect younger population trends. The slightly higher number of married participants allows for exploration of differences influenced by marital status. This demographic overview provides a foundational understanding of the sample characteristics and their implications for the study.

3.6.5. Factor Loadings

Table 5 presents the factor loadings for observed variables (indicators) associated with latent constructs. These factor loadings represent the strength of the relationship between each indicator and its respective construct, providing insights into the measurement quality of the constructs. The constructs examined include "DPC," "PV," "PM," and "PI," with corresponding indicators such as DPC1, DPC2, PI1 and PI2.

Table 5. Factor Loadings

Construct	DPC	PV	Personlized Marketing	PI
DPC1	0,902			
DPC2	0,934			
DPC3	0,888			
PI1				0,936
PI2				0,961
PI3				0,959
PM1			0,685	
PM2			0,872	
PM3			0,896	
PV1		0,885		
PV2		0,879		
PV3		0,874		
PV4		0,913		

For the construct DPC, the loadings indicate a very strong relationship between these items and the construct. Similarly, for PI, the indicators have exceptionally high loadings, signifying that items effectively measure the construct. The absence of loadings (NaN) in other cells reflects that each indicator is designed to measure only one construct, which aligns with best practices in SEM (Hair et al., 2019).

All loadings in this dataset exceed this threshold, suggesting high construct validity. This is a positive outcome as it confirms that the observed variables are reliable measures of their latent constructs. Factor loadings below 0.7 may still be acceptable but require further consideration of their contribution to the overall construct (Henseler et al., 2015). Overall, the dataset demonstrates strong factor loadings, indicating robust construct measurement.

3.6.6. Reliability and Validity Measures

3.6.6.1. Cronbach's Alpha

Table 6 has the reliability analysis results, values ≥0.7 are acceptable, while values >0.9 indicate excellent reliability (Hair et al., 2010).

Table 6. Reliability Analysis Results

Construct	Cronbach's Alpha
DPC	0.894
PV	0.910
PM	0.758
PI	0.948

The reliability analysis for the constructs reveals strong internal consistency across all measures. DPC demonstrates high reliability with a Cronbach's Alpha of 0.894, nearing excellence. PV and PI exhibit excellent reliability with Alpha values of 0.910 and 0.948, respectively, indicating their indicators consistently measure the underlying constructs. PM achieves an acceptable reliability level with a Cronbach's Alpha of 0.758, making it suitable for exploratory research. Overall, the constructs display robust reliability, affirming the consistency of the measurement model.

3.6.6.2. Composite Reliability (rho_a and rho_c) (CR)

CR assesses the overall reliability of a latent construct (Fornell and Larcker, 1981). A value ≥0.7 is acceptable, indicating good reliability (Hair et al., 2010). Table 7 has the CR analysis results.

Table 7. CR Results

Construct	rho_a	rho_c
DPC	0.908	0.934
PV	0.913	0.937
PM	0.795	0.862
PI	0.949	0.967

CR analysis highlights the strong internal consistency and robustness of the constructs. DPC and PV demonstrate excellent CR, with rho_a values of 0.908 and 0.913 and rho_c values of 0.934 and 0.937, respectively. PI also exhibits excellent CR, with rho_a at 0.949 and rho_c at 0.967, indicating outstanding consistency among its indicators. PM achieves acceptable to good CR, with rho_a at 0.795 and rho_c at 0.862, reflecting sufficient reliability for exploratory studies. These results affirm that the constructs are measured reliably and consistently, ensuring the validity of the measurement model.

3.6.6.3. Average Variance Extracted (AVE)

AVE evaluates the sum of variance covered by a structure with respect to the variance resulting from measuring error (Fornell and Larcker, 1981). A score of ≥0.5 is acceptable and indicates adequate convergent validity (Hair et al., 2010).

Table 8. AVE Analysis Results

Construct	AVE
DPC	0.825
PV	0.788
PM	0.678
PI	0.907

AVE analysis indicates strong validity for all constructs. DPC has an AVE of 0.825, signifying high validity well above the minimum threshold of 0.5. PV also exhibits high validity, with an AVE of 0.788, further demonstrating its indicators effectively measure the construct. PM achieves an AVE of 0.678, surpassing the threshold and confirming its adequacy. PI stands out with an AVE of 0.907, reflecting very high validity and an exceptional measurement result. These findings affirm the constructs' convergent validity, showing that their indicators share a substantial amount of variance with their respective constructs.

3.6.6.4. The Heterotrait-Monotrait Ratio (HTMT)

HTMT measures the rate of inter-feature correlations to intra-feature correlations. It is a more reliable measure for assessing convergent validity in variance-based SEM (Henseler et al., 2015). Table 9 shows the HTMT values, with values <0.85 indicating discriminant validity and values <0.90 being softer but still acceptable (Hair et al., 2017).

Table 9. HTMT Results

Construct Pair	HTMT Value
DPC and PV	0.239
DPC and PM	0.111
DPC and PI	0.293
PV and PM	0.283
PV and PI	0.268
PM and PI	0.177

All HTMT values are well below the stricter 0.85 threshold, confirming strong discriminant validity for all construct pairs. These results suggest that the constructs are distinct and do not overlap significantly.

3.6.6.5. VIF

VIF measures multicollinearity among predictor variables. High VIF values indicate redundancy or strong correlations between predictors (Hair et al., 2017). Table 10 has the VIF values, VIF ≤ 5 indicates acceptable multicollinearity and VIF > 5 suggests potentially problematic multicollinearity.

Table 10. VIF Values

Indicator	VIF Value	Interpretation
DPC1	2.553	Acceptable, no multicollinearity issues.
DPC2	3.147	Acceptable, no multicollinearity issues.
DPC3	2.566	Acceptable, no multicollinearity issues.
PI1	3.860	Acceptable, no multicollinearity issues.
PI2	3.110	Acceptable, no multicollinearity issues.
PI3	3.994	Acceptable, no multicollinearity issues.
PM1	1.275	Very low, no multicollinearity issues.
PM2	1.946	Acceptable, no multicollinearity issues.
PM3	2.073	Acceptable, no multicollinearity issues.
PV1	2.883	Acceptable, no multicollinearity issues.
PV2	2.463	Acceptable, no multicollinearity issues.
PV3	2.573	Acceptable, no multicollinearity issues.
PV4	3.478	Acceptable, no multicollinearity issues.

VIF values are below 5, indicating no serious multicollinearity issues for the majority of indicators.

3.6.6.6. Model Fit Indices (MFI)

CFI scores near 1 indicate good concordance. CFI of 0.90 or above is commonly recognized as acceptable (Bentler, 1990). Similar to the CFI, results of the TLI near 1 indicate a higher goodness of fit. A TLI value of 0.90 or above is regarded as acceptable (Hu and Bentler, 1999). RMSEA values less than 0.08 suggest a fair fit and below 0.05 suggest a close match (Steiger, 1990). Table 11 shows the related index values.

Table 11. MFI

Fit Index	Value	Threshold for Acceptable Fit
CFI	0.95	≥ 0.90
TLI	0.94	≥ 0.90
RMSEA	0.05	< 0.08

MFI indicate a strong and acceptable model fit. CFI is 0.95, surpassing the threshold of 0.90, suggesting an excellent fit between the hypothesized model and the observed data. Similarly, the Tucker-Lewis Index (TLI) is 0.94, also above the acceptable threshold of 0.90, reinforcing the model's robustness. RMSEA is 0.05, well below the threshold of 0.08, indicating a very good fit and minimal approximation error. These results collectively confirm that the model demonstrates a strong overall fit and is well-suited for explaining the data.

Table 12. SRMR, d_ULS, d_G, Chi-square and NFI Results

Metric	Saturated Model	Estimated Model
SRMR	0.047	0.047
d_ULS	0.201	0.201
d_G	0.140	0.140
Chi-square	331.322	331.322
NFI	0.902	0.902

SRMR (Standardized Root Mean Square Residual) quantifies average discrepancy among observed and predicted of correlations. Smaller results show higher model fit, SRMR $\leq$ 0.08 is reasonable (Hu and Bentler, 1999). d_ULS (Unweighted Least Squares Discrepancy) measures the inconsistency in the observed and implied covariance matrix. Smaller values suggest improved fit (Henseler et al., 2016). d_G (Geodetic Discrepancy) is another measure of model fit that compares covariance matrices with a focus on geodetic distances. Similar to d_ULS, smaller values suggest better fit (Henseler et al., 2016). The chi-square function assesses the inconsistency from observed to expected covariance data matrixes. An insignificant chi-square ($p > 0.05$) points to a favorable fit (Bentler, 1990). NFI (Normed Fit Index) measures the quality of the model fit of the predicted matrix in comparison to a null model. Readings approaching 1 signal a higher goodness of fit (Bentler and Bonett, 1980). The MFI in Table 12 reveals that both the saturated and estimated models show a good fit. The SRMR value of 0.047 is well below the recommended value of 0.08 and indicates an excellent match. Similarly, the NFI of 0.902 is above the 0.90 threshold value, supporting the overall model fit.

These findings verify the model is well specified as well as suitable for interpretation and hypothesis testing.

3.6.6.7. Path Coefficients and Significance Levels

Associations between structures in SEM are often evaluated through path coefficients and their respective levels of significance, which provide insight into the power and direction of the hypothesized linkages. Path coefficient represents a standardized estimate for the effect of an independent variable on a dependent variable within a structured model and its significance is assessed through statistical tests such as t-values and p-values (Hair et al., 2019).

Table 13. SEM Results

Path	Coefficient	Standard Error	t-value	p-value	Significance
H1: DPC → PV	-0.30	0.07	-4.29	<0.001	Significant
H2: DPC → PI	-0.15	0.08	-1.88	0.061	Not Significant
H3: PV → PI	0.55	0.09	6.11	<0.001	Significant
H4: PM → PV	0.45	0.08	5.63	<0.001	Significant
H5: PM → PI	0.20	0.10	2.00	0.045	Significant
H6: PM → DPC	0.10	0.08	3.71	0.223	Not Significant
H7: PM → PV → PI	0.25	0.05	5.00	<0.001	Significant
H8: DPC → PV → PI	-0.17	0.04	-4.25	<0.001	Significant

Table 13 shows the analysis of path coefficients and significance levels, reveals several key relationships among the constructs. A significant negative relationship exists between DPC and PV ($\beta = -0.30$, $p < 0.001$), while the direct effect of DPC on PI is not significant ($\beta = -0.15$, $p = 0.061$). PV strongly and positively influences PI ($\beta = 0.55$, $p < 0.001$). PM has a significant positive impact on PV ($\beta = 0.45$, $p < 0.001$) and a weaker but significant direct effect on PI ($\beta = 0.20$, $p = 0.045$). Additionally, PM positively influences PI indirectly through PV ($\beta = 0.25$, $p < 0.001$). DPC, however, exhibit a significant indirect negative effect on PI via PV ($\beta = -0.17$, $p < 0.001$). These findings highlight the critical mediating role of PV and the dual influence of PM on PI, while also illustrating the complex impact of DPC.

4. Discussion of Findings

The statistical outcomes from SEM results offer significant informations about the relationships between PM, DPC, PV and PI. These findings are interpreted in terms of the research questions and hypotheses as follows:

H1: DPC has a negative effect on PV. The path coefficient between DPC and PV is -0.30 ($p < 0.001$), validating Hypothesis 1. The results are in accordance with Malhotra, Kim and Agarwal (2004) who demonstrate that higher DPC leads toward less trust and PV in online interactions. The consistency of these results suggests that consumers' concerns about data privacy continue to significantly undermine their perceptions of value.

H2: DPC have a negative effect on PI. Contrary to expectations, our study did not find a significant direct effect of DPC on PI (coefficient = -0.15, $p = 0.061$). Previous studies, such as those by Dinev and Hart (2006), indicated that DPC negatively impact PIs. The difference in findings may be due to changes in consumer attitudes over time or the increasing prevalence of privacy regulations that mitigate some concerns.

H3: PV positively influences PI. Path coefficient for PV and PI is 0.55 ($p < 0.001$), which supports Hypothesis 3. This strong positive relationship indicates if individuals sense high value in PM, they have higher intention to buy the offered goods or services. PV has an essential role in driving consumers' buying decisions (Sweeney and Soutar, 2001).

H4: PM has a positive effect on PV. The path coefficient for PM to PV was 0.45 ($p < 0.001$), indicating a strong positive effect. This supports Hypothesis 4, suggesting that PM efforts significantly enhance the PV of products and services. This is consistent with previous research by Bleier and Eisenbeiss (2015), who also reported that personalized advertisements significantly enhance consumer perception of value. The similarity in findings reinforces the notion that PM efforts are effective in making consumers feel that the marketed products or services are more valuable.

H5: PM has a positive effect on PI. The path coefficient for PM to PI was 0.20 ($p = 0.045$), which is marginally significant, thus supporting Hypothesis 5. This finding is somewhat consistent with the work of Baek and Morimoto (2012), who found that personalized advertising positively influences PI, although their reported effect size was larger. The marginal significance in our study could be attributed to variations in sample characteristics or the specific context of PM.

H6: 6: PM has a negative effect on DPC. The analysis reveals that the hypothesized relationship between PM and DPC (H6) is not statistically significant, as indicated by a path coefficient of 0.10 ($p = 0.223$). This suggests that PM efforts do not have a direct impact on reducing or increasing DPC among consumers. These results are contrary to some prior studies, such as Dinev and Hart (2006), which highlighted that transparent and well-executed PM strategies can alleviate DPC by fostering trust. However, the findings of this study may reflect the nuanced reality of contemporary consumer perceptions. It is possible that consumers have become more accustomed to PM in digital environments and thus view it as a standard practice, independent of their privacy-related apprehensions.

H7: PV mediates the relationship between PM and PI. The indirect effect of PM on PI through PV was significant (coefficient = 0.25, $p < 0.001$), supporting Hypothesis 6. This finding indicates that PM enhances PV, which in turn drives PI. PV acts as a crucial mediator in this relationship, highlighting the importance of delivering value through personalization to influence consumer behavior (Sweeney and Soutar, 2001).

H8: PV mediates the relationship between DPC and PI. The indirect effect of DPC on PI through PV was significant (coefficient = -0.17, $p < 0.001$), supporting Hypothesis 7. This result suggests that DPC diminish PV, which subsequently reduces PI. The mediating role of PV underscores the impact of DPC on the overall consumer evaluation and their subsequent purchase decisions (Sweeney and Soutar, 2001; Culnan and Armstrong, 1999).

5. Implications

5.1. Practical Implications

Marketers should continue to invest in PM efforts, as they have been shown to positively impact PV and PI. By tailoring advertisements and recommendations to individual consumer preferences, companies can enhance the relevance and attractiveness of their offerings (Bleier and Eisenbeiss, 2015). However, marketers must also be mindful of DPC. Strategies should include transparent communication about data usage and robust data protection measures to mitigate consumer concerns and enhance trust (Malhotra, Kim and Agarwal, 2004).

Companies should find a balance between personalization and privacy by adopting best practices for data management. Implementing opt-in mechanisms, ensuring open confidentiality policies and letting individuals have control over their personal data could reduce DPC and improve PV (Dinev and Hart, 2006). As PV mediates the relationship between PM, DPC and PI, marketers should prioritize delivering high PV through the quality, relevance and benefits of personalized content (Sweeney and Soutar, 2001).

5.2. Theoretical Implications

This study contributes to the theoretical understanding of how PM and DPC affect consumer behavior. It validates the significant role of PV in mediating these relationships and aligns with established theories in marketing and consumer behavior (Sweeney and Soutar, 2001). The findings expand the privacy calculus model by highlighting the indirect effects of DPC on PI through PV. This offers a more nuanced view of how DPC influence consumer decisions beyond direct effects (Malhotra, Kim and Agarwal, 2004).

5.3. Policy Implications

Policymakers should continue to strengthen data privacy regulations to protect consumer data. Ensuring that companies comply with strict data protection standards can help reduce consumer concerns and increase trust in the Prime Minister (Dinev and Hart, 2006). Policies should encourage openness in data gathering and use policies. Giving individuals transparent information on the way their data is handled and giving them access to control of their personal information can help mitigate the DPC (Malhotra, Kim and Agarwal, 2004). Policymakers and industry bodies should promote educational initiatives to increase consumer education about digital privacy and the benefits of PD. Educated populations are more aware of the importance of data protection while appreciating the value of personalization (Sweeney and Soutar, 2001).

6. Conclusion

The findings from this study highlight the intricate dynamics between PM, DPC, PV and PI. PM positively influences both PV and PI, whereas DPC negatively affect PV. PV emerges as a critical mediator, emphasizing its central role in translating PM efforts and DPC into actual PIs. Marketers should focus on enhancing PV while addressing DPC to optimize the effectiveness of PM strategies. By balancing these aspects, businesses can foster stronger consumer trust and drive purchase behaviors more effectively.

6.1. Future Research Directions

Future research can explore other potential mediators and moderators such as consumer trust, brand loyalty and demographic factors to develop a broader insight into the dynamics between PM and consumer behavior.

6.2. Ethical Approval

Ethical approval for this research was granted by the Scientific Research and Publication Ethics Committee for Social Sciences and Humanities at Istanbul Beykent University, under approval number 163111, dated October 7, 2024.

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