Journal of Digital Content Management (JDCM)
Vol. 7, Issue 3, 2026; P 1-30
dcm.atu.ac.ir
DOI: 10.22054/dcm.2026.85668.1269

ATU PRESS

Original Research Received: 05-08-2025 Revised: 13-12-2025 Accepted: 22-12-2025
ISSN: 3116-1715 eISSN: 3116-1448

Personalization - privacy paradoxes: The personalized advertising privacy calculus and behavioral intentions of Generation Z consumers in online stores

Hesamoddin Mostafaei MSc in Business Administration, Faculty of Economics and Management, Urmia University, Iran

Bagher Asgarnezhad Nouri * Associate Professor of Business Administration, Faculty of Economics and Management, Urmia University, Iran

Hooshmand Bagheri Garbollagh Assistant Professor of Business Administration, Faculty of Economics and Management, Urmia University, Iran

Ramin Bashir Khodaparasti Associate Professor of Business Administration, Faculty of Economics and Management, Urmia University, Iran

Abstract

Purpose: This study investigates the personalization–privacy paradox and its influence on the behavioral intentions of Generation Z consumers. Specifically, it examines how personalized marketing affects consumers' perceptions of the benefits and threats of sharing personal information, as well as the role of privacy concerns in shaping their behavioral responses.

Method: The study population consisted of students at Urmia University aged between 18 and 27 years. Based on Cochran's formula, a sample of 384 participants was selected. Data were collected using a standardized questionnaire. The research model and hypotheses were analyzed using the

∗ Corresponding Author: b.asgarnezhad@urmia.ac.ir

How to Cite: Mostafaei, H., Asgarnezhad Nouri, B., Bagheri Garbollagh, H., Bashir Khodaparasti, R. (2026). Personalization - privacy paradoxes: The personalized advertising privacy calculus and behavioral intentions of Generation Z consumers in online stores, Journal of Digital Content Management, 7(3), 1-30. DOI: 10.22054/dcm.2026.85668.1269

Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with SPSS and SmartPLS software.
Findings: The results revealed that personalization has a significant positive effect on consumers' behavioral intentions, including purchase intention and viral behavioral intention. Personalization was also found to significantly influence consumers' perceptions of both the benefits and threats associated with sharing personal information. Perceived benefits positively affected the perceived value of information disclosure, whereas perceived threats had a negative effect on this value. Furthermore, the perceived value of information disclosure significantly enhanced consumers' behavioral intentions. The findings also indicated that privacy concerns negatively moderate the relationship between the perceived value of information disclosure and behavioral intentions.
Conclusion: The findings suggest that while personalized marketing can effectively enhance Generation Z consumers' behavioral intentions, its success depends on managing the privacy concerns associated with personal data disclosure. Therefore, marketers should develop personalization strategies that maximize perceived benefits while minimizing privacy-related concerns to foster positive consumer responses.

Keywords: Online Privacy, Data Disclosure, Targeted Advertising, , Digital Consumer Trust, Young Consumers

Introduction

Personalization refers to the process of delivering customized advertisements to individuals based on their preferences and interests. In personalized advertising, factors such as past purchase history, internet search behavior, and demographic information are utilized (Lee, 2016). This approach to advertising holds significant potential for enhancing the effectiveness of marketing strategies (Pavlou & Stewart, 2000). Personalized advertising enables manufacturers to engage with consumers on a more individualized level, fostering effective relationships and better addressing consumer needs (Shanahan et al., 2019). Personalization is a key marketing concept that significantly influences consumers' behavioral intentions. These intentions include purchase intention and viral behavioral intention, both of which are integral components of consumer behavior (Kulkarni et al., 2020). The increase in purchase intention resulting from personalization in marketing indicates a higher likelihood of purchase. This suggests that when advertisements align with consumers' desires, a positive interaction is created, encouraging them to make a purchase (Peña-García, 2020).

Viral behaviors are also known as focal activities on social media. Viral behavioral intention is broadly defined as consumers' interactions with user-generated content, such as liking, sharing, and commenting (Alhabash et al, 2013). As a result, by monitoring individuals' activity in virtual spaces, it is possible to deliver advertisements tailored to their wishes and preferences, ultimately leading to viral behavior (Alhabash, 2019).Research evidence shows that 68% of consumers hold an unfavorable view of personalized advertising due to privacy concerns (Smith, 2014).and high levels of personalized advertising lead to negative consumer reactions toward marketers' messages (Baek & Morimoto, 2012). Additionally, past research has shown that some consumers are turning to technologies that allow them to block mobile ads (Brinson et al., 2018). This contradiction between consumers' intention to protect their privacy and their tendency to act in a way that makes personal information available is known as the Privacy Paradox (Norberg et al., 2007). Personalization, despite its benefits, raises concerns about privacy and information security among consumers.

However, even with these threats, consumers often choose to provide their information, and the balance between the perceived benefits and risks of this decision is known as privacy calculus.

Researchers have applied privacy calculus theory to examine consumer behavior across various digital contexts, including mobile applications, virtual spaces, and other digital technologies (Jahari, et al., 2022; Hayes et al., 2021). This theory prompts consumers to weigh the benefits of personalization against their privacy concerns (Lee et al., 2016). This research examines Generation Z's reaction to personalized advertisements. Marketing researchers have long sought to better understand the needs, preferences, attitudes, and behaviors of different generational groups (Johnson & Chattaraman, 2019).

Generation Z includes individuals born between 1997 and 2012 (Dimock, 2019). They are the first generation to grow up in an era where digital technologies were widely accessible. From an early age, Generation Z was able to take full advantage of the Internet, which played a significant role in their upbringing, earning them the nickname 'the Internet generation.' This technological advantage was not available to previous generations (Childers & Boatwright, 2021). Research shows that Generation Z is increasingly using digital blocking software and secure browsers, as well as disabling location tracking, especially when personalization doesn't align well with their preferences (Brinson et al., 2018). When consumers are reluctant to share personal data, they take proactive measures to limit data tracking. Marketers are left with less information to create personalized marketing (Ackermann et al., 2022). Therefore, according to the explanations given in this research, this study aims to develop a model to investigate and analyze advertisement personalization and its effect on privacy calculus. Finally, it will examine the impact of personalization and the privacy paradox on the behavioral intentions of Generation Z consumers in online stores. Additionally, the moderating effect of privacy concerns and its influence on the relationship between the perceived value of information disclosure and the behavioral intentions of Generation Z consumers should be investigated. It should be noted that the relationship between personalization, privacy calculus, and behavioral intentions of Generation Z consumers, along with the moderating role of privacy concerns, has been less discussed in past research.

Literature Review

Personalization in marketing

Personalization in marketing is an important component of the marketing mix, where each customer is served using customized marketing strategies (Dawn, 2014). Personalization can be defined as 'the integration of recognizable aspects of a person in the context of marketing content.' These characteristics can include personal identity information, such as a person's name or photo, information resulting from a person's past behavior, such as websites visited or movies watched, and a set of characteristics, such as gender, that are common among a group of people (Pfiffelmann, 2020). In practice, personalization is considered a process designed to create relevant and personalized interactions that enhance the customer experience (Polk et al., 2020). Personalization requires customer involvement to create a tailored experience, which can be achieved through customer surveys, purchase data, and social media interactions, among others (Lim & Zhang, 2022). Personalized advertising based on customer interests or demographic data helps customers find the products or services they may need. Therefore, personalized advertisements are more informative and reliable than traditional advertisements (Kim & Han, 2014). In addition, customers find personalized ads more pleasant because these ads provide information that helps them meet their needs (Boerman et al., 2017).

The personalization paradox and privacy calculus

Privacy calculus, as a function of users' positive or negative perceptions (perceived benefits and threats of information disclosure), refers to the amount of information disclosed to others. Although consumers are clearly concerned about their privacy, they often share a significant amount of information in practice. Various explanations exist for such behaviors. For example, privacy calculus suggests that consumers accept the risks associated with losing privacy in exchange for benefits, such as more personalized offers and discounts (Xu et al., 2011; Sultan et al., 2009). On the other hand, a strong desire to receive personalized services can increase users' intentions to disclose their personal and descriptive information. However, in the event of a security threat, a negative perception may arise among users, prompting them to take preventive measures (Boehmer et al., 2015). Users consistently want to protect their personal information and avoid activities and behaviors that could pose a security threat (Lee & Larsen, 2009). However, if users feel they gain benefits such as better personalized service (Davenport et al., 2011), enjoyment (Kim et al., 2007), convenience (Milne & Gordon, 1993), or monetary rewards by disclosing their private information, they may be willing to give up some level of privacy in exchange for these benefits. This trade-off between personalization benefits and privacy risks has led to the identification of critical privacy concerns, termed the personalization-privacy paradox. Many studies have proposed solutions to this paradox, such as privacy assurance and personalization with consent. For example, Özpolat and Jank (2015) highlighted the importance of ensuring privacy in influencing purchasing behavior, while Goldfarb and Tucker (2011) found that personalized advertising increases purchases.

Development of hypotheses and conceptual model

Personalization is used by companies as a strategy to reduce costs, improve convenience, and customize products, prices, promotions, and distribution to enhance the customer experience. This strategy helps create purchase intention and, ultimately, leads to purchase action (Krishnaraju & Mathew, 2013). Content and products personalized based on customer preferences can reduce customer fatigue and the time required for selection, thereby lowering cognitive load (Chandra et al., 2022). Personalized advertising allows manufacturers to engage consumers on a personal level, aiming to develop an effective relationship and better serve consumer needs (Shanahan et al., 2019). This approach influences consumer behavioral intentions, including purchase intention as a pre-purchase behavior and viral behavior intention as a post-purchase action (Kotler & Keller, 2016).

Reena and Udita (2020) conducted research entitled The Effect of Personalized Advertisements in Social Media on Consumer Purchase Intention. The findings showed that the frequency of exposure to personalized advertisements, the relevance and perceived usefulness of advertisements, concerns related to privacy controls, and cognitive and emotional attitudes significantly affect consumers' perceptions and subsequent purchase intentions. Chu et al. (2024) conducted a study titled The Effect of Personalization on Viral Behavior Intentions in TikTok: The Role of Perceived Creativity, Originality, and the Need for Uniqueness. The findings showed that content personalization on TikTok has a positive relationship with perceived creativity and authenticity, which in turn leads to viral behavior intention on the platform.

According to the explanations provided, the research hypotheses can be stated as follows:

- H1: Personalization affects the viral behavior intention of Generation Z consumers.
- H2: Personalization affects the purchase intention of Generation Z consumers.

Personalization occurs when companies design products based on customers' specific tastes and offer products most closely aligned with the individual's preferences, which presents both advantages and risks from the customer's perspective (Hayes et al., 2021). Personalization creates several benefits for the consumer. For example, it enables consumers to save time searching for the exact information they need (Nyheim et al., 2015). Ho (2012) pointed out that personalized services deliver the right content in the right form to specific people at the best time and place. Additionally, personalization enhances valuable consumer experiences (Piccoli et al., 2017), making consumers feel they are receiving special care and attention from the company (Nyheim et al., 2015). Franke (2009) claimed that personalization provides additional benefits to customers by matching their preferences with service features. However, in order to provide personalized services, companies must recognize consumer needs, which inevitably requires consumers to disclose private information, including personal profiles, location data, and purchase history (Ho, 2012).

Xu et al. (2011) conducted research titled The Personalization Privacy Paradox: An Exploratory Study of the Decision-Making Process for Location-Aware Marketing. The results showed that the effects of personalization on privacy risk-benefit beliefs differ based on the type of personalization system. Covert and overt systems, along with personal characteristics, moderate the parameters and path structure of the privacy account model. Additionally, the impact of personalization on perceived privacy risk was significant in the covert approach but insignificant in the overt approach. Xu et al. (2011) demonstrated that personalization is linked to both the perceived threats and benefits of information disclosure, acting as a double-edged sword. Benefits and risks may not independently influence consumers' responses but jointly prompt them to evaluate the consequences of their potential choices. Kang and Namkung (2019) conducted research titled

"The Role of Personalization on Continuance Intention in Food Service Mobile Apps: A Privacy Calculus Perspective". The results showed that personalization significantly affected perceived benefits, perceived threats, and perceived ease of use. Perceived benefits had a positive effect on the perceived value of disclosure, while perceived threats had no effect on the perceived value of disclosure. According to the explanations provided, the research hypotheses can be stated as follows:

- H3: Personalization has an effect on the perceived benefits of information disclosure for Generation Z.
- H4: Personalization has an effect on the perceived threats of information disclosure for Generation Z.

The privacy calculus concept suggests that when consumers are asked to provide personal information to companies, they perform a risk-benefit analysis, weighing the disincentives and incentives to disclosure (Awad & Krishnan, 2006). The result of such calculations is considered the cognitive evaluation of risks and benefits, which leads to the perceived value of information disclosure (Chu et al., 2024). In today's digital world, users regularly perform a risk-benefit analysis whenever they are required to disclose personal information. Since many users today are aware of their privacy rights and the potential adverse effects of sharing private information, this analysis has become commonplace when evaluating any type of IT service (Milne et al., 2004). Therefore, even before consenting to the relevant stakeholders' use of their private information, users often weigh the advantages and disadvantages of such decisions. This contradiction between consumers' intention to protect their online privacy and their willingness to disclose personal information is called the privacy paradox (Norberg et al., 2007).

Hayes et al. (2021) conducted research titled The Influence of Consumer–Brand Relationship on the Personalized Advertising Privacy Calculus in Social Media. The results indicated that strong consumer-brand relationships influence the perceived value of information disclosure by enhancing perceived benefits and reducing perceived risks. Conversely, perceived risks affect privacy calculus decisions when weak consumer-brand relationships exist.Additionally, McKee et al. (2024) conducted research titled Gen Z's Personalization Paradoxes: A Privacy Calculus Examination of Digital Personalization and Brand Behaviors. The results showed that both the privacy-benefit paradox and the avoidance-harassment paradox strongly influence consumers' intentions to avoid brands that fail in personalizing marketing. Pal et al. (2020) conducted research titled Personal Information Disclosure via Voice Assistants: The Personalization–Privacy Paradox. The results showed that personalized service, perceived enjoyment, and perceived complementarity affect perceived benefits, which in turn positively influence personal information disclosure. Perceived strictness and perceived control positively affect perceived risks, while perceived trust negatively affects perceived risks, which in turn negatively relates to personal information disclosure. According to the explanations provided, the research hypotheses can be stated as follows:

- H5: The perceived benefits of Generation Z consumers affect the perceived value of information disclosure due to personalization.
- H6: The perceived threats of Generation Z consumers affect the perceived value of information disclosure due to personalization.

With the arrival of the digital age, an increasing number of people are concerned about the disclosure of personal information collected by organizations (Esmaeilzadeh, 2020). Based on the Privacy Calculus model introduced by Laufer and Wolfe (1977), users engage in a process of weighing social benefits against potential adverse consequences before deciding whether to disclose sensitive information. This model provides a comprehensive framework that explains the interplay between perceived costs and benefits in users' decision-making processes. Privacy calculation refers to the process by which users evaluate the perceived value of information disclosure by balancing its benefits and risks. This calculation ultimately affects consumers' behavioral intentions, including their purchase intention and viral behavior intention (Hayes et al., 2021; Chu et al., 2024). According to the explanations provided, the research hypotheses are stated as follows:

- H7: The perceived value of information disclosure due to personalization affects Generation Z consumers' viral behavior intention.
- H8: The perceived value of information disclosure due to personalization affects Generation Z consumers' purchase intention.

Researchers have found that privacy concerns play an important role in the effectiveness of personalized advertising (Baek & Morimoto, 2012; Tucker, 2014). Several studies have shown that perceived privacy risks directly and indirectly affect users' willingness to disclose personal information in domains such as online services (Zhou, 2011), social business (Sharma & Crossler, 2014), intention to pay for in-app mobile phone services (Keith et al., 2016), and mobile applications (Balapour et al., 2020). One of the main concerns of personalized advertising is the invasion of privacy (Burgoon et al., 1989), as online privacy is closely related to access to individuals' personal information (Barth & De Jong, 2017). Researchers have found that when ad personalization goes too far and consumers perceive the potential for harm, concerns about privacy and control over their data increase (Jung, 2017). If consumers believe they have no control over their online privacy, they may perceive personalized advertising on a website as inappropriate (Tucker, 2014). Therefore, privacy concerns arising from personalized advertisements may lead to unfavorable evaluations of ads (Jung, 2017).

Gana & Koce (2016) conducted research titled The Effect of Trust and Privacy Concerns on Consumers' Purchase Intentions. Their study showed that privacy risks negatively affect mobile phone electronic marketing. Similarly, Jang & Sung (2021) conducted a study entitled Beyond the Privacy Paradox: The Moderating Effect of Online Privacy Concerns on Online Service Use Behavior. The results showed that online services use and privacy concerns, both in principle and behavior, are not contradictory but can act as a negative influence or limitation. Furthermore, individuals with high levels of innovation actively use online services due to differences in innovation adoption and use. As online activities become more common, privacy concerns are likely to influence the level of online service usage by interacting with other personality traits. As a result, privacy concerns act as a moderating variable that influences the degree or intensity of an individual's use of online services. According to the explanations provided, the research hypotheses are stated as follows:

- H9: Privacy concerns play a moderating role in the relationship between the perceived value of information disclosure and the viral behavior intention of Generation Z consumers.
- H10: Privacy concerns play a moderating role in the relationship between the perceived value of information disclosure and the purchase intention of Generation Z consumers.

Based on the explanations provided, the conceptual model of the research is shown in Figure 1:

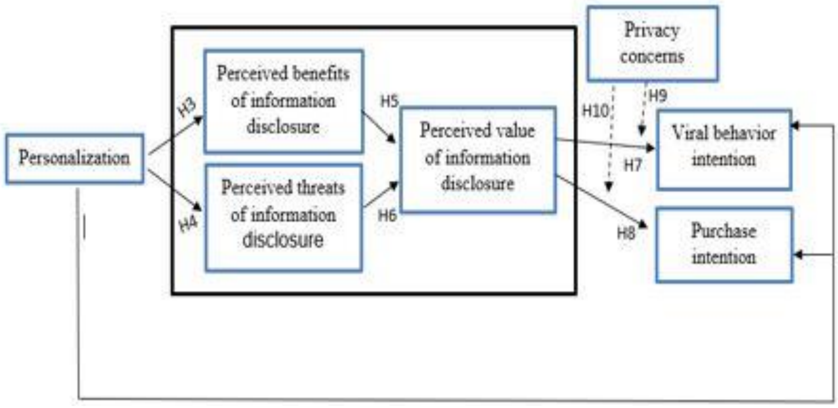

Figure 1. Conceptual model of research
(McKee et al.,2024; Chu et al., 2024; Xu et al., 2011; Ameen et al., 2022; Hayes et al., 2021; Ho et al., 2012)

Method

The statistical population of this research consists of Generation Z students from Urmia University, born between 1998 and 2012, who have had at least one shopping experience at Digikala. Digikala is one of the most successful e-commerce companies in Iran, utilizing the advantages of digital marketing to provide up-to-date services and effectively engage its target market. The company places particular emphasis on personalization in its marketing and advertising efforts and is a leader in this field. Digikala offers personalized advertisements based on factors such as customers' internet footprints, geographic location, age, and gender. For example, it uses personalized email campaigns, offering products and goods tailored to customers' unique characteristics to attract more customers and steadily increase its market share. To collect data, a standard questionnaire was used. The measurement tools included personalization (Chellappa & Sin, 2005), privacy calculus (Xu et al., 2011), privacy concern (McKee et al., 2024), purchase intention (Gefen & Straub, 2004), and consumer viral behavior intention (Alhabash et al., 2013). Given the unlimited statistical population, the sample size was determined to be 384 participants using Morgan's table. The questionnaires were distributed and collected in person through a convenience sampling method over several stages.

In this research, both descriptive and inferential statistics were used, along with SPSS and SMART PLS software, employing the partial least squares (PLS) method for data analysis. One of the key advantages of this approach is that it does not require the assumption of a normal data distribution. Structural equation modeling (SEM) was evaluated and interpreted using the PLS method in two stages: testing the measurement model and the structural model (Boniface et al., 2012). The PLS method employs several criteria to assess the fit of the measurement model, including construct validity, diagnostic validity, convergent validity, divergent validity, and reliability. Construct validity was tested using confirmatory factor analysis. Factor loadings were calculated by determining the correlation between the indicators of a construct and the construct itself. A factor loading of 0.4 or higher confirms that the variance between the construct and its indicators is greater than the measurement error of that construct, thereby indicating that the reliability of the measurement model is acceptable.

Findings

Demographic characteristics of the respondents

In this study, descriptive statistics methods, such as frequency distribution tables and percentage frequencies, were used with SPSS software to describe the demographic characteristics of Generation Z students at Urmia University. The demographic characteristics of the statistical sample are presented in Table 1.

Table 1. Demographic information of interviewees

Variable	Categories	Redundancy	Percent
Gender	Woman	212	55/2
	Man	172	44/8
Degree	Bachelor	274	71/4
	Master	107	27/9
	Phd	3	0/8
Faculty	Economics and management	162	42/2
	Literature and humanities	12	3/1
	Agriculture	21	5/5
	Veterinary medicine	3	0/8
	Electricity and computer	32	8/3

	Sports science	1	0/3
	Basic sciences	78	17/4 0/8
	Technical and engineering	67	
	Natural resources	3	1/3
	Art and architecture	5	17/4

Measurement model

To assess validity, structural, divergent, and convergent methods were used. Cronbach's alpha coefficients and composite reliability coefficients were employed to measure reliability, and the results are presented in Table 2.

Table 2. Cronbachs alpha, CR, and AVE values

Variable	Question	Factor load	t-statisticsof questions	Reliability coefficient (Cronbach's alpha)	Composite Reliability Coefficient (CR)	Average variance extracted (AVE)
Personalization	Q1	---	---	0/831	0/878	0/591
	Q2	0/798	30/028			
	Q3	0/838	37/421			
	Q4	0/705	13/600			
	Q5	0/766	21/533			
	Q6	0/731	20/760			
Perceived value of information disclosure	Q7	0/812	31/372	0/761	0/862	0/676
	Q8	0/849	43/494			
	Q9	0/805	32/440			
Perceived benefits of information disclosure	Q10	0/796	25/422	0/739	0/851	0/656
	Q11	0/841	42/970			
	Q12	0/793	33/297			

Perceived threats of information disclosure	Q13	0/942	114/550	0/934	0/958	0/883
	Q14	0/935	106/303			
	Q15	0/942	99/623			
Privacy concerns	Q16	0/850	28/253	0/889	0/923	0/750
	Q17	0/881	26/099			
	Q18	0/879	21/633			
	Q19	0/854	23/380			
Purchase intention	Q20	0/941	127/133	0/921	0/950	0/864
	Q21	0/926	70/551			
	Q22	0/921	82/831			
Viral behavior intention	Q23	0/894	63/334	0/950	0/961	0/833
	Q24	0/920	91/179			
	Q25	0/925	89/067			
	Q26	0/908	72/885			
	Q27	0/916	72/750			

In this research, the standard value for the factor loading was set at 0.4. To improve the indicators, question number 1, whose factor loading was less than 0.4, was removed(Tabachnik & Fidell, 2007). In Table 2, construct validity, diagnostic validity, convergent validity, and reliability have also been examined. Diagnostic validity is established if the extracted average variance (AVE) values are greater than the critical value of 0.5. The Dillon-Goldstein coefficient is used to assess the composite reliability of each construct. In the structural equation modeling methodology, a composite reliability coefficient higher than 0.7 indicates appropriate reliability for each construct (Davari & Rezazadeh, 2013). The values of this coefficient, which exceed 0.7, are shown in Table 2, confirming that the constructs have suitable composite reliability. Additionally, Cronbach's alpha was used to assess the internal consistency (reliability) of the research items. The coefficients were generally higher than 0.7, indicating a high level of internal coherence among the items. For the divergent validity test, the Fornell and Larcker matrix, which compares the correlation of a construct with its indicators against the correlation of that construct with other constructs, was used. The results are reported in Table 2. As shown, the values on the main diagonal are higher than those below in each column, indicating a stronger correlation of each construct with its indicators compared to its correlation with other constructs (Fornell & Larcker, 1981).

Table 3. The results of Fornell–Larcker Discriminant Validity Assessment

Variable	**Perceived value of information disclosure**	**Perceived threats of information disclosure**	**Personalization**	**purchase intention**	**Viral behavior intention**	**Perceived benefits of information disclosure**	**Viral behavior intention**
Perceived value of information disclosure	0/822						
Perceived threats of information disclosure	-0/307	0/889					
Personalization	0/418	-0/316	0/769				

purchase intention	0/554	-0/301	0/326	0/939			
Viral behavior intention	0/589	-0/292	0/330	0/927	0/911		
Perceived benefits of information disclosure	0/443	-0/237	0/456	0/482	0/460	0/810	
Viral behavior intention	-0/341	0/744	-0/221	-0/271	-/258	-0/199	0/867

Structural model

The Kolmogorov-Smirnov test was used to check the data distribution. In this test, the null hypothesis represents the assumption of normality for the data distribution. Table 4 shows the results of this test.

Table 3. The results of the Kolmogorov-Smirnov test on the normality of the research variables

Variables	Kolmogorov–Smirnov test	Level of significance
Personalization	0/124	0/00
Perceived benefits of information disclosure	0/146	0/00
Perceived threats of information disclosure	0/137	0/00

Perceived value of information disclosure	0/091	0/00
Purchase intention	0/131	0/00
Viral behavior intention	0/127	0/00
Privacy concerns	0/094	0/00

The results presented in Table 4 indicate that none of the variables follow a normal distribution, as the significance levels for these variables are less than 0.05. Therefore, due to the non-normal distribution of the variables, PLS software was used to implement methods related to structural equation modeling.

Figures 2 and 3 display the research model, including the latent and observed variables, in the form of measurement models. They also present the path coefficients between the variables, along with the determination coefficients and t-statistic values.

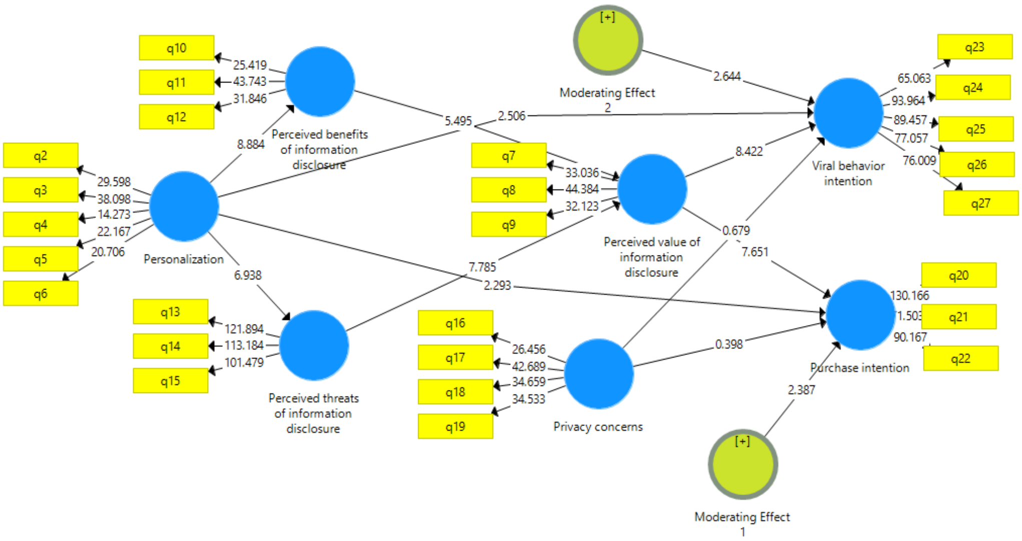

Figure 2. Values of Student's t statistic

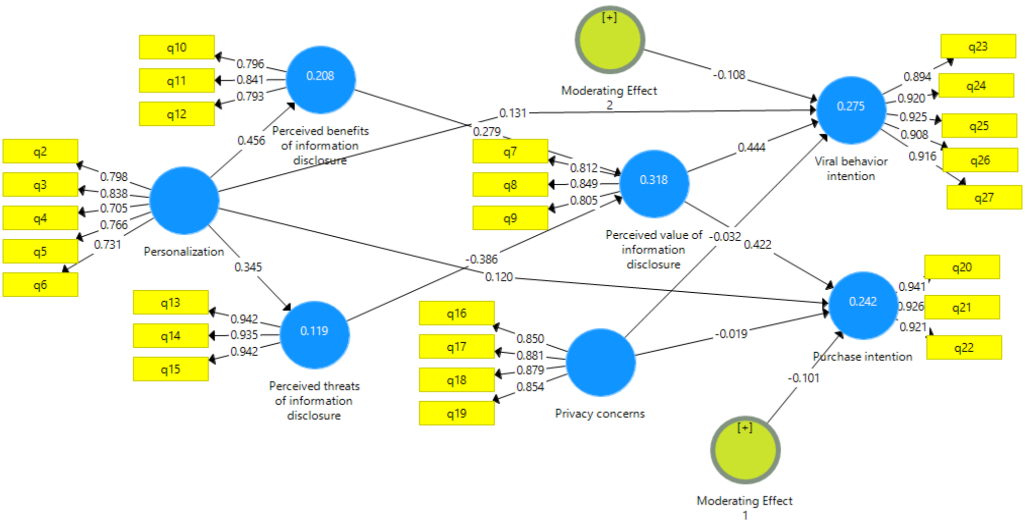

Figure 3. Path coefficients of the research model

According to the obtained results, in general, any path where the estimated t-statistic value is greater than 1.96 (Davari & Rezazadeh, 2013) indicates that the effect between the variables is significant at the 5% error level. R^2 is the coefficient of determination for the entire model, calculated based on the endogenous variables. It indicates the percentage of changes in the dependent variable that are explained by changes in the independent variables. In other words, the coefficient of determination serves as a criterion that connects the measurement part and the structural part of structural equation modeling, illustrating the effect of an exogenous (independent) variable on the endogenous (dependent) variable. Wynne (1998) identifies three threshold values of 0.19, 0.33, and 0.67 as criteria for weak, medium, and strong values of R^2.

Table 5. Values of coefficients of determination (R2) for endogenous variables

Endogenous variables	R^2
Personalization	--
Perceived benefits of information disclosure	0/208

Perceived threats of information disclosure	0/119
Perceived value of information disclosure	0/318
Viral behavior intention	0/275
Purchase intention	0/242
Privacy concerns	-------

According to Table 5, the value of R^2 for the variable of perceived benefits of information disclosure is 0.208, for the endogenous variable of perceived threats of information disclosure it is 0.119, for the perceived value of information disclosure it is 0.318, for purchase intention it is 0.242, and for viral behavior intention it is 0.275. Based on these criterion values, the model demonstrates a moderate structural fit.

The predictive fit criterion (Q^2) determines the predictive power of the model. Models that exhibit an acceptable structural fit should be able to predict indicators related to the endogenous constructs (Henseler, 2009). Regarding the intensity of the predictive power for endogenous structures, three threshold values have been established: 0.02, 0.15, and 0.35. If the value of Q^2 for an endogenous structure is close to 0.02, it indicates that the model has weak predictive power for the indicators of that structure. Similarly, a Q^2 value between 0.02 and 0.15 indicates relatively weak power, while a value from 0.15 to 0.35 indicates relatively strong power. A Q^2 value greater than 0.35 indicates strong predictive power (Henseler, 2009). The results related to the Q^2 index are presented in Table 6.

Table 6. Q^2values

Endogenous variables	Q^2
Perceived benefits of information disclosure	0/125
Perceived threats of information disclosure	0/099
Perceived value of information disclosure	0/199
Viral behavior intention	0/212
Purchase intention	0/195

As seen from the values in Table 6, the calculated values meet the required minimums, indicating an acceptable explanation of the relationships between the constructs and the endogenous constructs of the model. The GOF (Goodness of Fit) criterion is another metric for evaluating structural equations, indicating the degree of conformity between actual observations and the expected values of the model. Generally, the larger the GOF statistic, the more appropriate and desirable the fit of the models used in the research. Wetzels et al. (2009) introduced three threshold values of 0.01, 0.25, and 0.36 as indicators of weak, medium, and strong GOF, respectively. Table 7 presents the average values of the coefficient of determination for the endogenous variables, the average shared values, and the calculated value of the GOF statistic for the conceptual model of the research.

Table 7. Fit of the overall research model

Model	GOF	R^2	Communalities	GOF
Model related to research hypotheses	0/417	0/2324	0/75	0/417

The average value of the model's Coefficient of Determination (R^2) is 0.2324. Additionally, the GOF value is 0.417, indicating a very strong fit for the model. Therefore, it can be concluded that the model used in this research demonstrates high and acceptable desirability.

Table 8 presents the results of hypothesis testing, along with the path coefficients and t-statistics.

Table 8. Hypothesis test results

Hypothesis	Independent variable	Dependent variable	Modifier variable	Path coefficients	t values	Reslt
H1	Personalization	Viral behavior intention	---	0/131	2/448	Confirm
H2	Personalization	Purchase intention	---	0/120	2/227	Confirm
H3	Personalization	Perceived benefits of	---	0/456	8/457	Confirm

		information disclosure				
H4	Personalization	Perceived threats of information disclosure	---	0/345	6/988	Confirm
H5	Perceived benefits of information disclosure	Perceived value of information disclosure	---	0/279	5/389	Confirm
H6	Perceived threats of information disclosure	Perceived value of information disclosure	---	-0/386	8/073	Confirm
H7	Perceived value of information disclosure	Viral behavior intention	---	0/444	8/312	Confirm
H8	Perceived value of information disclosure	Purchase intention	---	0/422	7/520	Confirm
H9	Perceived value of information disclosure	Viral behavior intention	Privacy concerns	-0/108	2/686	Confirm
H10	Perceived value of information disclosure	Purchase intention	Privacy concerns	-0/101	2/483	Confirm

The t-statistic was calculated for the relationships between the endogenous (dependent) and exogenous (independent) variables. In general, for any path where the estimated t-statistic exceeds 1.96, the effect between the variables is considered significant at the 5% error level (Davari & Rezazadeh, 2013). Based on this criterion, it can be concluded that all relationships between the variables are significant and have been confirmed.

Conclusion

In this research, we aimed to investigate Personalization - privacy paradoxes: The personalized advertising privacy calculus and behavioral intentions of Generation Z consumers in online stores.To explore this topic, ten hypotheses were proposed. The results show that personalization has a significant positive effect on consumer behavioral intentions (purchase intention and viral behavior intention), aligning with the findings of Chu et al. (2024) and Wessel & Thies (2015). Additionally, personalization positively impacts the perceived threats and benefits of information disclosure, consistent with the research of Xu et al. (2011). The perceived benefits of information disclosure have a significant positive effect on the perceived value of information disclosure, in line with studies by Hayes et al. (2021) and Lee & Rha (2016). Conversely, the perceived threat of information disclosure has a significant negative effect on the perceived value of information disclosure, consistent with the findings of Xu et al. (2011) and Brinson et al. (2018). Moreover, the perceived value of information disclosure has a significant positive impact on consumer purchase intention and viral behavior intention, corroborating research by Zhao & Renard (2018) and Ponte et al. (2015). Lastly, privacy concerns negatively moderate the relationship between the perceived value of information disclosure and both purchase intention and viral behavior intention, echoing the findings of Jang & Sung (2021) regarding the moderating role of privacy concerns. Personalization of advertisements and products, due to their adaptability and alignment with consumers' unique characteristics (McKee et al., 2023)—such as personal interests, income, geographical location, and internet tracking—has long been important and useful for both consumers and marketers. Personalization fosters a sense of closeness to these products and services, making them more effective. The study also reveals the impact of personalization on the behavioral intentions of Generation Z and the generation's receptiveness to this style of advertising.

Given the influence of personalization on consumer behavioral intentions and privacy calculus, managers and decision-makers should recognize that addressing consumer privacy concerns is key to the success of personalized advertising. Privacy concerns are likely to moderate the extent of an individual's use of online services. The higher a person's privacy concerns, the less likely they are to engage with online services (Boerman et al., 2017; Jang & Sung, 2021). To enhance the effectiveness of personalized ads and products, companies should seek explicit consent for data collection and provide consumers with control over their data sharing. For consumers, the benefits of personalization are not the sole consideration. Many view companies with skepticism due to privacy concerns and mistrust, given the possibility of misuse or third-party sale of personal information (Stewart et al., 2002). This skepticism prompts consumers to weigh the advantages and risks carefully before making decisions. Legal frameworks, such as virtual contracts and consent mechanisms (e.g., cookie acceptance), can help address these concerns and ensure ethical data use. In light of the research findings, managers and planners should prioritize strategies to enhance information management and personalization capabilities. This includes familiarizing organizational leadership with the concepts of information management and personalization to drive success.

It is suggested that future research explores emerging trends in digital marketing, such as augmented reality technologies, virtual reality, and voice assistants, and their relationship to personalization. Additionally, the impact of personalization on other key marketing concepts, such as brand equity, warrants investigation. It would also be valuable to examine the use of personalized ads in political and election campaigns. To date, no studies have addressed the relationship between demographic factors and the personalization-privacy paradox in the context of personalized advertising. Although our study focused on privacy-related risks, a more comprehensive examination of other risks influencing perceived value is necessary. Moreover, using qualitative approaches such as content analysis, grounded theory, or phenomenology could yield valuable insights. Finally, future research could explore the impact of personality traits, such as selfishness and narcissism, on viral behavior.

Like any research effort, this study has its limitations. One major limitation is the widespread use of questionnaires in research today, leading to the issue of questionnaire bias. This can result in suboptimal cooperation from the research population in completing the questionnaires. The lack of accuracy and attention in responding to questions, along with some participants' unwillingness to cooperate, caused data inconsistencies, which posed challenges in data analysis.

This study was conducted cross-sectionally in the spring of 2024. As technology is expected to play an increasingly important role in customer experience, future research could benefit from a longitudinal design, allowing data to be collected at different points in time. This approach would provide deeper insights and enhance the findings.

CONFLICT OF INTEREST: The authors declare that they have no conflicts of interest regarding the publication of this manuscript.

References

Ackermann, K. A., Burkhalter, L., Mildenberger, T., Frey, M., & Bearth, A. (2022). Willingness to share data: Contextual determinants of consumers' decisions to share private data with companies. Journal of Consumer Behaviour, 21(2), 375-386. https://doi.org/10.1002/cb.2012

Alhabash, S., McAlister, A. R., Hagerstrom, A., Quilliam, E. T., Rifon, N. J., & Richards, J. I. (2013). Between likes and shares: Effects of emotional appeal and virality on the persuasiveness of anticyberbullying messages on Facebook. Cyberpsychology, Behavior, and Social Networking, 16(3), 175-182. https://doi.org/10.1089/cyber.2012.0265

Alhabash, S., Almutairi, N., Lou, C., & Kim, W. (2019). Pathways to virality: Psychophysiological responses preceding likes, shares, comments, and status updates on Facebook. Media Psychology, 22(2), 196-216. https://doi.org/10.1080/15213269.2017.1416296

Ameen, N., Hosany, S., & Paul, J. (2022). The personalisation-privacy paradox: Consumer interaction with smart technologies and shopping mall loyalty. Computers in Human Behavior, 126, 106976. https://doi.org/10.1016/j.chb.2021.106976

Awad, N. F., & Krishnan, M. S. (2006). The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization. MIS quarterly, 13-28. https://doi.org/10.2307/25148715

Baek, T. H., & Morimoto, M. (2012). Stay away from me. Journal of advertising,41(1),59-76.https://doi.org/10.2753/JOA0091-3367410105

Balapour, A., Nikkhah, H. R., & Sabherwal, R. (2020). Mobile application security: Role of perceived privacy as the predictor of security perceptions. International Journal of Information Management, 52, 102063. https://doi.org/10.1016/j.ijinfomgt.2019.102063

Barth, S., & De Jong, M. D. (2017). The privacy paradox–Investigating discrepancies between expressed privacy concerns and actual online behavior–A systematic literature review. Telematics and informatics, 34(7), 1038-1058. https://doi.org/10.1016/j.tele.2017.04.013

Boehmer, J., LaRose, R., Rifon, N., Alhabash, S., & Cotten, S. (2015). Determinants of online safety behaviour: Towards an intervention strategy for college students. Behaviour & Information Technology, 34(10), 1022-1035. https://doi.org/10.1080/0144929X.2015.1028448

Boerman, S. C., Kruikemeier, S., & Zuiderveen Borgesius, F. J. (2017). Online behavioral advertising: A literature review and research agenda. Journal of advertising, 46(3), 363-376. https://doi.org/10.1080/00913367.2017.1339368

Boniface, B., Gyau, A., & Stringer, R. (2012). Linking price satisfaction and business performance in Malaysia's dairy industry. Asia Pacific Journal of Marketing and Logistics, 24(2), 288-304. https://doi.org/10.1108/13555851211218066

Brinson, N. H., Eastin, M. S., & Cicchirillo, V. J. (2018). Reactance to personalization: Understanding the drivers behind the growth of ad blocking. Journal of Interactive Advertising, 18(2), 136-147. https://doi.org/10.1080/15252019.2018.1491350

Burgoon, J. K., Parrott, R., Le Poire, B. A., Kelley, D. L., Walther, J. B., & Perry, D. (1989). Maintaining and restoring privacy through communication in different types of relationships. Journal of social and personalrelationships,6(2),131-158. https://doi.org/10.1177/0265407589006002017urlappend=%3Futm_source%3Dresearchgate.net%26utm_medium%3Darticle

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. Psychology&Marketing,39(8),1529-1562. https://psycnet.apa.org/doi/10.1002/mar.21670

Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. Information technologyandmanagement,6(2),181-202. https://doi.org/10.1007/s10799-005-5879-y

Childers, C., & Boatwright, B. (2021). Do digital natives recognize digital influence? Generational differences and understanding of social media influencers. Journal of Current Issues & Research in Advertising, 42(4), 425-442. https://doi.org/10.1080/10641734.2020.1830893

Chu, S. C., Deng, T., & Mundel, J. (2024). The impact of personalization on viral behavior intentions on TikTok: The role of perceived creativity, authenticity, and need for uniqueness. Journal of Marketing Communications,30(1),1-20. https://doi.org/10.1080/13527266.2022.2098364

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. psychometrika, 16(3), 297-334. https://doi.org/10.1007/BF02310555

Davari, A., & Rezazadeh, A. (2013). Structural equation modeling with PLS. Tehran: Jahad University, 215(2), 224.

Davenport, T. H., Mule, L. D., & Lucker, J. (2011). Know what your customers want before they do. harvard Business review, 89(12), 84-92.

Dawn, S. K. (2014). Personalised Marketing: concepts and framework. Productivity, 54(4), 370.

Dimock, M. (2019). Defining generations: Where Millennials end and Generation Z begins. Pew Research Center, 17(1), 1-7. https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins

Esmaeilzadeh, P. (2020). The effect of the privacy policy of Health Information Exchange (HIE) on patients' information disclosure intention.Computers&Security,95,101819. https://doi.org/10.1016/j.cose.2020.101819

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

Franke, N., Keinz, P., & Steger, C. J. (2009). Testing the value of customization: when do customers really prefer products tailored to their preferences?. Journal of marketing, 73(5), 103-121. https://doi.org/10.1509/jmkg.73.5.103

Gana, M. A., & Koce, H. D. (2016). Mobile marketing: The influence of trust and privacy concerns on consumers' purchase intention. International Journal of Marketing Studies, 8(2), 121. https://doi.org/10.5539/ijms.v8n2p121?urlappend=%3Futm_source%3Dresearchgate.net%26utm_medium%3Darticle

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: experiments in e-Products and e-Services.Omega,32(6),407-424. https://doi.org/10.1016/j.omega.2004.01.006

Goldfarb, A., & Tucker, C. E. (2011). Privacy regulation and online advertising. Management science, 57(1), 57-71.

Hayes, J. L., Brinson, N. H., Bott, G. J., & Moeller, C. M. (2021). The influence of consumer–brand relationship on the personalized advertising privacy calculus in social media. Journal of Interactive Marketing, 55(1), 16-30. https://doi.org/10.1016/j.intmar.2021.01.001

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In New challenges to international marketing (pp. 277-319). Emerald Group Publishing Limited. https://doi.org/10.1108/S1474-7979(2009)0000020014

Ho, S. Y. (2012). The effects of location personalization on individuals' intention to use mobile services. Decision Support Systems, 53(4), 802-812. https://doi.org/10.1016/j.dss.2012.05.012

Jahari, S. A., Hass, A., Hass, D., & Joseph, M. (2022). Navigating privacy concerns through societal benefits: A case of digital contact tracing applications. Journal of Consumer Behaviour, 21(3), 625-638. https://doi.org/10.1002/cb.2029

Jang, C., & Sung, W. (2021). Beyond the privacy paradox: the moderating effect of online privacy concerns on online service use behavior. Telematics and Informatics, 65, 101715. https://doi.org/10.1016/j.tele.2021.101715

Johnson, O., & Chattaraman, V. (2019). Conceptualization and measurement of millennial's social signaling and self-signaling for socially responsible consumption. Journal of Consumer Behaviour, 18(1), 32-42. https://doi.org/10.1002/cb.1742

Jung, A. R. (2017). The influence of perceived ad relevance on social media advertising: An empirical examination of a mediating role of privacy concern. Computers in human behavior, 70, 303-309. https://doi.org/10.1016/j.chb.2017.01.008

Kamalul Ariffin, S., Mohan, T., & Goh, Y. N. (2018). Influence of consumers' perceived risk on consumers' online purchase intention. Journal of research in Interactive Marketing, 12(3), 309-327.

Kang, J. W., & Namkung, Y. (2019). The role of personalization on continuance intention in food service mobile apps: A privacy calculus perspective. International Journal of Contemporary Hospitality Management, 31(2), 734-752.

Keith, M. J., Babb, J., Furner, C., Abdullat, A., & Lowry, P. B. (2016). Limited information and quick decisions: consumer privacy calculus for mobile applications. AIS Transactions on Human-Computer Interaction (THCI), 8(3), 88-130.

Kim, H. W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: an empirical investigation. Decision support systems, 43(1), 111-126. https://doi.org/10.1016/j.dss.2005.05.009

Kim, Y. J., & Han, J. (2014). Why smartphone advertising attracts customers: A model of Web advertising, flow, and personalization. Computers in human behavior, 33, 256-269.

Kotler, P. dan Keller, K. L. (2016) Marketing Management. 15th ed. Boston: Pearson.

Kulkarni, K. K., Kalro, A. D., & Sharma, D. (2020). The interaction effect of ad appeal and need for cognition on consumers' intentions to share viral advertisements. Journal of Consumer Behaviour, 19(4), 327-338. https://doi.org/10.1002/cb.1809

Krishnaraju, V., & Mathew, S. K. (2013). Web personalization research: an information systems perspective. Journal of Systems and Information Technology, 15(3), 254-268. https://doi.org/10.1108/JSIT-11-2012-0065

Laufer, R. S., & Wolfe, M. (1977). Privacy as a concept and a social issue: A multidimensional developmental theory. Journal of social Issues, 33(3), 22-42. https://doi.org/10.1111/j.1540-4560.1977.tb01880.x

Lee, J. M., & Rha, J. Y. (2016). Personalization–privacy paradox and consumer conflict with the use of location-based mobile commerce. Computers in Human Behavior, 63, 453-462.

Lee, Y., & Larsen, K. R. (2009). Threat or coping appraisal: determinants of SMB executives' decision to adopt anti-malware software. European Journal of Information Systems, 18(2), 177-187.

Li, C. (2016). When does web-based personalization really work? The distinction between actual personalization and perceived personalization. Computers in human behavior, 54, 25-33.

Lim, J. S., & Zhang, J. (2022). Adoption of AI-driven personalization in digital news platforms: An integrative model of technology acceptance and perceived contingency. Technology in Society, 69, 101965. https://doi.org/10.1016/j.techsoc.2022.101965

McKee, K. M., Dahl, A. J., & Peltier, J. W. (2024). Gen Z's personalization paradoxes: A privacy calculus examination of digital personalization and brand behaviors. Journal of Consumer Behaviour, 23(2), 405-422. https://doi.org/10.1002/cb.2199

Milne, G. R., & Gordon, M. E. (1993). Direct mail privacy-efficiency trade-offs within an implied social contract framework. Journal of Public Policy & Marketing, 12(2), 206-215. https://doi.org/10.1177/074391569101200206

Milne, G. R., Rohm, A. J., & Bahl, S. (2004). Consumers' protection of online privacy and identity. Journal of Consumer Affairs, 38(2), 217-232. https://doi.org/10.1111/j.1745-6606.2004.tb00865.x

Norberg, P. A., Horne, D. R., & Horne, D. A. (2007). The privacy paradox: Personal information disclosure intentions versus behaviors. Journal of consumer affairs, 41(1), 100-126. https://doi.org/10.1111/j.1745-6606.2006.00070.x

Nyheim, P., Xu, S., Zhang, L., & Mattila, A. S. (2015). Predictors of avoidance towards personalization of restaurant smartphone advertising: A study from the Millennials' perspective. Journal of Hospitality and Tourism Technology, 6(2), 145-159. https://doi.org/10.1108/JHTT-07-2014-0026

Özpolat, K., & Jank, W. (2015). Getting the most out of third party trust seals: An empirical analysis. Decision Support Systems, 73, 47-56. http://dx.doi.org/10.1016/j.dss.2015.02.016

Pal, D., Arpnikanondt, C., & Razzaque, M. A. Personal information disclosure via voice assistants: the personalization–privacy paradox. SN Comput. Sci. 1 (5), 1–17 (2020). https://doi.org/10.1007/s42979-020-00287-9

Pavlou, P. A., & Stewart, D. W. (2000). Measuring the effects and effectiveness of interactive advertising: A research agenda. Journal of InteractiveAdvertising,1(1),61-77. https://doi.org/10.1080/15252019.2000.10722044

Peña-García, N., Gil-Saura, I., Rodríguez-Orejuela, A., & Siqueira-Junior, J. R. (2020). Purchase intention and purchase behavior online: A cross-cultural approach. Heliyon, 6(6). https://doi.org/10.1016/j.heliyon.2020.e04284

Pfiffelmann, J., Dens, N., & Soulez, S. (2020). Personalized advertisements with integration of names and photographs: An eye-tracking experiment. Journal of Business Research, 111, 196-207. https://doi.org/10.1016/j.jbusres.2019.08.017

Piccoli, G., Lui, T. W., & Grün, B. (2017). The impact of IT-enabled customer service systems on service personalization, customer service perceptions, and hotel performance. Tourism Management, 59, 349-362. https://doi.org/10.1016/j.tourman.2016.08.015

Polk, J., Tassin, C., & McNellis, J. (2020). Magic Quadrant for Personalization Engines. Gartner Report Reprint, 13.

Ponte, E. B., Carvajal-Trujillo, E., & Escobar-Rodríguez, T. (2015). Influence of trust and perceived value on the intention to purchase travel online: Integrating the effects of assurance on trust antecedents. Tourism management,47,286-302. https://doi.org/10.1016/j.tourman.2014.10.009

Reena, M., & Udita, K. (2020). Impact of Personalized Social Media Advertisements on Consumer Purchase Intention. Annals of the University Dunarea de Jos of Galati: Fascicle: I, Economics & Applied Informatics, 26(2). https://doi.org/10.35219/eai15840409101

Scarpi, D., Pizzi, G., & Matta, S. (2022). Digital technologies and privacy: State of the art and research directions. Psychology & Marketing, 39(9), 1687-1697. https://doi.org/10.1002/mar.21692

Shanahan, T., Tran, T. P., & Taylor, E. C. (2019). Getting to know you: Social media personalization as a means of enhancing brand loyalty and perceived quality. Journal of Retailing and Consumer Services, 47, 57-65. https://doi.org/10.1016/j.jretconser.2018.10.007

Sharma, S., & Crossler, R. E. (2014). Disclosing too much? Situational factors affecting information disclosure in social commerce environment. Electronic Commerce Research and Applications, 13(5), 305-319. https://doi.org/10.1016/j.elerap.2014.06.007

Smith, A. (2014). Half of online Americans don't know what a privacy policy is.

Sultan, F., Rohm, A. J., & Gao, T. (2009). Factors influencing consumer acceptance of mobile marketing: a two-country study of youth markets. Journal of interactive marketing, 23(4), 308-320.

Stewart, K. A., & Segars, A. H. (2002). An empirical examination of the concern for information privacy instrument. Information systems research, 13(1), 36-49. https://doi.org/10.1287/isre.13.1.36.97

Tabachnik, B. G., & Fidell, L. S. (2007). Using multivariate statistics Fifth Edition.

Tucker, C. E. (2014). Social networks, personalized advertising, and privacy controls. Journal of marketing research, 51(5), 546-562. https://doi.org/10.1509/jmr.10.0355

Vinzi, V. E., Trinchera, L., & Amato, S. (2010). PLS path modeling: from foundations to recent developments and open issues for model assessment and improvement. Handbook of partial least squares: Concepts, methods and applications, 47-82.

Wessel, M., & Thies, F. (2015). The effects of personalization on purchase intentions for online news: An experimental study of different personalization increments.

Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. MIS quarterly, 177-195. https://doi.org/10.2307/20650284

White, T. B., Zahay, D. L., Thorbjørnsen, H., & Shavitt, S. (2008). Getting too personal: Reactance to highly personalized email solicitations. Marketing Letters, 19, 39-50. https://doi.org/10.1007/s11002-007-9027-9

Wynne, C. W. (1998). Issues and opinion on structural equation modelling. Management Information Systems quarterly, 22(1), 1-8. https://doi.org/10.2307/249674 https://www.researchgate.net/publication/220260360_Issues_and_Opinion_on_Structural_Equation_Modeling

Xu, H., Luo, X. R., Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing. Decision support systems, 51(1), 42-52. https://doi.org/10.1016/j.dss.2010.11.017

Zhao, Z., & Renard, D. (2018). Viral promotional advergames: How intrinsic playfulness and the extrinsic value of prizes elicit behavioral responses. Journal of Interactive Marketing, 41(1), 94-103. https://doi.org/10.1016/j.intmar.2017.09.004

Zhou, T. (2011). The impact of privacy concern on user adoption of location-based services. Industrial Management & Data Systems, 111(2), 212-226. https://doi.org/10.1108/02635571111115146

How to Cite: Mostafaei, H., Asgarnezhad Nouri, B., Bagheri Garbollagh, H., Bashir Khodaparasti, R. (2026). Personalization - privacy paradoxes: The personalized advertising privacy calculus and behavioral intentions of Generation Z consumers in online stores, Journal of Digital Content Management, 7(3), 1-30. DOI: 10.22054/dcm.2026.85668.1269