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Article

AI Hyper-Personalization and Purchase Avoidance Behavior: The Mediating Role of Psychological Privacy Intrusion

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Abstract

This study investigates the impact of AI hyper-personalization on purchase avoidance behavior through the mediating role of Perceived Psychological Privacy Intrusion among Egyptian digital consumers. Drawing on Privacy Regulation Theory, Psychological Reactance Theory, and the Personalization–Privacy Paradox framework, the study develops a conceptual model explaining how AI-driven personalization may trigger negative consumer reactions in digital marketplaces. A quantitative research approach was employed using a structured online questionnaire distributed to Egyptian consumers who regularly interact with AI-powered shopping and recommendation platforms. The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that AI hyper-personalization does not directly influence purchase avoidance behavior. However, it significantly increases consumers' perceptions of psychological privacy intrusion, which subsequently leads to higher levels of purchase avoidance. Furthermore, the mediation analysis demonstrates that Perceived Psychological Privacy Intrusion fully mediates the relationship between AI hyper-personalization and purchase avoidance behavior. The study contributes theoretically by integrating multiple privacy and consumer behavior theories into a unified explanatory framework. Practically, the findings highlight the importance of transparent, ethical, and psychologically sensitive personalization strategies that balance personalization effectiveness with consumers' perceptions of privacy and autonomy.

Keywords: AI Hyper-Personalization; Purchase Avoidance Behavior; Psychological Privacy Intrusion; Personalization–Privacy Paradox; Digital Consumer Behavior.

1. Introduction

Digital markets have undergone a fundamental shift over the past decade. Algorithm-based recommendation systems, behavioral targeting, and predictive analytics have become integral parts of modern online shopping and social platforms. AI-powered hyper-personalization plays an increasingly important role in the field, allowing marketers to provide advertisements, product recommendations, and other messages with unparalleled levels of customization based on ever-updating data about individual consumers. Although studies have shown that some forms of hyper-personalized messages lead to greater efficiency of advertisement and higher conversion rates (Bleier & Eisenbeiss, 2015; Lambrecht & Tucker, 2013; An at el., 2024), mounting evidence suggests a worrying phenomenon—messages that are too personalized tend to create a sense of discomfort and drive consumers not only to ignore but also to avoid interacting with particular companies or platforms altogether.

This conflict between consumers' need for relevant experiences and their resistance to data mining is the essence of what the literature often describes as the Personalization–Privacy Paradox (Awad & Krishnan, 2006; Sutanto et al., 2013; Graham & Bonner, 2024). Modern, AI-enabled personalization goes even further in its ability to affect consumers negatively. While behavioral targeting and cookie retargeting were the focus of previous research, contemporary algorithms are capable of making assumptions about consumers' emotional states, predicting their purchasing decisions before consumers decide themselves, and sending messages that are perceived as deeply personal or private. When the degree of such intrusiveness surpasses the subjective threshold, consumers begin to perceive the intrusion of their mind, which creates what researchers have called a psychological experience of privacy intrusion (Cai & Mardani, 2023; Cloarec, 2020). This experience becomes more than an unpleasant feeling—it turns into a driving force behind certain behavior.

Although a lot of research has already been done regarding privacy concerns and the effects of personalization on consumer behavior, some critical gaps remain. First of all, previous studies focused on privacy attitudes rather than behaviors; when behaviors were examined, they were limited to ad avoidance or information disclosure rather than purchase avoidance as a different and distinctive type of response (Martin & Murphy, 2017; Smith et al., 2011; Hu et al., 2023). Furthermore, most of the existing research was conducted among consumers living in Western countries or East Asia; consequently, there was no data regarding Arab and Middle Eastern markets, especially when it came to such countries as Egypt, whose privacy norms and digital penetration might be very different from those of the US. Finally, the concept of psychological reactance had been proposed to explain the phenomenon of personalization-related avoidance behavior (Miron & Brehm, 2006; White et al., 2008); however, the exact mechanism of such behavior had rarely been modeled theoretically.

The purpose of this study is to fill in the identified gaps by developing a theory-based model of AI-powered hyper-personalization and the psychological mechanisms underlying consumer behaviors triggered by it, particularly avoidance of purchases. Specifically, this paper seeks to show that a sense of privacy intrusion is a key element behind the psychological motivation of purchase avoidance behavior. Drawing on Privacy Regulation Theory (Laufer & Wolfe, 1977), Psychological Reactance Theory (Miron & Brehm, 2006; Soni, 2024), and Personalization–Privacy Paradox (Awad & Krishnan, 2006) concepts, the study develops and empirically tests a theoretical model using quantitative surveys in Egypt's digital market environment.

Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the paper adds to the theory while yielding practical recommendations for marketers and platforms.

The paper makes three major contributions. Firstly, it combines three well-established theories and models to form a comprehensive explanation of the mechanism underlying AI hyper-personalization-related behaviors, something that had never been done before. Secondly, it contributes to academic knowledge as well as practical understanding with the data collected in an understudied but extremely promising consumer context, particularly Egypt. Finally, the paper allows firms to better predict and understand conditions under which personalization algorithms turn into a liability, not an asset.

2. Literature Review

2.1 AI Hyper-Personalization in Digital Marketing

In the development of digital advertising, data-driven targeting methods played a major role. Early personalization strategies required input from the consumer or relied on demographic criteria for grouping users (Milne & Gordon, 1993). Further improvements in technology made possible systems based on behavioral patterns, including browsing history, interaction duration, and social behavior. Regardless of these advances, studies conducted over the years showed that personalized advertisements increase consumer perception of relevancy and the number of clicks on ads provided they corresponded to content and time of publication (Bleier & Eisenbeiss, 2015; Goldfarb & Tucker, 2011). However, specific targeting that becomes visible can have opposite effects and trigger defensive attitudes of the target audiences according to results presented by Lambrecht and Tucker (2013), Aguirre et al. (2015), and Hannula et al. (2025). The change from contextually-based to identity-based personalization marks the point where earlier approaches fall short in their description.

Recently, an entirely new type of personalized content appeared due to advances in AI algorithms called hyper-personalization. This type of personalization relies on behavioral analysis, psychographics, and predictions to develop individualized content based on multiple data points. Research papers by Cai and Mardani (2023) and Cloarec (2020) examine the implications of hyper-targeting and hyper-personalization for the contemporary world, positioning algorithmic targeting as the main factor that has turned consumers into subjects rather than objects of interest. By that token, this approach to advertising has introduced another dimension previously not accounted for by models concerned solely with the issues of efficiency—namely, the experience of being subjected to tracking and behavioral modeling that knows more about the person than they do themselves.

2.2 The Personalization–Privacy Paradox and Its Limits

Personalization–Privacy Paradox has served as one of the central ideas in this research area due to the fact that Awad and Krishnan (2006) proved that consumers are keen on both using personalized products and avoiding the need for sharing personal data. Further studies have replicated and expanded the initial findings through exploring related issues within the context of mobile commerce (Guo et al., 2016; Lee & Rha, 2016), social media advertising (Jung, 2017; Tucker, 2014), and location-based services (Huang & Zhou, 2018; Naboureh et al., 2023). Overall, the above examples prove that the paradox does not constitute a state of balance but implies dynamic tensions resolved depending on certain situational factors (e.g., transparency and the presumed intentions behind collecting information from users). In particular, Culnan and Armstrong (1999) found that procedural fairness in dealing with personal data, i.e., being adequately informed and having enough control over their information, moderated privacy-utility trade-off. Similarly, Dinev and Hart (2006) and Malhotra et al. (2004) revealed that the same principles were valid for privacy concerns in the context of e-commerce operations.

However, it should be noted that the above definition and understanding of the paradox are based on relatively simple cases of personalization. For example, Sutanto et al. (2013) conducted a field study on smartphone personalization and showed how sensitive to the issue people are. Cloarec (2020) expands the idea and shows that hyper-personalization changes the nature of the problem by introducing new variables (as opposed to the conventional ones in the literature): in addition to utility versus privacy dichotomy, the author emphasizes the fact that hyper-personalization involves the element of surveillance which is very uncomfortable for consumers.

2.3 Privacy Concerns, Psychological Intrusion, and Behavioral Outcomes

While the relationship between privacy concerns and consumer behavior has received much research attention, there have been developments in the understanding of privacy harms. According to Erlei et al. (2026), Smith et al. (2011), and Pavlou (2011), reviews of literature show that privacy concerns are reliable predictors of decreased transactional willingness, lower levels of trust, and greater protective actions with varying effect sizes dependent on measures used and situational factors. Cognitive privacy concerns, which can be understood as broader attitudes towards data use, do not get sufficient recognition in comparison with perceived psychological intrusion, an acute emotional reaction to a concrete event of surveillance. This issue needs consideration since a behavioral reaction is much more likely to be associated with this variable rather than privacy concerns.

Research shows that the latter construct should indeed be considered separately. Specifically, Baek and Morimoto (2012) revealed that those customers who viewed advertisements as intrusive were willing to avoid purchase even though they realized its relevance. Similarly, the research conducted by White et al. (2008) found that a high level of personalization leads to greater reactance to emails despite the benefit of having accurate information provided. Chen et al. (2022) proved that the process of web personalization triggers simultaneous activation of trust and reactance with reactance taking dominance if personalization is perceived as intrusive. In their study of consumer responses to privacy intrusion s, Li et al. (2017) used cognitive appraisal and emotions frameworks to state that protection mechanisms are triggered by affect, not cognition alone.

2.4 Research Gaps

Despite the considerable body of previous literature in the area, there are still some gaps that have yet to be bridged. For example, early studies rarely differentiate between purchase avoidance and advertisement avoidance as separate behavioral results, thus treating different reactions to privacy intrusion as equivalent phenomena. Additionally, the mediating effect of psychological privacy intrusion between the use of AI personalization and avoidance behaviors has not been empirically examined; most studies have treated privacy intrusion concerns as moderators or dependent variables instead of mediators in the chain. Moreover, most studies to date have used data from either Western or East Asian cultures, resulting in geographical and cultural biases that may limit their universality. This current research aims to fill these gaps by (a) focusing on purchase avoidance as the principal outcome of interest, (b) incorporating psychological privacy intrusion as a mediator into the model, and (c) conducting the investigation among Egyptians who are using digital products online.

3. Theoretical Framework and Hypotheses Development

3.1 Theoretical Foundations

This research adopts the theoretical underpinnings of three overlapping frameworks, namely, Privacy Regulation Theory, Psychological Reactance Theory, and the Personalization–Privacy Paradox. Privacy Regulation Theory postulates that people engage in boundary management between themselves and their social world to ensure equilibrium in their interpersonal transactions and informational control. In essence, people regulate their personal boundaries based on the perception of intrusion from outside actors. In this regard, Laufer and Wolfe (1977) emphasize that people tend to experience disequilibrium once outsiders, including businesses, trespass on their personal boundaries unilaterally. The application of this theoretical framework in digital marketing suggests that consumers will actively resist AI personalization systems' intrusions because they are perceived to breach their personal boundaries by modeling their attributes. According to the Privacy Regulation Theory, the intrusion of the boundary management process triggers motivational disequilibrium in consumers, motivating them to act towards restoration. Consistent with this theory, Malhotra et al. (2004) found that consumer information privacy concerns are highest when the data collection process is perceived to exceed tacit consumer agreement. Similarly, Culnan and Armstrong (1999) reported that consumers tend to resist information privacy breaches in online settings through self-protection and active behavioral avoidance of intrusive websites.

Psychological Reactance Theory postulates that the perception of restricted freedom of actions triggers motivational arousal among consumers to restore lost freedoms. Essentially, this theory highlights the role of the affective dimension in motivation and behavior in contrast to the cognitive aspect. Based on this theory, White et al. (2008) observed that hyper-personalized emails induce psychological reactance among consumers to avoid purchase decisions. Similarly, Chen et al. (2022) found that consumers' positive reactions to personalized content in email marketing campaigns coexist with psychological reactance. However, reactance is prioritized over positive responses to relevant personalized emails, which explains consumers' aversion towards purchases even on otherwise valuable platforms. Therefore, psychological reactance serves as an additional mechanism to explain consumer resistance towards hyper-personalized emails.

Finally, the Personalization–Privacy Paradox framework empirically describes the trade-off between consumer objectives of personalized experiences and informational autonomy. In this regard, the increasing sophistication of AI-powered personalization systems intensifies this paradox because the accuracy of such systems increases the transparency of data collection processes to consumers. According to Cloarec (2020), the attention economy exacerbates the impact of this paradox to the extent that consumers negatively react to personalized experiences when they are informed of the inferences made about them. Consequently, Cloarec (2020) suggests a tipping point in the relationship between personalized experiences and consumer responses. Hence, this framework provides the basis for the present research to theorize that hyper-personalized marketing campaigns using AI trigger psychological privacy intrusion as a proximal mechanism of consumer avoidance behavior.

3.2 Study Model

As illustrated in Figure 1 below, AI hyper-personalization is positioned as the independent variable, Purchase Avoidance Behavior as the dependent variable, and Perceived Psychological Privacy Intrusion as the mediating construct. The proposed hypotheses include a direct effect of hyper-personalization on avoidance (Hypothesis 1), an indirect effect through Perceived Psychological Privacy Intrusion (Hypotheses 2 and 3), and the mediating effect of Perceived Psychological Privacy Intrusion (Hypothesis 4). These constructs provide the foundation for a theoretical hypothesis that AI hyper-personalization influences purchase avoidance behavior either directly or indirectly through boundary infringement.

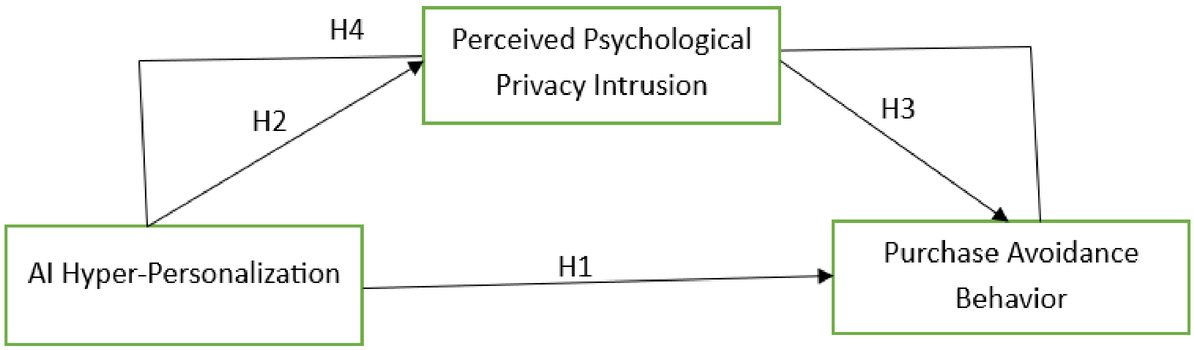

Figure 1: Study Model

3.3 Hypotheses Development

3.3.1 AI Hyper-Personalization on Purchase Avoidance Behavior

The relationship between hyper-personalization and avoidance of purchase is predicated on two convergent theoretical perspectives. Firstly, Privacy Regulation Theory holds that when corporate systems can be seen to accurately represent a consumer's private characteristics, then the resultant boundary regulation reaction will involve a retreat from the scenario where the infringement took place, which would be the online purchasing realm. Secondly, Psychological Reactance Theory stipulates that consumers who feel threatened by their ability to make purchases in terms of algorithmic manipulation will react to the situation by ensuring that the predicted effect is not achieved, thereby making the decision not to purchase since they feel that they are being manipulated into buying something (White et al., 2008; Miron & Brehm, 2006). This relationship has empirical backing: Baek and Morimoto (2012) demonstrate significant intentions for avoidance due to invasive advertisement targeting, while Cai and Mardani (2023) identify purchase resistance triggered by intelligent personalization techniques once the threshold for intimacy is exceeded. Extending this literature:

H1: *AI hyper-personalization has a significant positive effect on purchase avoidance behavior.*

3.3.2 AI Hyper-Personalization and Perceived Psychological Privacy Intrusion

The link between hyper-personalization and the feeling of intrusion of one’s psychological privacy would be considered the most straightforward connection in the theoretical model; nevertheless, it must be built on a robust theoretical base. According to Privacy Regulation Theory, what triggers people’s reactions is not the actual process of data collection but rather the violation of boundaries felt by individuals (Laufer &

Wolfe, 1977). As a result, identical data collection methods used in various studies result in different consumer reactions depending on how salient these activities are (Dinev & Hart, 2006; Smith et al., 2011). Personalized advertising using AI technologies makes the data collection process more noticeable because of its effectiveness: the deeper the system understands the consumer's unvoiced wishes, the more obvious the surveillance is. Both Cloarec (2020) and Cai and Mardani (2023) found that the degree of inference made by personalized systems is the main determinant of intrusion perceptions, and Hallam and Zanella (2017) proved that when the perceived costs of intrusion outweigh the perceived benefits of personalization, intrusion takes precedence over other constructs. Consequently:

H2: *AI hyper-personalization has a significant positive effect on Perceived Psychological Privacy Intrusion.*

3.3.3 Perceived Psychological Privacy Intrusion on Purchase Avoidance Behavior

Once it is established that the hyper-personalization via AI technology induces a feeling of intrusion of privacy, the current model proposes that such feeling acts as an antecedent driver for not purchasing products/services. The theoretical grounding for this statement may be provided through Psychological Reactance Theory, according to which the feeling of being invaded with regard to one's privacy represents a motivation towards restoring freedom (Miron & Brehm, 2006). Among the options to restore freedom available in the digital environment, non-purchase, i.e., the act of not making a transaction encouraged by algorithms, appears to be the easiest one. Li et al. (2017) proved that the affective component of privacy threats had higher behavioral impact compared to the cognitive one, while Chen et al. (2022) empirically proved that reactance towards web personalization led to consumers' actual disengagement from commercial activities. The same applies to Martin and Murphy (2017) who identified purchase withdrawal as a reaction to the intrusion of informational privacy caused by marketers' manipulations. Thus:

H3: *Perceived Psychological Privacy Intrusion has a significant positive effect on purchase avoidance behavior.*

3.3.4 The Mediating Role of Perceived Psychological Privacy Intrusion

The complete mediation theory encapsulates all the aforementioned discussions within a processual approach: the act of hyper-personalization using AI technology leads to a sense of psychological privacy violation that, in turn, causes an aversion towards buying; a significant amount of the impact is achieved through this indirect route. The mediation theory adheres to the Personalization–Privacy Paradox theory's principle of using the psychological reaction as the mediating factor (Awad & Krishnan, 2006; Sutanto et al., 2013) and follows the tenets of cognitive appraisal theory, in which the affective reactions to privacy intrusion constitute the immediate reasons behind avoidance behavior (Li et al., 2011; Cao et al., 2026). Most notably, while complete mediation is assumed, there is scope left open by H1 for direct effects based on a subconscious level of reactance to occur. Regardless of any further implications, the key theoretical contribution here would be identifying perceived psychological privacy intrusion as the mediating mechanism.

H4: *Perceived Psychological Privacy Intrusion mediates the relationship between AI hyper-personalization and purchase avoidance behavior.*

4. Methodology

4.1 Research Design and Approach

This research applied a quantitative research methodology based on a deductive epistemology. Starting with theoretical propositions, the study employed primary survey data to test the hypothesized structural model. This conforms to a common approach employed in studies within the domain of information systems and digital marketing (Malhotra et al., 2004; Smith et al., 2011; Qin et al., 2026). The cross-sectional design was selected since the objectives of the study focused on establishing structural relationships between variables without being concerned with behavioral changes over time.

4.2 Study Context: Egyptian Digital Consumers

The selection of Egypt as the setting for this research had practical as well as theoretical reasons. From a practical standpoint, there has been significant development in Egypt's digital marketplace in recent years. Indeed, the use of AI-driven platforms, including such well-known brands as Amazon Egypt, Noon, TikTok Shop, Instagram Shopping, and Facebook Marketplace, is on the rise and attracts millions of active users. At the same time, personalized recommendation algorithms are being integrated into all of the aforementioned services more actively than ever before, creating a unique environment for hyper-personalization that can be felt by many consumers. Moreover, on a theoretical level, Arabs have remained understudied in terms of their reactions to issues of privacy and personalization in marketing, as most of the relevant literature tends to use American, European, and East Asian samples for its analyses. As regional cultures vary greatly when it comes to notions of personal boundaries, trust in businesses, and perceptions of surveillance, this research benefited not just geographically but theoretically as well from the inclusion of Egyptian participants.

4.3 Population and Sampling

The target population consisted of Egyptian adults who use one or more AI-based digital shopping platforms and have been exposed to personalized ads before. The reason why the researcher decided to concentrate on this particular group of people is that the key construct explored in the study (hyper-personalization due to the use of AI) can only be experienced by the respondents who interact with the technology on a regular basis. Hence, by limiting the sample to such individuals, the study ensured better validity and decreased the likelihood of getting uninformed answers to the questions in the questionnaire. Eligibility criteria required the respondents to have made at least one online purchase or interacted with an AI-based recommendation system within the last three months prior to the survey.

A purposive sampling method was used. Data were gathered via an online structured questionnaire which was administered among several groups of Egyptians on Facebook, focusing on topics related to online purchases and social commerce. Moreover, the researchers also utilized several chatrooms on Telegram and Instagram where users share their experience in relation to online shopping. Furthermore, the questionnaire was administered to Egyptian students enrolled in Egyptian universities. Prior to data collection, the questionnaire was reviewed by academic experts to ensure clarity and content validity.

To ensure data quality, all collected responses underwent a systematic screening process before analysis. Specifically, duplicate submissions were identified and removed by cross-referencing IP addresses and submission timestamps. Low-quality responses were flagged and excluded based on three criteria: (1) responses completed in an implausibly short time (below the pre-determined minimum completion threshold), (2) responses exhibiting straight-lining patterns (i.e., selecting the same scale point across all items), and (3) responses failing attention-check items embedded within the questionnaire. Following this screening procedure, the total number of valid responses retained was 407.

Following the recommendations put forward by Hair et al. (2019) regarding adequate sample size for analysis using PLS-SEM, the appropriate minimum sample size for the current research project was identified. The total number of collected valid responses exceeded 407. It should be mentioned that this size exceeds the minimum required according to the number of constructs and structural relationships examined in the model.

4.4 Measurement Instrument

The survey was designed via a structured and self-administered questionnaire constructed based on existing conventions for developing psychometric scales. This included three major sections: screening and demographic questions, questions pertaining to the three core constructs of the study, and a final section capturing platform usage behavior. Responses to the questions measuring each of the three constructs followed a five-point Likert scale, where 1 equals strongly disagree while 5 equals strongly agree. Such an approach is frequently used for measuring similar constructs and concepts in relevant literature concerning privacy issues and consumer behavior studies (Baek & Morimoto, 2012; Martin & Murphy, 2017).

Each of the three constructs in focus, namely, AI hyper-personalization, Perceived Psychological Privacy Intrusion, and purchase avoidance behavior, was measured through six questions formulated based on validated scales found in the literature. Questions measuring AI hyper-personalization were adapted from Bleier and Eisenbeiss (2015), Cai and Mardani (2023), and Cloarec (2020) with necessary changes in wording to include AI systems with capabilities to predict behaviors in real time and gather data across multiple platforms. For Perceived Psychological Privacy Intrusion, questions were based on items of scales introduced by Malhotra et al. (2004), Smith et al. (2011), and Li et al. (2017). These items particularly emphasized the psychological aspect of intrusion rather than general attitudes towards privacy concerns. Purchase avoidance behavior questions were based on scales by Baek and Morimoto (2012) and Cai and Mardani (2023) that distinguish between purchase and advertising avoidance. Translation into Arabic and back-translation into English were conducted independently by two bilingual academics to achieve equivalence.

4.5 Ethical Considerations

All of these processes adhered to ethical considerations regarding conducting social scientific research among human subjects. Specifically, before commencing the process of data gathering, all respondents were informed of the purpose of the study, their voluntary participation, anonymity of their responses, and the exclusive purpose of using data for scholarly reasons. Informed consent was obtained electronically at the start of filling out the questionnaire, where participation depended on an explicit consent. All personal identifiers were omitted throughout the entire process of gathering data; all responses were anonymized and saved in password-protected databases. Considering the fact that this study focused on the issue of consumer perception of intrusion and surveillance, special attention was paid to ensuring that there would be no possibility for the data collection tool to replicate the dynamic being studied by conducting any kind of behavioral tracking, cookie targeting, or data mining during the recruiting and administering of the survey.

5. Data Analysis and Result

5.1 Measurement Model Assessment

The measurement model was assessed based on the evaluation of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity in the context of PLS-SEM, based on the recommendations of Hair et al. (2019) and Sarstedt et al. (2021).

First, the indicators' reliability was checked based on the loadings of all measurement indicators, as presented in Table 1. It can be seen that the loadings of all indicators exceed the threshold value of 0.70 (Hair et al., 2019). Namely, the AI hyper-personalization (HP) indicators had loadings between 0.852 and 0.930, purchase avoidance behavior (PAB) indicators between 0.866 and 0.893, and Perceived Psychological Privacy Intrusion (PPPI) indicators between 0.871 and 0.911. Therefore, the findings prove that all indicators have good reliability and properly represent the underlying latent constructs.

Table 1: Outer Loadings of Measurement Items

	Outer Loadings		**Outer Loadings**		**Outer Loadings**
HP1	0.930	**PAB1**	0.866	**PPPI1**	0.911
HP2	0.868	**PAB2**	0.886	**PPPI2**	0.894
HP3	0.852	**PAB3**	0.890	**PPPI3**	0.871
HP4	0.895	**PAB4**	0.893	**PPPI4**	0.891
HP5	0.868	**PAB5**	0.884	**PPPI5**	0.897
HP6	0.880	**PAB6**	0.874	**PPPI6**	0.902

Next, the measurement model was assessed based on the assessment of internal consistency reliability and convergent validity through the use of Cronbach's Alpha, Composite Reliability (rho_a and rho_c), and Average Variance Extracted (AVE). Based on the results presented in Table 2, Cronbach's Alphas vary between 0.943 and 0.950, which exceeds the recommended minimum threshold of 0.70 (Cronbach, 1951; Hair et al., 2019). All Composite Reliability values exceed the threshold of 0.90, showing a high level of internal consistency reliability. AVE ranges from 0.778 to 0.800, being higher than 0.50 recommended by Fornell and Larcker (1981). Hence, satisfactory convergent validity is confirmed.

Table 2: Construct Reliability and Convergent Validity

	Cronbach's Alpha	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**Average Variance Extracted (AVE)**
HP	0.943	0.946	0.955	0.779
PAB	0.943	0.943	0.955	0.778
PPPI	0.950	0.951	0.960	0.800

Moreover, the discriminant validity was determined using the Fornell-Larcker criterion and heterotrait-monotrait ratio (HTMT) based on the suggestions made by Henseler et al. (2015). As shown in Table 3, the square root of the AVE values for each construct was higher than the correlation coefficients between the constructs, thus indicating the presence of discriminant validity (Fornell & Larcker, 1981).

Table 3: Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Fornell–Larcker Criterion	HP	PAB	PPPI
HP	**0.883**		
PAB	0.472	**0.882**	
PPPI	0.685	0.703	**0.894**

In addition, the discriminant validity test was conducted using the HTMT ratio. From the results obtained as presented in Table 4, it is evident that all HTMT ratios lie between 0.349 and 0.703. The ratios are lower than the recommended value of 0.85 by Henseler et al. (2015). The findings therefore reinforce the evidence of discriminant validity and show that the constructs have been independently developed.

Table 4: Heterotrait–Monotrait Ratio (HTMT) of Correlations

HTMT	HP	PAB	PPPI
HP			
PAB	0.349		
PPPI	0.452	0.568	

5.2 Structural Model Assessment

After confirming the validity of the measurement model, structural model evaluation involved collinearity statistics, R^2 values, f^2 values, and fit measures according to the criteria set by Hair et al. (2019) and Sarstedt et al. (2021).

Firstly, collinearity among predictor constructs was established using Variance Inflation Factor (VIF). As seen in Table 5, all VIF values lie between 1.000 and 1.740, lower than the critical value of 5.0 recommended by Kock (2015) and Hair et al. (2019). The results indicate no presence of multicollinearity in the structural model, implying that there is minimal overlap among predictor constructs. In an attempt to assess the possible occurrence of common method variance, a detailed analysis of collinearity was undertaken, following the guidelines by Kock (2015). In all instances, the VIF scores were found to be less than the stipulated value of 3.3, which is indicative of the lack of common method variance.

Table 5: Collinearity Statistics (VIF)

	VIF
HP to PAB	1.740
HP to PPPI	1.000
PPPI to PAB	1.740

Secondly, the explanatory power of the model was examined by analyzing the coefficient of determination (R^2). Table 6 reveals that the R^2 of PAB is 0.446, implying that AI hyper-personalization and PPPI collectively explain 44.6% of the variance in PAB. Furthermore, the R^2 for PPPI is 0.425, signifying that AI hyper-personalization accounts for 42.5% of the variance in PPPI. According to Hair et al. (2019), these results denote moderate explanatory power of the structural model. The adjusted R^2 values are close to their corresponding R^2 values, which further support the robustness of the model.

Table 6: Coefficient of Determination (R^2) Results

	R-square	R-square Adjusted
PAB	0.446	0.435
PPPI	0.425	0.419

Thirdly, f^2 values were used to evaluate the strength of effect of each predictor on the dependent variable. According to Table 7, AI hyper-personalization has a strong effect on PPPI ($f^2 = 0.740$), while PPPI has a moderate-to-strong effect on PAB ($f^2 = 0.441$). However, the effect of AI hyper-personalization on PAB is very weak ($f^2 = 0.001$). Based on Cohen's criteria and PLS-SEM practice, the results imply that AI hyper-personalization has a stronger effect on purchase avoidance through PPPI than the direct effect.

Table 7: Effect Size (f^2) Assessment

f-square Matrix	**HP**	**PAB**	**PPPI**
HP		0.001	0.740
PAB			
PPPI		0.441	

Lastly, the model fit was measured using Standardized Root Mean Square Residual (SRMR), d_ULS, d_G, Chi-Square, and Normed Fit Index (NFI). According to Table 8, the SRMR is 0.043, lower than the suggested critical value of 0.08 (Hair et al., 2019). Furthermore, the NFI is 0.917, higher than the critical value of 0.90. Thus, the structural model demonstrates adequate goodness-of-fit measures.

Table 8: Model Fit Indices

	Saturated Model	Estimated Model
SRMR	0.043	0.043
d_ULS	0.319	0.319
d_G	0.270	0.270
Chi-square	151.160	151.160
NFI	0.917	0.917

5.3 Hypotheses Testing

Embedded hypotheses within the proposed conceptual model were tested using bootstrapping in SmartPLS based on the approach by Hair et al. (2019). Structural relationships among the constructs were evaluated by using path coefficients (β), t-statistics, and p-values. The results of the testing structural model are presented in Figure 2, and those of individual hypotheses in Table 9.

Hypothesis 1 (H1): AI hyper-personalization positively influences purchase avoidance behavior. According to the findings, the impact of AI hyper-personalization on purchase avoidance behavior was not statistically significant ($\beta = 0.024$, $t = 0.232$, $p = 0.817$). Since the value of p exceeded the commonly used threshold of

0.05, H1 could not be accepted. In other words, AI hyper-personalization alone does not lead to purchase avoidance behavior in the considered sample.

Hypothesis 2 (H2): AI hyper-personalization positively impacts Perceived Psychological Privacy Intrusion. According to Table 9, there was a statistically significant and positive relationship between these two variables ($\beta = 0.652$, $t = 12.044$, $p < 0.001$). Thus, H2 was supported. It can be concluded that the use of AI-based tools for hyper-personalization increases the level of perceived psychological privacy intrusion. This is consistent with prior findings indicating that high personalization triggers the feeling of surveillance (Cloarec, 2020; Cai & Mardani, 2023).

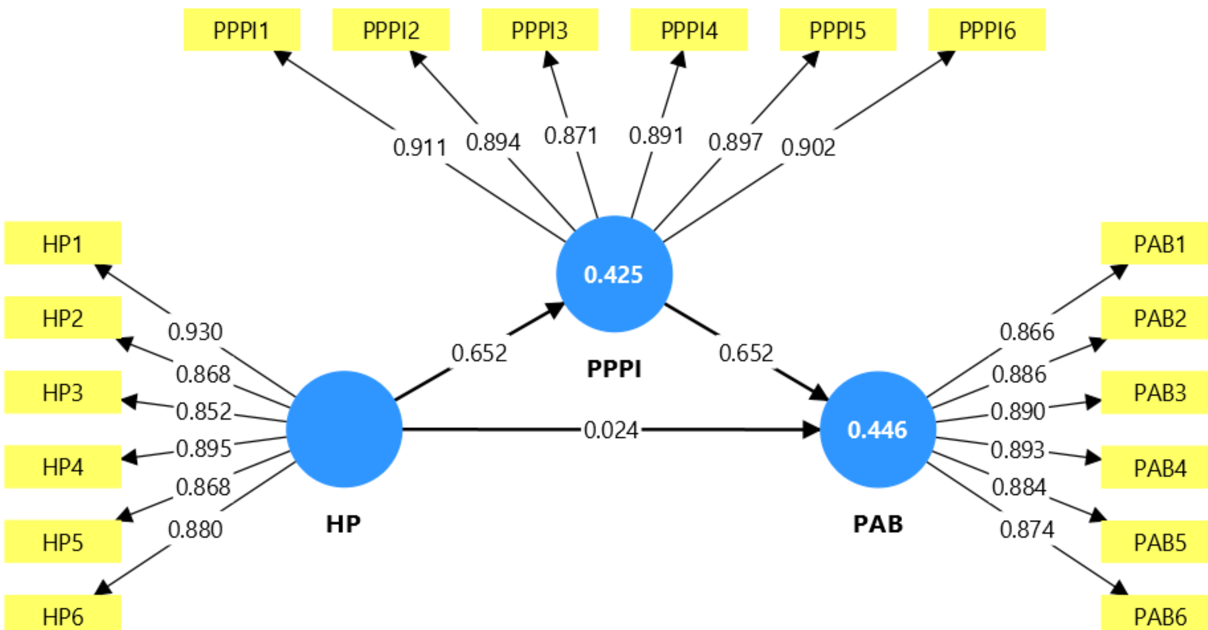

Figure 2: PLS-SEM Structural Model Results

Hypothesis 3 (H3): Perceived Psychological Privacy Intrusion positively impacts purchase avoidance behavior. There was a statistically significant and positive relationship between these two variables ($\beta = 0.652$, $t = 6.932$, $p < 0.001$), which implies acceptance of H3. From this finding, it can be deduced that consumers who feel intruded upon by AI-powered hyper-personalization are less likely to make purchases. The result is in line with predictions made by Psychological Reactance Theory according to which an infringement on personal freedom triggers protective responses (Miron & Brehm, 2006; White et al., 2008).

Table 9: Hypotheses Testing Results

Hypothesis	Relationship	Path Coefficient (β)	t-Value	p-Value	Decision
H1	AI Hyper-Personalization to Purchase Avoidance Behavior	0.024	0.232	0.817	Not Supported
H2	AI Hyper-Personalization to Perceived Psychological Privacy Intrusion	0.652	12.044	0.000	Supported

H3	Perceived Psychological Privacy Intrusion to Purchase Avoidance Behavior	0.652	6.932	0.000	Supported

In conclusion, based on the obtained results, AI hyper-personalization did not have a significant direct effect on purchase avoidance behavior when considered independently. However, it significantly increases Perceived Psychological Privacy Intrusion, which positively correlates with purchase avoidance behavior. Figure 2 further highlights the nature of the relationships among the variables under consideration.

5.4 Mediation Analysis

In order to test whether Perceived Psychological Privacy Intrusion serves as a mediator between AI hyper-personalization and purchase avoidance behavior, the bootstrapping method for testing mediation was applied following the guidelines provided by Preacher and Hayes (2008) and Hair et al. (2019).

The results of the analysis show that the indirect effect of AI hyper-personalization on purchase avoidance behavior through Perceived Psychological Privacy Intrusion was positive and significant ($\beta = 0.425$, $t = 5.890$, $p < 0.001$). Thus, hypothesis four is confirmed. The finding means that AI hyper-personalization enhances the perception of psychological privacy intrusion, leading to increased purchase avoidance behavior.

Table 10: Mediation Analysis Results

Hypothesis	Indirect Relationship	Indirect Effect (β)	t-Value	p-Value	Mediation Result
H4	AI Hyper-Personalization to Perceived Psychological Privacy Intrusion to Purchase Avoidance Behavior	0.425	5.890	0.000	Supported (Full Mediation)

It should be mentioned that according to the mediation analysis, there was no significant direct effect of AI hyper-personalization on purchase avoidance behavior ($\beta = 0.024$, $p = 0.817$) as it can be seen from Table 9 above. Nevertheless, the indirect path via PPPI is still significant. According to the rules formulated by Hair et al. (2019), such a situation represents the case of full mediation, which means that the effect of AI hyper-personalization on purchase avoidance behavior is achieved primarily through consumers' psychological perception of privacy intrusion.

Overall, the results obtained above provide solid evidence for theoretical assumptions based on Privacy Regulation Theory and Psychological Reactance Theory. Namely, the findings mean that it does not necessarily lead to the avoidance of purchases if a person is subject to personalization. Instead, people tend to avoid purchasing goods only if they perceive the process of personalization as psychologically invasive and threatening to their personal space and freedom (Laufer & Wolfe, 1977; Miron & Brehm, 2006). Moreover, the conclusions made are consistent with other researchers who have found that people tend to react defensively to intrusive personalization strategies (White et al., 2008; Cai & Mardani, 2023).

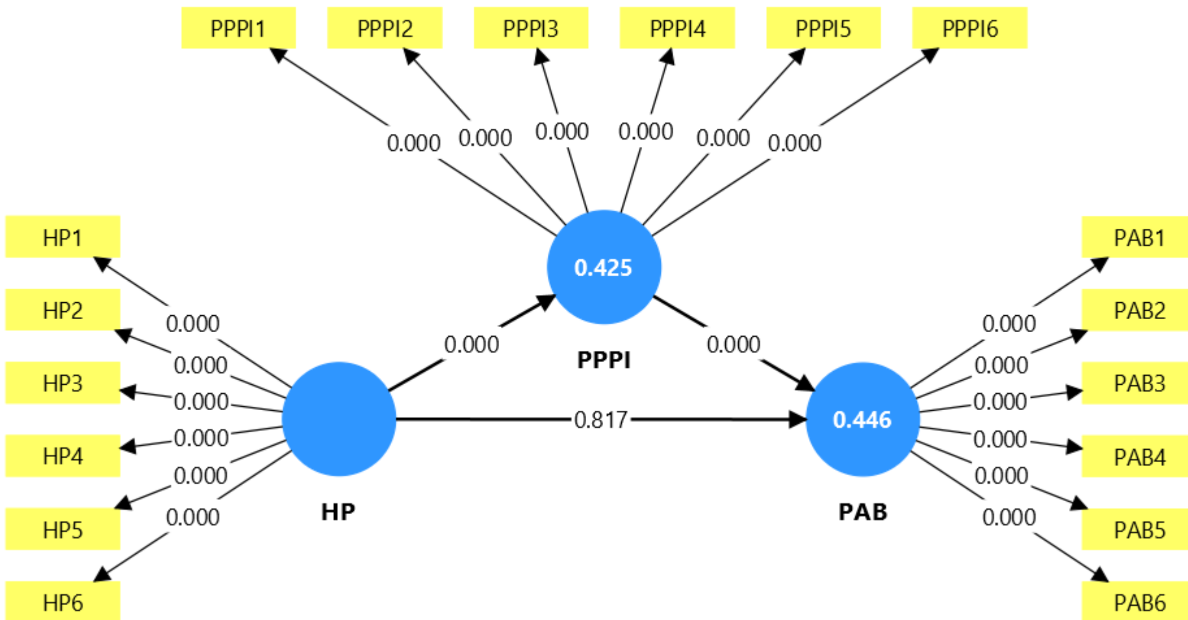

Figure 3: Bootstrapping Results of the Structural Model

6. Discussion

First and foremost, the study demonstrates that AI hyper-personalization has a complex relationship with purchase avoidance behavior in digital marketplaces that cannot be described by a simple correlation or causation. Instead of providing evidence of the direct relationship between the two constructs, it demonstrates the role of psychological factors in mediating this association. According to the presented findings, consumers do not simply avoid buying items from digital marketplaces that employ AI hyper-personalization techniques since personalization is used to deliver advertisements to users. On the contrary, they avoid purchases as a consequence of perceiving personalization algorithms as a violation of their psychological privacy. Indeed, the lack of the direct association between the independent variable and purchase avoidance behavior and the significance of the indirect one through Perceived Psychological Privacy Intrusion (Tables 9, 10) support this conclusion.

It is vital to note that this result is consistent with the Personalization–Privacy Paradox according to which consumers may enjoy personalization while at the same time rejecting intrusive privacy management tactics that allow marketers to personalize digital advertisements (Awad & Krishnan, 2006; Sutanto et al., 2013; Cloarec, 2020; Qadri et al., 2026). In other words, personalization and privacy are not mutually exclusive concepts that could easily cause consumer avoidance behavior in the context of AI technology application. Instead, they interact to produce a variety of consumer responses depending on the specifics of marketing strategies and the way in which users perceive them.

The next contribution lies in the evidence of the impact of AI hyper-personalization on Perceived Psychological Privacy Intrusion demonstrated in Table 9. In particular, the significant coefficient suggests that consumers may perceive their psychological space as invaded when the digital marketplace they use employs advanced personalization algorithms. This finding is consistent with Privacy Regulation Theory as the latter explains how people regulate the access to their personal boundaries and what psychological effects it produces when outsiders attempt to penetrate these boundaries (Laufer & Wolfe, 1977). Moreover, it corroborates earlier findings regarding the negative impact of overt personalization practices on consumer attitudes and subsequent actions (Aguirre et al., 2015; Lambrecht & Tucker, 2013; Tucker, 2014; Erlei et al., 2026).

At the same time, the lack of a direct relationship between AI hyper-personalization and purchase avoidance behavior represents an interesting contribution since it does not appear to be obvious. Prior studies tend to establish direct relationships between personalization, intrusion, targeting, and consumer avoidance behaviors (Baek & Morimoto, 2012; White et al., 2008; Cao et al., 2026). Nevertheless, the presented findings provide no evidence of such a correlation. More specifically, the insignificant coefficient (Table 9) indicates that consumers' avoidance behavior may depend on several psychological aspects associated with their attitudes towards personalization. Thus, personalization does not necessarily have a negative impact on purchasing behavior as long as consumers perceive it as a positive practice.

This finding is valuable in the context of the literature review insofar as it does not refute prior knowledge. On the contrary, it explains why consumers may perceive hyper-personalization as a positive practice as opposed to privacy violation or intrusion. The effectiveness of personalization practices depends on various factors, including context, consumers' trust, content relevance, and their level of control over these technologies (Bleier & Eisenbeiss, 2015; Goldfarb & Tucker, 2011; Culnan & Armstrong, 1999). Accordingly, it is essential to conclude that purchase avoidance does not result from personalization but occurs when users view it as a threat.

The third significant contribution of the research consists of the demonstration of the impact of Perceived Psychological Privacy Intrusion on purchase avoidance behavior. Namely, the significant positive coefficient indicates that intrusion affects consumer decision-making process significantly. Consumers feel disturbed when their personal information is revealed by digital marketplaces and used to deliver advertisements accordingly (Table 9). These findings are consistent with Psychological Reactance Theory as the latter postulates that consumers will defend their choice freedom when they think it is violated (Miron & Brehm, 2006). This theoretical contribution is confirmed by existing empirical findings (Baek & Morimoto, 2012; White et al., 2008; Martin & Murphy, 2017; Qin et al., 2026).

Purchase avoidance may thus be viewed as a response to personalization and psychological privacy intrusion (Smith et al., 2011; Pavlou, 2011). In the framework of this explanation, consumers avoid transactions and choose to exit digital marketplaces where they experience intrusions because these platforms violate their boundaries and invade their psychological privacy.

Finally, the mediation analysis result is valuable for several reasons. First, it explains the process of purchase avoidance behavior development when AI hyper-personalization takes place. Namely, it proves that there is full mediation when psychological privacy intrusion occurs (Table 10). Second, it helps to understand how consumers develop certain attitudes in response to specific stimuli. This contribution allows applying Privacy Regulation Theory and Psychological Reactance Theory in combination with each other as well as incorporating the Personalization–Privacy Paradox into the framework of consumer behavior models. Finally, this contribution helps to interpret consumer behavior from a psychological perspective rather than a general one since privacy intrusions cause a variety of emotional reactions.

Methodologically, the study contributes to literature by introducing a focus on psychological privacy intrusion as opposed to privacy concerns. Traditionally, the former is a narrower construct since researchers consider privacy as a general concept. Thus, they usually focus on the cognitive component of privacy as well as consumers' awareness regarding personal data processing in digital environment (Malhotra et al., 2004; Dinev & Hart, 2006; Qadri et al., 2026). The present findings shift attention to privacy intrusion which is a much stronger stimulus for consumer behavior than mere awareness. Hence, the contribution is methodological.

From a contextual standpoint, the study demonstrates an important contribution by providing information about purchase avoidance behavior that occurs in the Egyptian digital market environment. In fact, most empirical evidence of the relationships between variables is collected among Western customers of social networks and digital marketplaces (Guo et al., 2016; Lee & Rha, 2016; Huang & Zhou, 2018). In this case, it may be possible to assume that the Personalization–Privacy Paradox does not apply to non-Western environments and that consumers are less concerned about privacy intrusion. However, this assumption would be false.

In conclusion, the study makes a range of theoretical contributions including the introduction of Psychological Reactance Theory in combination with Privacy Regulation Theory as well as the identification of the Personalization–Privacy Paradox in the context of purchase avoidance behavior. Practically, personalization practices may be beneficial when marketers ensure their customers feel comfortable despite being offered customized products.

7. Conclusion

In conclusion, this study attempts to explore the effect of AI hyper-personalization on purchase avoidance behavior via the mediating role of Perceived Psychological Privacy Intrusion among digital consumers from Egypt. According to the findings, the AI hyper-personalization strategy fails to elicit purchase avoidance behavior; however, it strongly increases the perception of psychological privacy intrusion, thereby triggering purchase avoidance behavior. Specifically, mediation analysis confirms that Perceived Psychological Privacy Intrusion fully mediates the effect of AI hyper-personalization on purchase avoidance behavior. As such, consumer negative reactions toward personalization can be attributed to the intrusiveness of personalization as perceived psychologically. Overall, the current paper highlights that the efficiency of AI-based personalization depends on how consumers perceive the personalization experience psychologically.

8. Theoretical Implications

Overall, this study makes an important contribution to the existing research related to consumer resistance to AI hyper-personalization in light of Privacy Regulation Theory, Psychological Reactance Theory, and the Personalization–Privacy Paradox. Differently from most previous studies that mainly concentrate on the examination of generalized privacy issues and advertisement avoidance behaviors, this paper specifically examines the mediating role of Perceived Psychological Privacy Intrusion between AI hyper-personalization and purchase avoidance behavior. In this way, this study enhances the personalization-privacy literature by highlighting the indirect effect of intrusive personalization through the psychological aspect. Moreover, it expands on previous studies by testing relationships among these constructs in an

Egyptian digital market, thus filling a research gap regarding the Arab and Middle Eastern populations' perceptions.

9. Practical Implications

Overall, this study provides an important lesson in the importance of balancing the benefits of hyper-personalized AI marketing in the context of strategy design. On the one hand, the use of AI can lead to great improvements in the precision and efficiency of content personalization. On the other hand, if the latter is implemented solely from the organizational perspective, without taking into account consumers' emotional responses, there is a risk of creating overly invasive content that will cause negative associations and will decrease the likelihood of making purchases. For the creation of positive user experience and development of long-term relationships, businesses are advised to implement ethical approaches to personalized content marketing. The following managerial recommendations can be given in this context.

To begin with, digital companies, e-commerce platforms, and online marketers need to incorporate the process of transparent information sharing regarding the collection, processing, and use of consumer data into their business processes. It implies informing customers during data gathering about what particular data are collected, processed, and passed to third-party companies. Such transparency can be achieved with the help of embedded privacy dashboards, instant notifications upon receiving of recommendations generated based on behavior analysis, and periodic summary reports, allowing consumers to see their data profiles. Research shows that transparency significantly contributes to reducing intrusion perception and building necessary trust in personalized content and services (Martin & Murphy, 2017).

Secondly, to give back to consumers control over their personal data, companies need to establish effective opt-out procedures and make it clear where they can be found. Namely, consumers must have access to clearly marked and simple tools for controlling which personalization activities will continue or stop working. This means that users should not have to find such options themselves in numerous pages of terms of service but should be able to find them instantly. Moreover, granular opt-out procedures can be considered as a way of allowing users to retain control over some personalization activities while opting out of others (for instance, agreeing to personalized product recommendations but refusing to track their behavior across multiple platforms). This way, businesses will take into account consumers' psychological reactance to intrusive personalized content and avoid decreasing purchase intentions.

Finally, marketers need to set up ethical standards for personalizing content using AI algorithms. Namely, algorithms should not combine certain types of consumer data, especially related to their health status or financial activity. This combination is very intrusive and causes negative perceptions among consumers. In addition, organizations can conduct regular consumer sentiment surveys to find out how consumers perceive current practices of personalization and make changes to algorithms accordingly. Moreover, it might be worth considering privacy-by-design frameworks for personalized content products during product development.

10. Limitations and Suggestions for Future Research

Although the current paper provides several insights concerning the effect of AI personalization on consumer behavior and perceptions, there are still several limitations associated with this research. For instance, cross-sectional methodology does not allow tracking changes in the dependent variable over time, so further longitudinal studies are needed to confirm hypotheses stated above. Second, this study specifically focuses on Egyptian consumers, which restricts the generalizability of findings to other cultures. Cross-cultural studies are also recommended to get more insights. Another limitation concerns the choice of only one mediating variable. Further research could test a number of additional mediators/motivators. Moreover, this study concentrates on the consumer digital market generally, and future research might consider other contexts (such as healthcare or fintech industries).

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