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MODELING THE IMPACT OF PERSONALIZED SOCIAL MEDIA ADVERTISEMENTS ON ONLINE IMPULSE BUYING INTENTION

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Abstract: This study aims to investigate how personalized social media advertisements influence consumers' propensity for online impulse buying, using structural equation modeling. A quantitative research design was employed, analyzing the responses of 291 social media users in Romania through the PLS-SEM technique. The findings confirm that personalized advertising has a positive effect on perceived relevance, novelty, and advertising value, which in turn strongly influence consumers' online impulse buying intentions through their attitudes toward the advertisement. This research offers both theoretical and practical contributions to the fields of online advertising and consumer behavior, advancing our understanding of the mechanisms through which personalized advertising shapes impulsive purchasing behavior in online environments.

JEL classification: M30, M31, M37

Keywords: personalized advertising, social media advertising, online impulse buying, consumer behavior, structural equation modeling

1. Introduction

The global social media advertising market exceeded USD 228 billion in 2024 and is projected to reach USD 256.5 billion by 2025, with forecasts indicating potential growth to as much as USD 412 billion by 2033, driven by continuous digital and mobile-based advertising expansion (The Business Research Company, 2025; Verified Market Reports, 2025). Personalized, data-driven campaigns increasingly fuel this growth, as consumers tend to respond more positively to advertisements that are relevant and tailored to their individual preferences (The Business Research Company, 2025). This strong growth highlights the increasing importance of personalized, data-driven advertising strategies in effectively engaging consumers.

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According to Epsilon Marketing (2018), 80% of consumers are more likely to purchase from brands that offer personalized experiences, based on a survey of 1,000 U.S. adults conducted through an online questionnaire. Similarly, McKinsey's global analysis highlights the business value of personalization, showing that effective personalization can reduce customer acquisition costs by up to 50%, increase revenues by 5–15%, and improve marketing ROI by 10–30%, drawing on multiple case studies from various industries (McKinsey, 2021). Accenture's international survey, involving thousands of consumers across the U.S. and Europe, found that 91% prefer brands that recognize and treat them personally. However, the study also revealed a gap between consumer expectations and the reality of personalization efforts (Accenture, 2018). Deloitte's Global Marketing Trends 2022 report, based on responses from 11,500 consumers and 1,099 executives across 19 countries, emphasizes that while consumers view personalized messages as helpful, they also consider excessive data collection and geo-targeting intrusive, highlighting the need for both technological precision and ethical responsibility in personalization strategies (Deloitte Insights, 2022). The effectiveness of personalization is closely tied to the variety of social media advertising formats, which enable the creative delivery of targeted messages.

Social media advertising includes strategies like display ads, sponsored content, influencer marketing, and video ads, each tailored to platform-specific features to boost engagement (Hamouda, 2018; Nizam et al., 2024). Display ads appear as banners or feed posts to track impressions and clicks, while sponsored content blends with user posts for a more organic feel. Influencer marketing leverages trusted social media figures to promote products, enhancing credibility and reach (Aydin et al., 2021; Chen et al., 2023; Hani et al., 2024). These methods highlight a dynamic digital landscape where businesses use diverse content formats to connect with consumers (He et al., 2023; Lee et al., 2018). Personalized advertising, a subset of social media advertising, is defined as the practice of tailoring content to individual users based on their behaviors, preferences, and demographic profiles (Carah et al., 2023). This approach utilizes algorithms to analyze user data and craft messages that resonate with their specific interests, thereby enhancing user engagement and conversion potential (Efendioğlu & Durmaz, 2022; Novianti & Erdiana, 2020).

Beyond its benefits, personalized advertising raises significant ethical and legal concerns regarding consumer privacy and data protection, as the extensive data collection required to personalize ads can lead to legal implications under regulations such as the EU's General Data Protection Regulation (GDPR, 2016/679, came into effect in 2018) and California Consumer Privacy Act (CCPA, 2018) impose strict rules on how user data can be collected, processed, and used for targeted advertising. Research indicates that a lack of transparency and misuse of personal data can result in consumer distrust and ad avoidance (Parfeniuk, 2024). Ethical challenges include the risk of manipulation, discrimination through algorithmic targeting, and "creepy" advertising experiences when users perceive ads as overly intrusive or predictive (Herder & Zhang, 2019). As a result, advertisers are under increasing pressure to balance personalization with user autonomy, emphasizing consent-based targeting and transparent data practices to maintain trust and legal compliance.

Recent research extensively examines how personalized social media ads influence consumers: Aslam et al. (2021) linked personalized ads' relevance and novelty to heightened impulse-buying intentions; Setyani et al. (2019) identified perceived novelty and relevance as mediators between ad personalization and impulse purchases; Li et al. (2023) found affective and cognitive responses to ad value boost impulse purchases; Syaputra & Azhar (2025) demonstrated that personalized ads deepen emotional attachment and engagement; and Nyrhinen et al. (2024) confirmed social media ads increase impulse-buying behavior; De Keyzer et al. (2024) found that perceived personalization boosts brand engagement but also induces creepiness, leading to ad avoidance; Aguirre et al. (2015) confirmed the personalization-privacy paradox, showing that covert data use heightens privacy worries and reduces click intentions unless moderated by trust; Christian et al. (2021) further linked high personalization to adverse affective reactions and psychological reactance.

Previous research has examined various factors linking personalized social media advertising to online impulse buying. Still, few studies have simultaneously addressed both positive (e.g., relevance, advertising value) and negative (e.g., privacy concerns, creepiness) effects within one model (Aslam et al., 2021; Christian et al., 2021; Dodoo & Wu, 2019). While Christian et al. (2021) explored similar constructs, their study focused solely on Indonesian millennials, leaving a gap regarding how these dynamics manifest in Eastern European contexts, where empirical research remains scarce. To address this theoretical gap, our study adopts the Stimulus-Organism-Response (S-O-R) paradigm to conceptualize how personalized social media ads (stimulus) influence cognitive and emotional evaluations (organism) and, ultimately, online impulse buying tendencies (response).

A quantitative research design was employed, utilizing a self-administered online questionnaire distributed via Facebook and Instagram, which yielded 291 valid responses from Romanian social media users. The proposed model and hypotheses were tested through Partial Least Squares Structural Equation Modeling (PLS-SEM), a method well-suited for analyzing complex relationships between latent constructs and providing robust insights into consumer behavior in digital environments.

The paper is structured to provide a clear and logical flow from theory to empirical analysis. First, the literature review outlines the theoretical foundations of advertising, with a particular focus on personalized social media advertising and online impulse buying and introduces the S-O-R framework as the basis for the conceptual model and hypotheses. This is followed by the methodology and data analysis section, which presents the research design, sampling approach, and the results of the PLS-SEM analysis. The paper concludes with a discussion of the theoretical and managerial implications, highlights the study's limitations, and offers suggestions for future research directions.

2. Literature Review

This chapter provides an overview of the key theoretical foundations and research areas relevant to this study, focusing on advertising, the Stimulus-Organism-Response (S-O-R) model, personalized advertising on social media, and online impulse buying. It introduces the essential concepts, theoretical frameworks, and empirical findings that form the basis of the research, highlighting the links between advertising personalization and impulsive consumer behavior.

2.1. Theoretical background of advertising

Advertising is a key element of marketing communication, designed to influence consumer perceptions, attitudes, and purchase intentions. Defined as a paid, non-personal form of communication (Kotler & Keller, 2016), it operates at the intersection of psychology, economics, and communication theory, using both rational and emotional appeals (Belch & Belch, 2021). Foundational models such as AIDA (Attention, Interest, Desire, Action) and the Hierarchy of Effects (Lavidge & Steiner, 1961) describe advertising as a stepwise process that moves consumers from awareness to purchase. Persuasion theories like the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986) suggest that messages are processed through central routes (logical evaluation) or peripheral routes (visuals or endorsements), depending on consumer involvement.

Behavioral frameworks, particularly the Stimulus-Organism-Response (S-O-R) model, highlight how advertising stimuli trigger internal emotional or cognitive reactions that shape behavior (Mehrabian & Russell, 1974). Modern interpretations emphasize emotional engagement, storytelling (Edson Escalas, 2004), and personalization as critical factors for effectiveness (Chandra et al., 2022). In the digital era, data-driven and interactive formats, such as social media and programmatic ads, have transformed advertising dynamics, making consumer engagement more personalized and measurable (De Keyzer et al., 2024).

2.2. Importance of Stimulus-Organism-Response (S-O-R) model

The Stimulus-Organism-Response (S-O-R) model, developed by Mehrabian and Russell, (1974), describes how external stimuli (S) influence internal psychological processes (O), which in turn lead to behavioral responses (R). Bagozzi (1986) refined the framework by defining stimuli as external factors such as marketing mix elements or environmental cues, while the organism represents internal states, perceptions, emotions, and thoughts that mediate the stimulus–response relationship. In advertising, stimuli refer to marketing communications or brand messages that evoke cognitive and emotional reactions, ultimately influencing responses such as purchase intention or brand loyalty (Donovan & Rossiter, 1982).

Studies have highlighted that advertising effectiveness depends mainly on the ability of stimuli (e.g., ad design, personalization, interactivity) to elicit favorable organismic states like trust, positive affect, and perceived value (Eroglu et al., 2001; Lee & Jeong, 2014).

This framework is relevant to the current study, as it has been successfully applied in research on online consumer behavior. For example, Parboteeah et al. (2009) explored how website design influences impulse buying. Wang et al. (2011) examined how online store features affect consumer responses. More recently, Wang et al. (2022) studied how perceived risk drives avoidance of targeted advertising.

2.3. Personalized Advertising on Social Media

Personalized advertising in social media has fundamentally changed how brands interact with consumers (Xu et al., 2011). By analyzing user data, such as interests, preferences, and past behavior, marketers can create tailored content that feels more relevant and engaging (Chandra et al., 2022). These customized messages are more likely to prompt desired reactions, including purchase intent (Pavlou & Stewart, 2000).

Studies have repeatedly shown that personalization can improve advertising effectiveness by increasing user involvement (Kaspar et al., 2019; Pavlou & Stewart, 2000; Tucker, 2014; Yuan & Tsao, 2003). At the same time, researchers have noted potential drawbacks. When consumers perceive that their personal data is being used without adequate transparency, it may lead to discomfort or resistance (Kim et al., 2022; Li & Huang, 2016; Maslowska et al., 2016; Sheehan & Gleason, 2001).

This form of advertising relies on the collection of user data from multiple sources, including web searches, social media activity, and user interactions such as likes, shares, and posts (Snapchat, 2023). Platforms like Meta go further, collecting information on device use, location, transactions, and even messages, as outlined in their data policies (Curran et al., 2011; Meta, 2022; Xiphcyber, 2022).

Advances in data science have made this process even more precise. Technologies like machine learning and natural language processing allow platforms to analyze conversations and emotional reactions, helping brands fine-tune their targeting strategies (ElBermawy, 2022; Gu et al., 2018; Lee et al., 2017). These tools also support real-time responses to user behavior, increasing the likelihood of impulse purchases (Setyani et al., 2019).

Ultimately, personalized social media ads play a significant role in shaping consumer perceptions and intentions (Alalwan, 2018; Sriram. et al., 2021). However, their influence depends not only on the ad content but also on individual differences among users and the specifics of each campaign. The impact is shaped by a complex interplay of marketing strategy, brand identity, and user psychology (Mehta & Udita, 2020).

2.4. Consumers' Online Impulse Buying

Consumers' online impulse buying has become an increasingly common behavior in digital commerce, reflecting a key aspect of modern consumer behavior. This type of purchase is characterized by unplanned, spontaneous decisions made in online environments and influenced by various psychological and contextual factors (Zhang et al., 2014). These decisions are typically made quickly and are often driven by emotions, without careful evaluation of the product's necessity or the consequences of the purchase (Parboteeah et al., 2009; Verhagen & van Dolen, 2011). Emotional drivers tend to outweigh rational thought, resulting in a largely automatic action–reaction process (Törőcsik, 2016).

Although still limited in number, several empirical studies have shown that personalization can significantly influence online impulse buying (Aslam et al., 2021; Christian et al., 2021; Dodoo & Wu, 2019). These studies suggest that personalized content in social media advertisements can trigger emotional responses that facilitate impulsive purchasing.

A broader review of the literature reveals a multi-layered connection between personalized advertising and impulse buying, as illustrated in Table 1. Personalization has consistently been shown to enhance perceived ad relevance (Kim & Huh, 2017), novelty, and advertising value (Kim & Han, 2014), which in turn increases consumers' willingness to make impulsive purchases (Lina & Ahluwalia, 2021). However, the effect is not one-dimensional. Factors such as perceived intrusiveness and privacy concerns also play a significant role (Segijn et al., 2021; Zhu & Chang, 2016), shaping consumer responses in nuanced ways (Segal & Podoshen, 2013; Tifferet & Herstein, 2012). Interestingly, while personalization tends to boost impulse buying, its influence may be moderated by users' privacy concerns or negative emotional reactions, potentially reducing its overall impact (Table 1). Taken together, prior research points to a fundamental tension in the effects of personalized social media advertising. While personalization is frequently framed as a tool that facilitates decision-making and enhances advertising effectiveness, several studies indicate that the same mechanism can heighten consumers' awareness of being targeted or monitored, triggering discomfort and resistance (Aguirre et al., 2015; Herder & Zhang, 2019; Ur et al., 2012).

This contradiction suggests that personalization operates as an ambivalent stimulus rather than a uniformly persuasive one, with its impact depending on consumers' perceptions of intent, transparency, and control (Morimoto, 2021; Youn & Kim, 2019). Recent work further supports this view by showing that personalization can simultaneously enhance relevance while undermining consumer well-being through creepiness-related responses (De Keyzer et al., 2024).

Table 1: Summary of relevant studies regarding social media personalized advertising

Authors	Theory	Methodology	Independent variables	Dependent variables
Khokhar, A., Qureshi, P., Murtaza, F., & Kazi, A.G. (2019)	Social influence theory	Survey with 196 respondents from Pakistan.	Social Network Marketing Electronic Word-of-Mouth Hedonic Motivation Trust	Impulse Buying Behavior
Setyani, V., Zhu, Y.Q., Hidayanto, A.N., Sandhyaduhita, P.I., & Hsiao, B. (2019)	S.O.R., Uses and Gratifications Theory, Hedonic and utilitarian consumption theory	Survey with 862 respondents from Indonesia.	Personalization of advertisements Perceived advertising value constructs (Informativeness, Credibility, Creativity, Entertainment) Click-through motivations (Utilitarian click-through motivation, Hedonic click-through motivation)	Urge to Buy Impulsively
Dodoo, N.A. & Wu, L. (2019)	-	Survey with 249 undergraduate students from USA.	Perceived personalization of social media ads Perceived relevance Perceived novelty Perceived advertising value Privacy concern	Online impulse buying tendency
Aslam, H., Rashid, M., & Chaudhary, N. (2021)	-	Survey with 250 respondents from Pakistan.	Perceived Personalized Advertisement Perceived Novelty Perceived Relevance Online Payment Facility Privacy Concerns	Online Impulse Buying Behavior

Authors	Theory	Methodology	Independent variables	Dependent variables
Christian, J., Karissa, F., Handoyo, B., & Antonio, F. (2021)	Theory of interpersonal behavior	Survey with millennial social media users from Indonesia.	Perceived Novelty Privacy Concern Advertising Value Perceived Relevance Creepiness Affective Reactance Attitudes Toward Ads Purchase Frequency	Online Impulse Buying Tendency

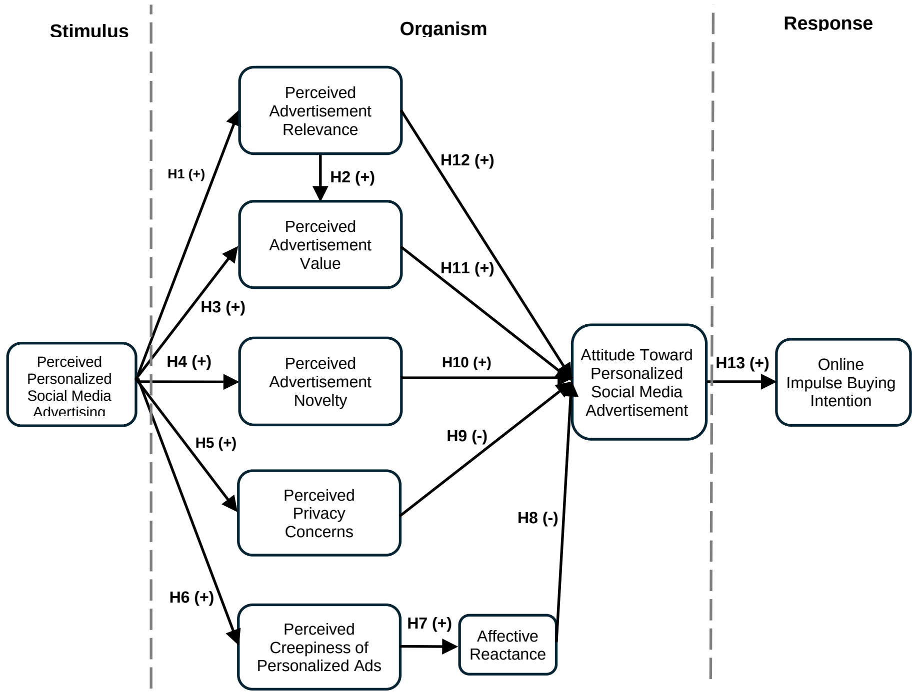
Source: Author's own compilation

3. Conceptual framework and Hypotheses development

This chapter presents the variables identified through the literature review, as well as the relationships to be examined among them. Based on prior research findings, a set of hypotheses is developed and integrated into a conceptual model grounded in the S-O-R framework.

The proposed model outlines the key constructs and their hypothesized connections, as illustrated in Figure 1. In this model, personalized advertising serves as the stimulus (S), while the organism (O) includes perceived novelty, relevance, ad value, privacy concerns, creepiness, affective response, and attitude toward the ad. The response (R) is defined as the consumer's online impulse buying intention.

Figure 1: Conceptual framework



Source: Author's own compilation

3.1. The Influence of Personalized Social Media Advertising on Key Constructs

When consumers encounter advertisements, their perception of how closely the content aligns with their needs and values plays a critical role in shaping their attitudes (Tran, 2017). Perceived relevance refers to the mental process by which individuals assess the meaning of an ad concerning their personal goals (Celsi & Olson, 1988; Xia & Bechwati, 2008). Ads perceived as highly relevant tend to attract more attention, elicit more favorable attitudes, and increase purchase intention for the promoted products or services (Jung, 2017; Nasir et al., 2021). Dodoo and Wu (2019) found that perceived personalization in social media advertising significantly enhances relevance, which in turn predicts online impulse buying. Similarly, De Keyzer et al. (2015) showed that ad personalization improves consumer responses to Facebook ads by increasing relevance. Aslam et al. (2021) also reported that when an advertisement reflects aspects of a consumer's self-concept, the likelihood of engagement rises, linking relevance to higher online impulse buying behavior. Based on these findings, the following hypotheses are proposed:

H1: Perceived personalized social media advertising positively influences perceived advertisement relevance.

H2: Perceived advertisement relevance positively influences perceived advertisement value.

Ad value is a multidimensional concept reflecting how consumers perceive, interpret, and evaluate advertisements based on their informativeness, entertainment value, and potential to irritate (Ducoffe, 1995). This evaluation is shaped by how well the ad content meets or exceeds consumer expectations (Ducoffe & Curlo, 2000). Lina and Ahluwalia (2021) found that personalized advertising enhances ad value, which can lead to increased impulse buying, especially among users who are highly engaged with social media. Similarly, Aydin (2018), using Ducoffe's ad value model, confirmed that personalization significantly influences ad value, which in turn shapes attitudes toward social media ads. Furthermore, Van-Tien Dao et al. (2014) argue that informative content, entertainment, and interactivity strongly enhance the perceived value of advertisements, which in turn positively influences users' attitudes and purchase intentions. The following hypothesis is therefore proposed:

H3: Perceived personalized social media advertising positively influences perceived advertisement value.

Perceived novelty refers to how original, unique, or unexpected an advertisement appears to consumers (Mercanti-Guérin, 2008; Sheinin et al., 2011). It involves introducing fresh elements that deviate from typical advertising patterns. Ads that are both novel and relevant tend to generate more favorable consumer responses (Ang et al., 2014). Christian et al. (2021) found that perceived personalization positively influences novelty, which in turn enhances attitudes toward the ad and increases impulse buying intention. Therefore, the following hypothesis is proposed:

H4: Perceived personalized social media advertising positively influences perceived advertisement novelty.

In the context of personalized advertising, privacy concerns refer to consumers' discomfort or anxiety about the potential misuse or unauthorized access to their personal data (Gironda & Korgaonkar, 2018; Mican et al., 2022). While personalization can increase purchase intention by offering relevant content, high levels of privacy concern may diminish these benefits (Smit et al., 2014). Tucker (2014) found that higher perceived control over personal data nearly doubled the likelihood of users clicking on personalized ads. Jung et al. (2016) also found that privacy concerns significantly reduce both attitudes and behavioral intentions toward Facebook ads, especially when perceived intrusiveness is high. Furthermore, according to Morimoto (2021), higher levels of privacy concerns negatively affect the acceptance of personalized advertisements. The sense of information control reduces these concerns, while persuasion knowledge strengthens consumers' critical perspective toward ads. Hence:

H5: Perceived personalized social media advertising positively influences perceived privacy concerns.

Highly personalized social media ads, especially those based on behavioral data, can evoke a sense of being watched or tracked, leading to what users often describe as a "creepy" feeling (Nyheim et al., 2015; Ur et al., 2012). In response, consumers may experience negative emotions such as irritation, anger, or discomfort, resulting in resistance to the ad, lower evaluations, and reduced purchase intent (Fachryto & Achyar, 2018). Groot (2022) explored the personalization paradox and found that while personalization may enhance brand perception through relevance, this effect weakens when the ad is perceived as intrusive. Herder and Zhang (2019) also noted that unexpected data use, vague justifications, or repetitive targeting can trigger anxiety and mistrust, reinforcing feelings of creepiness and emotional resistance. In addition, Youn and Kim (2019) state that the intrusiveness of advertisements, concerns about personal data, and the adverse emotional effects of ads all contribute to an increase in psychological reactance, which directly influences ad avoidance behavior. Therefore:

H6: Perceived personalized social media advertising positively influences perceived creepiness of personalized ads.

H7: Perceived creepiness of personalized social media advertising positively influences affective reactance.

3.2. The Impact of Key Constructs on Attitude Toward the Advertisement

Previous studies (Aslam et al., 2021; De Keyzer et al., 2015; Dodoo & Wu, 2019; Xu, 2006) indicate that perceived relevance, novelty, ad value, and privacy concerns strongly influence the formation of consumer attitudes toward advertisements. Aydin (2018) and Lina and Ahluwalia (2021) highlighted that ad value is a crucial determinant of positive ad evaluations, while Jung et al. (2016) and Tucker (2014) confirmed that privacy concerns can reduce favorable assessments. Additionally, Groot (2022) and Fachryto and Achyar (2018) observed that negative affective responses, stemming from feelings of creepiness, may lower ad acceptance. These findings lead to the following hypotheses:

H8: Affective reactance negatively influences attitude toward personalized social media advertisement.

H9: Perceived privacy concerns negatively influence attitude toward personalized social media advertisement.

H10: Perceived advertisement novelty positively influences attitude toward personalized social media advertisement.

H11: Perceived advertisement value positively influences attitude toward personalized social media advertisement.

H12: Perceived advertisement relevance positively influences attitude toward personalized social media advertisement.

3.3. The Effect of Attitude Toward the Advertisement on Online Impulse Buying

Attitude toward the advertisement refers to the audience's behavioral and emotional response to a given ad (Birmingham, 1969). Kotler (2000) describes attitude as a learned predisposition that reflects a person's evaluation, emotional connection, and behavioral tendency toward an object or idea. In advertising contexts, this translates into consumers' favorable or unfavorable reactions to a specific ad (MacKenzie & Lutz, 1989; Wells et al., 2011). Additionally, Koay et al. (2021) highlighted that interactivity, entertainment, and relevant content have a significant positive impact on consumers' tendency toward impulse buying. According to Mehta (2000), attitude toward an ad is a key indicator of advertising effectiveness, as it reflects the consumer's cognitive and emotional responses, which in turn shape their evaluation of the ad. Aslam et al. (2021) confirmed that attitudes toward personalized ads, particularly those shaped by relevance and novelty, significantly influence purchase intentions and predict the likelihood of online impulse buying. Therefore:

H13: Attitude toward personalized social media advertisement positively influences online impulse buying intention.

4. Research methodology and Data collection

This study follows a quantitative, descriptive research design. Data were collected via a self-administered online questionnaire created in Microsoft Forms, available in both Hungarian and Romanian. The survey was distributed primarily through Facebook and Instagram, where participants were also encouraged to share the questionnaire with others, following a snowball sampling method. This approach proved effective in reaching individuals outside the initial sampling frame who could still provide relevant insights. Data collection took place over ten days, between April 3 and April 12, 2024.

Facebook and Instagram were chosen intentionally, as they are among the most widely used social platforms in Romania: 88.7% of internet users aged 16–64 use Facebook, while 64.8% use Instagram (Statista Research Department, 2025). Although WhatsApp and Messenger are even more popular, their messaging-based nature makes them less suitable for wide-scale survey distribution. Therefore, Facebook and Instagram were deemed the most effective channels.

The questionnaire began with an instructional introduction aimed at ensuring participants had a clear understanding of personalized advertising. To this end, respondents were asked to watch a two-minute educational video illustrating three forms of ad personalization, based on prior search history, location targeting, and interest-based categorization, on social media platforms. Following the video, screening questions were included to ensure only relevant participants were retained. First, a yes/no question asked whether the respondent had viewed the video; those who answered “no” were excluded. Second, another yes/no item assessed whether the respondent had ever encountered personalized ads on social media; again, “no” responses led to exclusion. Additionally, only individuals aged 18 or older were eligible to complete the survey.

The questionnaire included established 7-point Likert scales adapted from prior studies to measure the constructs of interest (see Table 2). Perceived personalization of ads (Tran, 2017; Xu et al., 2011) was treated as the independent variable. Mediator constructs included perceived novelty (Mercanti-Guérin, 2008; Sheinin et al., 2011), relevance (Alalwan, 2018; Nasir et al., 2021), ad value (Ducoffe, 1995; Van-Tien Dao et al., 2014), privacy concerns (Gironda & Korgaonkar, 2018; Morimoto, 2021), creepiness (De Keyzer et al., 2024), affective response (Nyheim et al., 2015; Youn & Kim, 2019), and attitude toward the ad (Xu, 2006). The dependent variable, online impulse buying intention, was measured using scales from Koay et al. (2021) and Wells et al. (2011). Demographic variables, including gender, age, place of residence, income level, and educational attainment, were also recorded to provide further insight into the sample composition.

Table 2: Measurement model constructs

PA	**Perceived Personalized Social Media Advertising** *(Tran, 2017; Xu et al., 2011)* Personalized ads on social media…
PA1	provide shopping recommendations that match my needs.
PA2	allow me to order products I’m genuinely interested in.
PA3	are tailored to my specific situation.
PA4	are customized to my preferences.
PA5	offer recommendations aligned with my interests.
PA6	provide promotional information adjusted to my preferences.
PN	**Perceived Advertisement Novelty** *(Mercanti-Guérin, 2008; Sheinin et al., 2011)* Personalized ads on social media…
PN1	are original.
PN2	are visually interesting.
PN3	grab my attention.
PN4	are imaginative.
PN5*	are different from usual.
PR	**Perceived Advertisement Relevance** *(Alalwan, 2018; Nasir et al., 2021)* Personalized ads on social media…
PR1	appeal to me.
PR2	are a good fit for me.
PR3	match my lifestyle.
AV	**Perceived Advertisement Value** *(Ducoffe, 1995; Van-Tien Dao et al., 2014)* Personalized ads on social media…
AV1	are valuable to me.
AV2	are useful to me.
AV3	are effective.

PC	**Perceived Privacy Concerns** *(Gironda & Korgaonkar, 2018; Morimoto, 2021)* I am concerned that personalized ads on social media…
PC1	collect too much information about me.
PC2	do not store my data securely.
PC3*	may misuse my personal information.
PC4	pose a serious risk to my privacy through data access.
CR	**Perceived Creepiness of Personalized Ads** *(De Keyzer et al., 2024)* Personalized ads on social media…
CR1	are disturbing.
CR2*	are frightening.
CR3	are irritating.
CR4	are strange.
AR	**Affective Reactance** *(Nyheim et al., 2015; Youn & Kim, 2019)* I... personalized ads on social media
AR1	ignore them.
AR2*	pay no attention to them.
AR3	would prefer if they didn't exist.
ATA	**Attitude Toward Personalized Social Media Advertisement** *(Xu, 2006)* Personalized ads on social media…
ATA1	seem like a good idea to me.
ATA2*	I consider their use to be a good idea.
ATA3	are believable.
ATA4	are interesting.
OIB	**Online Impulse Buying Intention** *(Koay et al., 2021; Wells et al., 2011)* As a result of personalized ads on social media...
OIB1	I feel the urge to buy products/services outside of my original intentions.
OIB2*	I want to buy items unrelated to my initial shopping goals.
OIB3	I feel inclined to buy products/services not connected to my planned purchases.

* were removed from the final model
Source: Author's own compilation

Given the number of variables and relationships involved, this study applies a complex model that requires a multivariate analysis approach, where multiple variables may simultaneously influence others (Hair et al., 2016). To test the conceptual model, structural equation modeling (SEM) was employed, as this technique is well-suited for analyzing models with a large number of indicators and latent constructs (Magno et al., 2022). Specifically, the study used Partial Least Squares Structural Equation Modeling (PLS-SEM), a method capable of providing reliable results even with smaller sample sizes or non-normally distributed data. PLS-SEM is particularly appropriate for estimating complex, hierarchical theoretical models (Hair et al., 2016).

5. Data analysis

This chapter presents the analysis of the data collected through the questionnaire. After data cleaning, a total of 291 valid responses were retained for analysis. The section begins with a description of the sample characteristics, followed by the testing of hypothesized relationships using structural equation modeling. To examine the proposed model, PLS-SEM was applied using SmartPLS version 4.1.0.2, which is suitable for analyzing complex variable relationships. Descriptive statistics of the sample were generated using IBM SPSS version 22.

5.1. Sample characteristics

An analysis of the demographic profile reveals that the majority of respondents (63.9%) completed the survey in Hungarian, while 36.1% responded in Romanian. Participants were drawn from 27 counties across Romania, with the highest representation from Mureș (25.8%), Cluj (20.6%), Covasna (11%), Harghita (10.3%), and Brașov (6.5%) counties.

Regarding gender, the sample was predominantly female (75.6%), with male respondents accounting for 24.4%. In terms of age, the largest group consisted of individuals aged 18–25, making up more than half the sample (52.2%), while other age groups were represented to a much smaller extent. As for educational background, the largest segment held a high school diploma (37.1%), followed by those with a bachelor's degree (34.7%). Respondents with a master's degree accounted for 15.1%, while 13.1% reported having completed vocational or technical school. In terms of income, most participants fell into the lower-middle income categories. Specifically, 17.2% reported a monthly income between 2,001 and 3,000 RON, while 22.7% fell in the 3,001–4,000 RON range. The lowest income group (under 1,000 RON) represented 9.6% of the sample, whereas the highest income group (above 8,000 RON) accounted for 5.2% (see Table 3).

Table 3: Demographic characteristics of the sample

Demographic variable		**Frequency**	**Percentage (%)**
Survey language	Hungarian	186	63.9
	Romanian	105	36.1
Place of residence	Mureș	75	25.8
	Cluj	60	20.6
	Covasna	32	11
	Harghita	30	10.3
	Brașov	19	6.5
	Bucharest – Ilfov	16	5.5
	Bihor	15	5.2
	Other	44	15.1
Gender	Male	71	24.4
	Female	220	75.6
Age group	18–25	152	52.2
	26–35	55	18.9
	36–45	38	13.1
	46–55	36	12.4
	56–65	10	3.4
Education level	High School	108	37.1
	Vocational School	38	13.1
	Bachelor's Degree	101	34.7
	Master's Degree	44	15.1
Income level	Below 1000 RON	28	9.6

Demographic variable		Frequency	Percentage (%)
	1000 – 2000 RON	53	18.2
	2001 – 3000 RON	50	17.2
	3001 – 4000 RON	66	22.7
	4001 – 5000 RON	37	12.7
	5001 – 6000 RON	23	7.9
	6001 – 7000 RON	12	4.1
	7001 – 8000 RON	7	2.4
	Above 8000 RON	15	5.2

Source: Author's own compilation

5.2. Structural Equation Modeling

5.2.1. Measurement model assessment

The evaluation of the measurement model was conducted in several steps. First, we examined potential collinearity among the measurement indicators (see Table 4, 5). Next, we assessed internal consistency using Cronbach's alpha and composite reliability (rho_A) values (see Table 6) (Hair et al., 2016). Discriminant validity was then tested using the Heterotrait–Monotrait (HTMT) ratio, which captures the degree of similarity between latent constructs (Henseler et al., 2015) (see Table 7). Finally, we included model fit indices in the overall assessment.

The path coefficients of the structural model, which describe relationships between latent constructs, were estimated through a series of regression equations. As point estimates and standard errors can be distorted by high intercorrelations among predictor indicators (Sarstedt & Mooi, 2019), we also tested for multicollinearity. VIF (Variance Inflation Factor) values above 5 indicate problematic collinearity (Becker et al., 2014). Our analysis showed that PC2, PC3, AR1, AR2, ATA1, ATA2, OIB2, and OIB3 had VIF values exceeding this threshold and were therefore they need to be corrected.

Table 4: Collinearity diagnostics of indicators

Variable	Indicator	VIF	Result
Perceived Personalized Social Media Advertising	PA1	2.607	none
	PA2	2.341	none
	PA3	4.102	moderate
	PA4	4.809	moderate
	PA5	2.697	none
	PA6	2.755	none
Perceived Advertisement Novelty	PN1	1.962	none
	PN2	2.859	none
	PN3	3.198	moderate
	PN4	2.453	none
	PN5	1.391	none
Perceived Advertisement Relevance	PR1	2.539	none
	PR2	3.791	moderate
	PR3	2.595	none

Variable	Indicator	VIF	Result
Perceived Advertisement Value	AV1	2.572	none
	AV2	4.505	moderate
	AV3	3.638	none
Perceived Privacy Concerns	PC1	3.478	moderate
	PC2	6.206	strong
	PC3	7.456	strong
	PC4	3.673	moderate
Perceived Creepiness of Personalized Ads	CR1	3.312	moderate
	CR2	1.714	none
	CR3	3.670	moderate
	CR4	2.461	none
Affective reactance	AR1	6.178	strong
	AR2	6.221	strong
	AR3	2.145	none
Attitude Toward Personalized Social Media Advertisement	ATA1	5.341	strong
	ATA2	6.364	strong
	ATA3	3.301	moderate
	ATA4	3.402	moderate
Online Impulse Buying Intention	OIB1	3.025	moderate
	OIB2	5.564	strong
	OIB3	5.446	strong

Source: Author's own compilation

To eliminate multicollinearity, indicators with high VIF values were removed from the model, as addressing such issues can enhance the accuracy of estimated correlations between latent variables (Grewal et al., 2004). We removed the indicators one by one, starting with those showing the highest VIF values. It was not necessary to eliminate all eight indicators; removing PC3, AR2, ATA2 and OIB2 was sufficient to resolve the multicollinearity issue (see Table 5).

Table 5: Results after removing indicators with high collinearity

Variable	Indicator	VIF	Result
Perceived Privacy Concerns	PC1	3.285	moderate
	PC2	4.367	moderate
	PC4	2.816	none
Affective Reactance	AR1	2.034	none
	AR3	2.034	none
Attitude Toward Personalized Social Media Advertisement	ATA1	2.550	none
	ATA3	3.135	moderate
	ATA4	3.244	moderate
Online Impulse Buying Intention	OIB1	2.702	none
	OIB3	2.702	none

Source: Author's own compilation

All variables and their indicators included in the analysis exhibit high factor loadings (see Table 6), generally exceeding 0.8. This indicates that the indicators effectively represent their associated latent constructs and significantly contribute to their definition. The indicators CR2 and PN5 were excluded from the model due to factor loadings below the acceptable threshold of 0.7, specifically, 0.696 and 0.674, respectively.

The values for Cronbach's alpha, composite reliability (rho_A), and average variance extracted (AVE) are also high across all constructs. Both Cronbach's alpha and rho_A mostly exceed 0.8, indicating excellent internal consistency (Henseler et al., 2015). The high composite reliability values further reinforce that the constructs are reliably measured using the corresponding indicators. Moreover, all AVE values surpass the 0.5 threshold, and in fact, exceed 0.7 in all cases, demonstrating strong convergent validity, as the indicators explain a substantial portion of the variance in each construct (Tabachnick & Fidell, 2007).

These results collectively indicate that the measurement model is robust and provides a solid foundation for further structural analysis and interpretation.

Table 6: Assessment of internal and external reliability

Variable	Indicator	Factor loadings	Cronbach's Alpha	Composite reliability (rho_A)	Average variance extracted (AVE)	Result
Perceived	PA1	0.844	0.931	0.935	0.744	reliable
Personalized	PA2	0.828				reliable
Social Media	PA3	0.891				reliable
Advertising	PA4	0.915				reliable
	PA5	0.840				reliable
	PA6	0.854				reliable
Perceived	PN1	0.742	0.883	0.886	0.740	reliable
Advertisement	PN2	0.873				reliable
Novelty	PN3	0.881				reliable
	PN4	0.825				reliable
Perceived	PR1	0.896	0.893	0.895	0.823	reliable
Advertisement	PR2	0.940				reliable
Relevance	PR3	0.885				reliable
Perceived	PR1	0.893	0.913	0.916	0.852	reliable
Advertisement	PR2	0.950				reliable
Value	PR3	0.926				reliable
Perceived	PC1	0.901	0.914	0.938	0.852	reliable
Privacy Concerns	PC2	0.944				reliable
	PC4	0.924				reliable
Perceived	CR1	0.911	0.884	0.921	0.811	reliable
Creepiness of	CR3	0.694				reliable
Personalized Ads	CR4	0.923				reliable
Affective	AR1	0.908	0.832	0.855	0.855	reliable
reactance	AR3	0.941				reliable
Attitude Toward	ATA1	0.899	0.904	0.905	0.839	reliable
Personalized	ATA3	0.920				reliable
Social Media Advertisement	ATA4	0.928				reliable
Online Impulse	OIB1	0.960	0.885	0.925	0.895	reliable
Buying Intention	OIB3	0.933				reliable

Source: Author's own compilation

The HTMT ratios represent one of the modern and reliable indicators of discriminant validity, reflecting the correlations between the different variables. Generally, values below 0.90 suggest that the constructs are adequately distinct from one another (Henseler et al., 2015). Overall, the variables demonstrate satisfactory discriminant validity, as the HTMT values fall below the 0.90 threshold. This indicates that the constructs are well differentiated and accurately capture the phenomena they are intended to represent within the model.

Table 7: Heterotrait-Monotrait (HTMT) ratios of the variables

	Perceived Privacy Concerns	Affective Reactance	Perceived Advertisement Relevance	Perceived Advertisement Novelty	Perceived Creepiness of Personalized Ads	Online Impulse Buying Intention	Perceived Advertisement Value	Attitude Toward Personalized Social Media Advertisement
Affective Reactance	0.461							
Perceived Advertisement Relevance	0.096	0.467						
Perceived Advertisement Novelty	0.049	0.406	0.779					
Perceived Creepiness of Personalized Ads	0.629	0.832	0.399	0.351				
Online Impulse Buying Intention	0.136	0.422	0.471	0.442	0.276			
Perceived Advertisement Value	0.181	0.604	0.816	0.710	0.464	0.507		
Attitude Toward Personalized Social Media Advertisement	0.254	0.560	0.749	0.647	0.492	0.533	0.801	
Perceived Personalized Social Media Advertising	0.060	0.275	0.756	0.644	0.197	0.298	0.612	0.563

Source: Author's own compilation

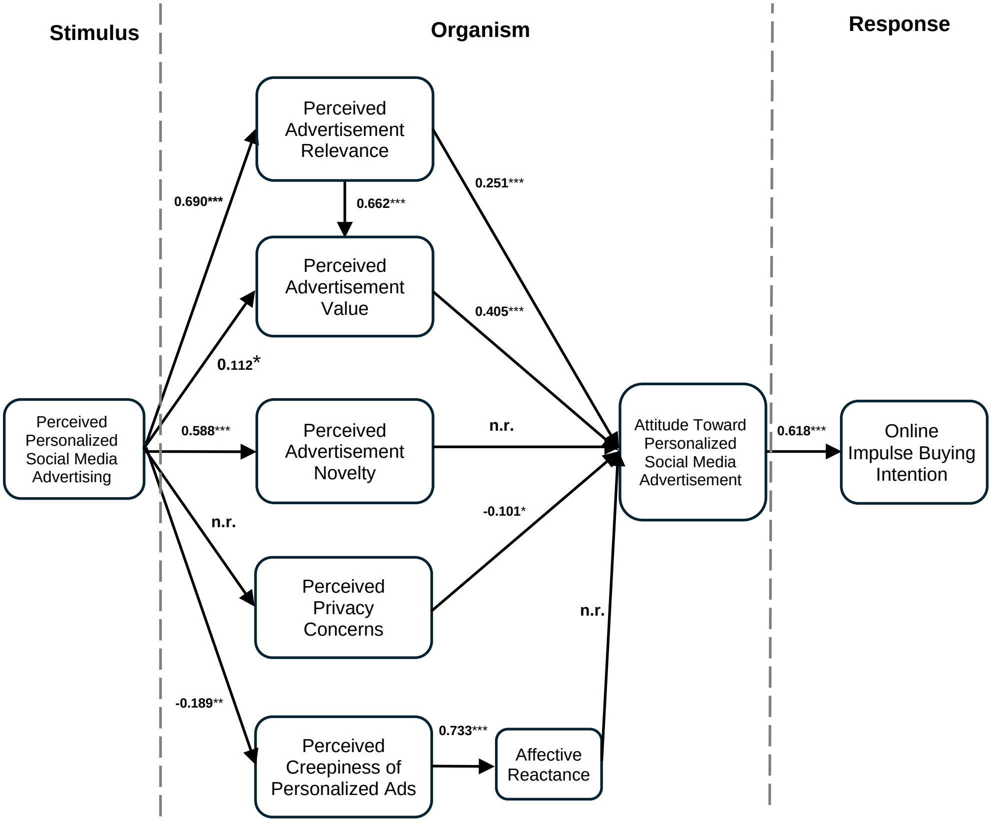
To assess the goodness-of-fit of the structural equation model, the SRMR (Standardized Root Mean Square Residual) and NFI (Normed Fit Index) indices were used. SRMR represents the square root of the difference between the observed and predicted covariance matrices. SRMR values range between 0 and 1, with values below 0.05 indicating a good fit (Byrne, 1998; Diamantopoulos & Siguaw, 2000), though values up to 0.08 are considered acceptable (Hu & Bentler, 1999). The NFI takes model complexity into account by comparing the chi-square value of the proposed model to that of the null model, which assumes that all observed variables are uncorrelated. NFI values also range from 0 to 1, with Bentler and Bonett (1980) recommending a threshold of 0.90 for good model fit.

In the present study, the SRMR was 0.051, meeting the accepted threshold. However, the NFI value was 0.826, which falls slightly short of the recommended cut-off. Based on these indicators, the model demonstrates moderate fit.

5.2.2. Hypothesis testing

To examine the direction and strength of the hypothesized relationships, standardized beta coefficients were used. These values range between –1 and 1, where coefficients between 0.1 and 0.3 indicate weak relationships, 0.3 to 0.5 indicate moderate relationships, and values above 0.5 suggest strong relationships. To assess statistical significance, both t-values and p-values were considered. A relationship is deemed significant if the absolute value of the t-statistic exceeds 1.96, based on a 95% confidence interval. For p-values, three levels of significance were used: $p < 0.001$, $p < 0.01$, and $p < 0.05$ (Figure 2) (Kline, 2016).

Figure 2: Diagram of the relationships between constructs



n.r. – no relationship
Source: Author's own compilation

The results indicate (see Table 8) that Perceived Personalized Social Media Advertising has a significant, positive, and strong effect on Perceived Advertisement Relevance (β = 0.690; t = 20.368; p < 0.001), thus supporting H1. Perceived Advertisement Relevance also has a significant, positive, and strong effect on Perceived Advertisement Value (β = 0.662; t = 12.885; p < 0.001), confirming H2. The impact of Perceived Personalized Social Media Advertising on Perceived Advertisement Value is significant, positive, but weak (β = 0.112; t = 2.073; p = 0.038), supporting H3, and its impact on Perceived Advertisement Novelty is significant, positive, and strong (β = 0.588; t = 14.178; p < 0.001), confirming H4. However, Perceived Personalized Social Media Advertising shows no significant effect on Perceived Privacy Concerns (t = 0.333; p = 0.739), leading to the rejection of H5, while its impact on Perceived Creepiness of Personalized Ads is significant, negative, but weak (β = –0.189; t = 2.729; p = 0.006). Despite the significance, H6 is rejected because the relationship is negative, contrary to the hypothesized positive direction.

Perceived Creepiness of Personalized Ads has a significant, positive, and strong effect on Affective Reactance (β = 0.733; t = 24.863; p < 0.001), confirming H7. The impact of Affective Reactance on Attitude Toward Personalized Social Media Advertisement is not significant (t = 1.731; p = 0.084), resulting in the rejection of H8. In contrast, Perceived Privacy Concerns have a significant, negative, but weak impact on Attitude Toward Personalized Social Media Advertisement (β = –0.101; t = 2.390; p = 0.017), supporting H9. Perceived Advertisement Novelty does not significantly influence Attitude Toward Personalized Social Media Advertisement (t = 1.631; p = 0.103), leading to the rejection of H10.

On the other hand, both Perceived Advertisement Value (β = 0.405; t = 5.247; p < 0.001) and Perceived Advertisement Relevance (β = 0.251; t = 3.241; p = 0.001) have significant, positive effects on Attitude Toward Personalized Social Media Advertisement, confirming H11 and H12. Finally, Attitude Toward Personalized Social Media Advertisement has a significant, positive, and strong effect on Online Impulse Buying Intention (β = 0.618; t = 7.030; p < 0.001), supporting H13.

Table 8: Summary of hypothesis testing results

Hypothesis		β	Standard Deviation	t-value	p-value	Result
H1	PA à PR	0.690	0.034	20.368	0.000***	supported
H2	PR à AV	0.662	0.051	12.885	0.000***	supported
H3	PA à AV	0.112	0.054	2.073	0.038*	supported
H4	PA à PN	0.588	0.041	14.178	0.000***	supported
H5	PA à PC	- 0.024	0.073	0.333	0.739	not supported
H6	PA à CR	- 0.189	0.069	2.729	0.006**	not supported
H7	CR à AR	0.733	0.029	24.863	0.000***	supported
H8	AR à ATA (-)	- 0.095	0.055	1.731	0.084	not supported
H9	PC à ATA (-)	- 0.101	0.042	2.390	0.017*	supported
H10	PN à ATA	0.110	0.068	1.631	0.103	not supported
H11	AV à ATA	0.405	0.077	5.247	0.000***	supported
H12	PR à ATA	0.251	0.078	3.241	0.001***	supported
H13	ATA à OIB	0.618	0.088	7.030	0.000***	supported

*** p<0,001; ** p<0,01; * p<0,05; (-) hypothesized negative relationship
Source: Author’s own compilation

6. Discussion and conclusions

With the growing popularity of personalized advertisements on social media, it is crucial to understand how these ads affect users and how they relate to purchasing intentions. This study aimed to explore the psychological mechanisms and underlying structures that shape users' responses to personalized advertisements by developing a conceptual model and testing it using structural equation modeling (SEM).

The results indicate that personalized advertising, by deviating from ordinary or typical patterns, significantly influences perceived novelty, in line with the findings of Ang et al. (2014). However, contrary to Christian et al. (2021), no significant relationship was found between perceived novelty and attitude toward the advertisement. Furthermore, consistent with the conclusion of Dodoo and Wu (2019), advertisements have a strong impact on perceived relevance by aligning with users' needs and values. This relevance influences perceived advertising value and predicts attitudes toward the ad, as also highlighted by Aslam et al. (2021) and De Keyzer et al. (2015). In addition, advertising value, defined as the user's evaluation of the ad, was found to be positively associated with advertising attitude, supporting Aydin's (2018) findings. Although Tucker (2014) reported that personalized advertising positively affects privacy concerns, no significant relationship between these two variables was found in the present sample. However, similar to the conclusion of Jung et al. (2016), the intrusive nature of ads and fear of data misuse had a negative impact on advertising attitude. Although a positive relationship between personalized ads and the feeling of creepiness was expected, consistent with Groot (2022), this hypothesis was not confirmed. In this sample, the relationship turned out to be negative, though still statistically significant. One possible explanation is that the personalized ads they encountered were mostly based on their previous searches, thus they were perceived as less creepy, as the content aligned with products they had consciously looked for. By contrast, the positive association between creepiness and affective response, as demonstrated by Herder and Zhang (2019), was confirmed in this study. However, no significant link was found between affective response and attitude toward the advertisement. The study's key hypothesis, that personalized social media ads influence online impulse buying tendencies through advertising attitude, was supported, consistent with the findings of Aslam et al. (2021) and Christian et al. (2021).

The findings of this study may hold significant implications for companies advertising on social media, as well as for professionals managing these campaigns. As users spend increasing amounts of time on these platforms, businesses understandably invest substantial resources to reach and convert them. However, it is crucial to understand what strategies truly work and how immediate purchases can be effectively encouraged. The results highlight the importance of delivering advertisements that meet or exceed user expectations. In this study, perceived ad value had the strongest impact on advertising attitudes, suggesting that ads offering accurate and personally relevant information, both about the user and the product, can enhance both perceived value and user attitudes. Moreover, this research contributes to the underdeveloped literature on personalized social media marketing and online impulse buying, offering insights into consumer behavior through the lens of psychological mechanisms.

Several limitations should be noted. First, the lack of consistent literature required reliance on sources outside the context of social media or digital personalization.

Second, the data were collected through cross-sectional, self-reported surveys using snowball sampling, thus not capturing actual purchasing behavior. Future research could address this with longitudinal designs and real transaction data to better establish causal links between personalization and impulse buying. The sample was also skewed toward women and younger users; future studies may improve generalizability through stratified or quota sampling. Finally, the unexpected negative link between personalization and perceived creepiness suggests the value of categorizing ad types (e.g., based on previous searches, geolocation, or interests) to obtain a more nuanced understanding of user responses.

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