


## ARTICLE OPEN ACCESS

# Buy Now, Think Later: The Role of Behavioural Biases in Impulse Spending

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## ABSTRACT

This study explores the relationships between present bias, emotional reactivity and perceived digital advertising exposure in relation to impulse spending behaviour. The aim is to examine how these psychological factors and marketing perceptions are associated with impulsive consumer purchases. Using a quantitative survey design, data were collected from 617 UK-based consumers who reported their tendencies toward impulse spending, emotional responses and exposure to personalised ads. The findings indicate that present bias is significantly associated with impulse spending, whereas emotional reactivity strengthens this relationship. Furthermore, perceived digital advertising exposure is associated with the relationship between present bias and impulse spending, highlighting its potential to reinforce impulsive tendencies. On the basis of these findings, the study recommends that businesses adopt ethical marketing strategies that address consumers' psychological vulnerabilities, such as promoting responsible consumption and financial education. For consumers, it suggests the importance of emotional regulation and awareness of cognitive biases. The study contributes to the understanding of impulse spending by integrating cognitive, emotional and environmental factors, providing insights for businesses, policymakers and consumers to better understand impulsive spending behaviours.

**JEL Classification:** D12, D90, M31, G02

## 1 | Introduction

Impulse spending is characterised by unplanned purchases driven by immediate desires rather than long-term goals, shaped by a complex interplay of internal and external factors (Iyer et al. 2020; Putra et al. 2022). At the individual level, one key internal driver is present bias, a cognitive tendency to overvalue immediate rewards relative to future benefits (Silvera et al. 2008; Feng et al. 2024). Present bias encourages consumers to prioritise short-term gratification over long-term financial goals, often resulting in unplanned purchases. Alongside cognitive biases, emotional reactivity further exacerbates impulsive tendencies. Emotions, such as stress, excitement or low mood, can act as powerful triggers for impulse spending behaviour, amplifying

the likelihood of spontaneous consumption (Barboza 2018; Wang et al. 2022; Arruda and Oliveira 2023). The interaction between cognitive biases, such as present bias, and emotional responses creates an environment conducive to impulsive decision-making, underscoring the multifaceted nature of impulse spending.

External factors, particularly in digital and retail contexts, also play a critical role in shaping consumer behaviour. Personalised digital advertising that leverages individual preferences, scarcity cues and social proof can reduce psychological barriers to spending and encourage unplanned purchases (Zafar et al. 2020; Feng et al. 2024). Similarly, influencer marketing and live-streaming advertisements amplify impulsive tendencies by creating a sense of urgency, social trust and engagement (Yan et al. 2023; Lin

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et al. 2023). In physical retail environments, environmental cues such as store layout, lighting, promotional displays and limited-time offers further enhance emotional responses, stimulating impulse spending behaviour (Khan et al. 2022; Tahiry et al. 2025; Khetarpal and Singh 2024). Collectively, these internal and external drivers challenge traditional models of consumer behaviour, which often focus solely on rational decision-making, underscoring the need to account for psychological, emotional and environmental factors in explaining impulsive spending.

Understanding impulse spending has both theoretical and practical significance. For consumers, impulsive purchases can lead to unplanned debt, financial stress and long-term financial instability, highlighting the need for improved financial literacy and budgeting practices (Amasino et al. 2023; Mazlan 2024). From a business perspective, understanding the determinants of impulsive behaviour is crucial for crafting targeted marketing strategies, particularly in digital spaces where personalised advertisements and influencer promotions have become dominant channels (Yan et al. 2023; Zafar et al. 2020). The increasing prevalence of digital payment systems that reduce the psychological friction of spending further intensifies the importance of examining the broader cognitive and emotional context of consumer decision-making (Faraz and Anjum 2025; Redine et al. 2023). For policymakers and financial educators, promoting self-control and fostering healthy consumption habits is essential, especially in the digital era where impulsive buying can be easily facilitated (Iyer et al. 2020; Goel et al. 2022).

Despite extensive research on general impulsive behaviour, there remain significant gaps in the literature. Most studies focus on broad impulsive tendencies without isolating present bias as a specific predictor of impulse spending (Iyer et al. 2020; Redine et al. 2023; Asgari and Pouralimardan 2024). Furthermore, although emotional states are acknowledged as influential, few studies examine their moderating effects on the relationship between cognitive biases, such as present bias and impulsive buying behaviour. Emotional reactivity—manifested as stress, excitement or low mood—may strengthen or weaken the impact of present bias on unplanned purchases, yet empirical evidence on this interaction is limited (Barboza 2018; Wang et al. 2022; Arruda and Oliveira 2023). In addition, although the role of digital advertising in stimulating impulse spending has been widely studied, the mediating effect of personalised ads in the relationship between present bias and impulsive behaviour remains underexplored (Zafar et al. 2020; Yan et al. 2023; Feng et al. 2024). Personalised ads that leverage scarcity, social proof or recommendation algorithms may act as facilitators, translating an individual's cognitive biases into actual impulsive purchases, yet this mechanism is insufficiently examined in current research.

To address these gaps, this study aims to investigate the combined influence of present bias, emotional states and personalised digital advertising on impulse spending. Specifically, the research examines the following:

1. The direct effect of present bias on impulse spending frequency. Although previous studies have examined general impulsive tendencies (Iyer et al. 2020; Redine et al. 2023; Asgari and Pouralimardan 2024), the specific role of present bias in driving unplanned purchases remains unclear. **RQ1:**

*To what extent does present bias influence the frequency of impulse spending?* (Silvera et al. 2008; Feng et al. 2024).

2. The moderating role of emotional states. Emotional reactivity may amplify or attenuate the impact of present bias on impulsive buying, yet empirical evidence is limited regarding this interaction (Barboza 2018; Wang et al. 2022; Arruda and Oliveira 2023). **RQ2:** *How do emotional states moderate the relationship between present bias and impulse spending?* (Barboza 2018; Wang et al. 2022; Arruda and Oliveira 2023).
3. The mediating effect of personalised digital advertising. Digital advertisements may serve as a mechanism that links present bias with actual purchasing behaviour. However, the interaction between personalised ads and cognitive biases remains insufficiently addressed (Zafar et al. 2020; Yan et al. 2023; Feng et al. 2024). **RQ3:** *Does exposure to personalised digital advertising mediate the relationship between present bias and impulse spending?* (Zafar et al. 2020; Yan et al. 2023; Feng et al. 2024).

By explicitly linking each research question to specific gaps in the literature, this study seeks to clarify the psychological and behavioural mechanisms underlying impulse spending. Investigating the direct role of present bias, the moderating effect of emotional states, and the mediating influence of personalised digital advertising will advance theoretical understanding and provide actionable insights for consumers, businesses and policymakers navigating an increasingly digital marketplace.

## 2 | Literature Review

### 2.1 | Impulse Spending and Present Bias

Impulse spending is a well-documented behaviour where consumers make spontaneous, unplanned purchases, often without considering their long-term financial consequences. Present bias is identified as a critical driver of this behaviour, as individuals tend to prioritise immediate rewards over future benefits (Barboza 2018; Feng et al. 2024). The concept of intertemporal choice underpins this, explaining why people often undervalue future costs, such as the inability to save for retirement, in favour of short-term gratification (Feng et al. 2024; Asgari and Pouralimardan 2024). This bias contributes to impulsive buying, which leads to financial outcomes contrary to the goals of saving and financial security (Heilman et al. 2021). By examining these connections, we can better understand why consumers engage in behaviours that might seem irrational from a long-term perspective.

The relationship between present bias and impulsive buying is supported by studies showing that present-biased individuals often exhibit reduced self-control, leading to impulsive spending (Silvera et al. 2008; Iyer et al. 2020). Neuropsychological evidence suggests that such consumers respond more strongly to immediate rewards when exposed to time-sensitive offers (Ranawat 2025). They are also more prone to procrastination, such as delaying credit card payments, with long-term financial consequences (Barboza 2018). Marketers exploit these tendencies through limited-time offers and algorithmic recommendation systems that continuously present gratification opportunities

based on users' behaviour (Khetarpal and Singh 2024; Wang 2025), reinforcing impulsive purchases and prioritisation of short-term rewards over long-term financial health.

However, although present bias helps explain impulse spending, it also offers potential for behavioural interventions that could mitigate its effects. By leveraging insights into present bias, policymakers and businesses can implement strategies to reduce impulsive spending. Behavioural nudges, such as reminders to save or restrictions on impulsive purchases, could counteract the natural inclination toward present-biased decision-making (Faraz and Anjum 2025). Recent technological interventions, including 'cooling-off' periods in digital payment systems and AI-driven spending alerts, have shown promising results in reducing impulse purchases among present-biased consumers (Shekhawat and Kaur 2025). These interventions could help individuals make better financial choices, promoting a healthier balance between immediate desires and long-term financial well-being. Ultimately, addressing present bias offers a way forward for improving both individual financial decision-making and broader economic stability.

## 2.2 | Impulse Spending and Emotional Reactivity

Impulse spending is strongly influenced by emotional reactivity, where consumers' emotional states play a significant role in driving spontaneous purchasing decisions. Emotional triggers such as stress, anxiety, excitement or even boredom often encourage individuals to make unplanned purchases, frequently prioritising short-term emotional relief over long-term financial planning (Silvera et al. 2008; Faraz and Anjum 2025). Negative emotions such as sadness or frustration often prompt consumers to engage in impulse spending as a means of coping, a behaviour often referred to as 'retail therapy' (Arruda and Oliveira 2023). Conversely, positive emotional states, such as happiness, excitement or a sense of celebration, can also stimulate indulgent spending, where consumers treat themselves to hedonic or luxury goods as a reward (Putra et al. 2022; Khetarpal and Singh 2024). This illustrates how both positive and negative emotions can simultaneously encourage impulsive behaviours, making emotional reactivity a key driver of unplanned spending.

Affective forecasting theory helps explain the link between emotional reactivity and impulse spending, as individuals often overestimate the satisfaction from a purchase while underestimating future consequences (Heilman et al. 2021). Emotional arousal can reduce self-control, leading to hasty purchases motivated by the expectation of mood enhancement (Feng et al. 2024; Redine et al. 2023). This effect is particularly evident in online shopping, where ease of purchase and instant gratification amplify impulsivity (Faraz and Anjum 2025). Recent research shows that digital interface elements, such as vibrant colours, dynamic content and interactive prompts, further heighten emotional arousal, intensifying impulsive behaviour beyond levels observed in traditional retail settings (Shi et al. 2025). Consequently, consumers may make repeated unplanned purchases in a short time span, often without fully considering the financial or long-term implications. Understanding these mechanisms highlights the importance of designing interventions that can help consumers regulate emotional impulses in digital shopping environments.

Marketers exploit emotional reactivity through strategies such as limited-time offers, scarcity messages and time-sensitive discounts, which drive impulsive purchases (Khan et al. 2022; Zafar et al. 2020). Time scarcity messages heighten emotional arousal, increasing impulsivity even when purchases may be unnecessary or unaffordable (Khetarpal and Singh 2024). On social media, algorithmic amplification of emotionally charged content further reinforces impulsive behaviour, creating a feedback loop that encourages repeated unplanned spending (Andary and Auza 2025; Amin 2025). This combination of emotional triggers and algorithmic reinforcement can make consumers more vulnerable to overconsumption and financial strain. Understanding these mechanisms underscores the need for both ethical marketing practices and consumer education to help mitigate impulsive purchasing tendencies.

Given the emotional drivers of impulse spending, there are significant implications for both consumers and businesses. On the consumer side, emotional regulation can play a key role in mitigating impulsive spending. Encouraging consumers to be aware of how their emotions influence their purchasing decisions could help them make more mindful and intentional choices (Mazlan 2024). From a business perspective, although emotional reactivity can increase sales, it also raises ethical concerns, as companies may take advantage of consumers' emotional vulnerabilities. The ethical implications of emotion-based algorithmic targeting have prompted calls for regulatory oversight, particularly regarding the collection and use of emotional data (Chaudhary et al. 2025). Retailers and marketers could benefit from implementing strategies that balance emotional engagement with responsible consumption practices. For instance, providing consumers with tools to track their spending, or offering emotional support through customer service, could reduce the likelihood of impulsive decisions driven by emotional distress (Feng et al. 2024).

## 2.3 | Impulse Spending and Personalised Digital Advertising

Personalised digital advertising has significantly reshaped consumer behaviour, with tailored ads increasing the likelihood of impulse spending. These ads are specifically designed based on individual data, such as browsing history, past purchases and demographic information, allowing marketers to create highly relevant offers. Research indicates that personalised ads are more likely to engage consumers, leading to higher impulsive buying behaviour (Amasino et al. 2023; Zafar et al. 2020). By leveraging consumer data, these ads align closely with personal preferences, thereby reducing the cognitive effort required to make purchasing decisions (Faraz and Anjum 2025). The evolution of programmatic advertising and real-time bidding has enabled unprecedented levels of personalisation, with algorithms now capable of predicting purchase intent with remarkable accuracy (Meirezaldi 2023; Kumar et al. 2025).

A core feature of personalised advertising is behavioural targeting, where data analytics predict and influence consumer preferences. For instance, personalised ads can evoke a sense of immediacy, encouraging consumers to act on impulse rather than deliberate thought. According to Feng et al. (2024), this form of

advertising not only appeals to immediate desires but also creates a psychological sense of urgency through scarcity tactics, such as limited-time offers or exclusive deals. These ads capitalise on consumers' fear of missing out (FOMO), which is a well-known driver of impulse spending (Redine et al. 2023). Studies by Patil (2024) demonstrate that AI-driven personalisation can increase impulse purchase conversion rates by up to 40% compared to generic advertising approaches.

Furthermore, personalised advertising integrates seamlessly into digital platforms, where consumers are already engaged, making the path from desire to purchase even shorter. E-commerce platforms and social media, where personalised ads appear as part of the browsing experience, reduce friction in the purchasing process. This ease of access significantly boosts impulse spending, as consumers can buy products with just a few clicks (Yan et al. 2023). The role of influencers in these digital spaces also magnifies this effect. Influencers, by endorsing products in a personalised manner, build trust and emotional connections with their audience, which increases the likelihood of impulse purchases (Zafar et al. 2020).

In addition to immediate gratification, emotional engagement is a key factor in the success of personalised ads. Consumers often form emotional attachments to the brands they interact with, particularly when ads are aligned with their self-image or emotional state (Silvera et al. 2008). Personalised advertising often taps into these emotions by displaying products that consumers feel a personal connection to, further driving impulse purchases. As noted by Iyer et al. (2020), such emotional triggers increase the intensity of the purchase decision, making it harder for consumers to resist the urge to buy.

Moreover, research shows that personalised ads also exploit consumers' behavioural biases. As identified by Barboza (2018), present bias amplifies the effectiveness of these ads. Consumers are more likely to make impulsive purchases when they are presented with personalised offers that appeal to their current desires, despite the long-term financial consequences. This aligns with the findings of Faraz and Anjum (2025), who argue that the convenience of digital payments further facilitates impulsive decisions, allowing for immediate gratification without significant delays.

## 2.4 | Theoretical Framework

Understanding impulse spending in the context of personalised digital advertising requires a multi-theoretical perspective that captures intertemporal decision-making, persuasive information processing and affect-driven consumption. This study integrates intertemporal choice theory (ICT), the Elaboration Likelihood Model (ELM) and Affective Response Theory (ART) to explain how present-oriented cognitive bias, perceived advertising exposure, and emotional states interact to shape impulsive buying behaviour.

ICT provides the behavioural-economic foundation for the model by explaining how individuals evaluate trade-offs between immediate and delayed rewards. The central concept of present bias suggests that consumers systematically overvalue immediate

gratification while discounting long-term consequences (Ainslie 2023; Wang and Wang 2024). This temporal distortion has been widely linked to impulsive consumption because it weakens financial self-control and increases susceptibility to short-term rewards (Feng et al. 2024). Empirical studies show that individuals with stronger present-oriented preferences are more likely to engage in spontaneous and unplanned purchases, particularly in digitally mediated environments where transaction friction is low (Barboza 2018; Silvera et al. 2008). Personalised digital advertising intensifies this mechanism by presenting time-sensitive offers, instant checkout options and algorithmically tailored product recommendations that align with consumers' immediate consumption motives (Zafar et al. 2020; Yu and Liu 2022).

However, ICT alone cannot explain why some present-biased consumers perceive higher levels of advertising exposure or why the same temporal bias does not lead to identical behavioural outcomes across individuals. Time preferences are not entirely stable and can be influenced by contextual and psychological factors, such as cognitive load, financial stress and emotional states (Feng et al. 2024). Moreover, ICT does not explain how consumers cognitively process persuasive stimuli. To address these limitations, the ELM is incorporated to explain differences in attention, perception and processing of personalised advertising.

ELM posits that persuasion occurs through two routes: A central route based on effortful cognitive evaluation and a peripheral route driven by heuristic and affective cues (Petty and Cacioppo 1986). In digital consumption environments characterised by information overload, entertainment-oriented content and continuous scrolling behaviour, consumers are more likely to rely on peripheral processing (Yu and Liu 2022; Chen et al. 2022). Present-biased individuals, who are already oriented toward immediate rewards, are less motivated to engage in extensive cognitive evaluation and therefore become more attentive to cues that signal instant gratification. This increases the likelihood that they notice, recall and cognitively register personalised advertising. Consequently, perceived advertising exposure is conceptualised as a psychological and attentional outcome rather than a purely platform-driven phenomenon (Iyer et al. 2020; Khetarpal and Singh 2024). This perspective explains why individuals differ in their reported exposure to personalised advertising even when objective ad delivery may be similar.

Although ELM explains how persuasive cues are processed, it does not fully account for the emotional mechanisms that translate attention into action. ART addresses this gap by emphasising that consumption decisions are often driven by emotional reactions rather than rational evaluation. Emotional arousal—such as excitement, urgency or FOMO—reduces self-regulation and accelerates decision-making speed, thereby increasing impulsive purchases (Iyer et al. 2020; Zafar et al. 2020). Digital advertising environments are specifically designed to evoke such affective responses through scarcity cues, social proof and visually stimulating content (Khan et al. 2022; Faraz and Anjum 2025).

At the same time, emotional responses are not uniform across individuals. Emotional stability, self-control and emotional intelligence influence whether affective arousal leads to impulsive behaviour or is cognitively regulated (Arruda and Oliveira 2023; Barboza 2018). This suggests that emotional states

do not simply act as direct predictors of impulse spending but condition the strength of the relationship between behavioural bias and impulsive behaviour.

By integrating ICT, ELM and ART, the present study proposes a sequential and conditional mechanism. Present bias increases consumers' attentional orientation toward immediate reward cues, which heightens their perceived exposure to personalised advertising through peripheral processing. This perceived exposure reinforces impulse spending tendencies, whereas emotional states determine whether present bias translates into actual purchasing behaviour. This integrated framework provides a dynamic explanation of impulsive consumption that moves beyond static time preference models and uniform persuasion assumptions.

## 2.5 | Hypothesis Development

ICT posits that individuals systematically discount delayed outcomes relative to immediate rewards (Ainslie 2023; Wang and Wang 2024). Present bias reflects this cognitive distortion and has been consistently identified as a key determinant of impulsive consumption behaviour. Individuals with stronger present-oriented preferences exhibit lower financial self-control, higher temporal discounting and an increased likelihood of spontaneous purchasing decisions (Feng et al. 2024; Silvera et al. 2008; Wang and Wang 2024).

Empirical evidence indicates that present bias is particularly influential in online environments, where gratification is immediate, and payment processes are simplified (Feng et al. 2024; Zafar et al. 2020). Digital retail platforms reduce transaction friction through stored payment information, one-click purchasing mechanisms and instant confirmation systems, thereby reducing the psychological salience of future financial consequences (Zafar et al. 2020). Moreover, limited-time promotions and personalised offers further align with short-term consumption motives, reinforcing present-oriented decision-making (Yu and Liu 2022; Zafar et al. 2020).

Consistent with ICT and prior empirical findings, present bias constitutes the cognitive foundation of impulse spending. This led to the first hypothesis:

**H1.** *Present bias positively predicts the likelihood of impulse spending.*

Although ICT explains why individuals may be predisposed toward immediate gratification, it does not fully account for how digital environments activate and reinforce this predisposition. The ELM provides a persuasive processing framework that clarifies this mechanism (Yu and Liu 2022).

ELM distinguishes between central and peripheral routes to persuasion. In digitally saturated contexts characterised by information overload, rapid scrolling and visual stimulation, consumers are more likely to rely on peripheral cues rather than engage in effortful cognitive evaluation (Yu and Liu 2022; Zafar et al. 2020). Personalised advertising—particularly messages

emphasising scarcity, urgency and tailored recommendations—functions as a powerful peripheral cue associated with immediate rewards (Zafar et al. 2020).

Importantly, individuals differ in how they attend to and cognitively process such stimuli. Present-biased individuals, who prioritise immediate gratification, may exhibit greater online engagement with consumption-related content, thereby increasing the salience of personalised advertisements in their digital environment (Yu and Liu 2022; Feng et al. 2024). Cognitive research suggests that individuals with stronger present-oriented tendencies are more attentive to stimuli associated with instant rewards, heightening their perception of frequent targeting by relevant advertisements (Feng et al. 2024; Iyer et al. 2020).

Thus, present bias does not necessarily increase objective ad delivery; rather, it enhances attentional sensitivity to reward-related stimuli, resulting in greater perceived digital advertising exposure (Khetarpal and Singh 2024; Yu and Liu 2022). This perceived exposure, in turn, may reinforce impulsive purchasing by increasing the salience of immediate consumption opportunities (Zafar et al. 2020).

Accordingly, perceived personalised advertising serves as a psychological mechanism linking cognitive bias to impulsive behaviour. This led to the second hypothesis:

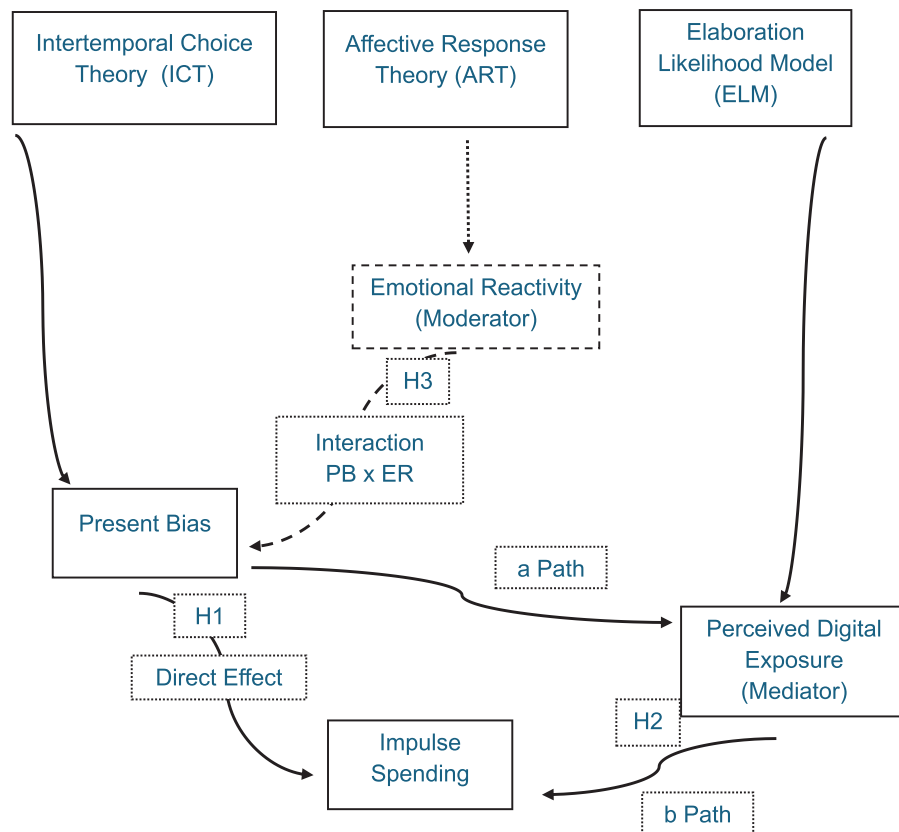
**H2.** *Perceived digital advertising exposure mediates the relationship between present bias and impulse spending.*

Although ICT explains cognitive predisposition and ELM clarifies persuasive activation, these frameworks do not specify the emotional conditions under which present-oriented tendencies are translated into action. ART addresses this limitation by emphasising the role of emotional arousal in shaping behavioural regulation (Iyer et al. 2020).

ART suggests that heightened emotional states, such as excitement, urgency, stress or FOMO, reduce reflective processing and weaken self-control mechanisms (Iyer et al. 2020). Empirical studies demonstrate that emotionally aroused consumers exhibit stronger impulsive buying tendencies, whereas emotionally stable individuals are better able to delay gratification and regulate consumption behaviour (Arruda and Oliveira 2023; Barboza 2018).

This distinction clarifies the theoretical logic underlying moderation. Emotional states do not uniformly increase impulse spending. Rather, they condition the behavioural expression of present bias. When emotional reactivity is high, the cognitive distortion associated with present bias is more likely to manifest in immediate purchasing behaviour due to reduced regulatory capacity. Conversely, when emotional reactivity is low, individuals may retain sufficient cognitive control to attenuate the influence of present-oriented preferences (Arruda and Oliveira 2023; Iyer et al. 2020).

Thus, emotional states operate as a conditional amplifier of the present bias–impulse spending relationship.



**FIGURE 1** | Theoretical framework. [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

**H3.** Emotional states moderate the relationship between present bias and impulse spending.

As shown in Figure 1, the study’s conceptual framework examines the interplay between cognitive, emotional and environmental drivers of impulse spending, with present bias as the primary predictor, perceived digital advertising exposure as a mediating mechanism and emotional reactivity as a moderator that strengthens these relationships.

### 3 | Methodology

#### 3.1 | Research Design

The study adopts a quantitative, cross-sectional survey design, which is appropriate for identifying patterns and establishing relationships between present bias, emotional reactivity and perceived digital advertising exposure and their impact on impulse spending behaviour at a single point in time. Given the focus on immediate behavioural responses to online shopping stimuli, this design is well-suited for capturing relevant data in a timely manner.

#### 3.2 | Participants and Sampling

Data were collected from 617 digitally active UK consumers recruited through social media platforms such as LinkedIn, X and Facebook. A combination of purposive and snowball

sampling techniques was employed to reach individuals likely to have relevant online shopping experience. As a result, the sample primarily reflects digitally active, social-media-using UK consumers rather than the UK population as a whole. The recruitment strategy was appropriate for accessing individuals engaged in online consumption behaviours; however, it does not constitute a probability-based or nationally representative sample.

To qualify for participation, respondents were required to meet the following inclusion criteria: they had to be between 18 and 65 years of age, reside in the United Kingdom, and have made at least one online purchase in the past week. These criteria ensured the sample comprised active digital consumers with recent, relevant experience of online shopping behaviours, aligning with the study’s focus on impulse spending in contemporary digital environments.

Prior to analysis, the dataset was screened for incomplete responses, outliers and missing values. Surveys with substantial missing responses were excluded from the dataset. The remaining data were examined for normality and extreme values to ensure suitability for regression-based analyses.

Table 1 presents the demographic profile of the 617 UK-based participants. The sample included a balanced gender distribution, with 56.7% female and 43.3% male respondents. A majority (58.3%) were aged between 25 and 44, indicating a concentration within the most digitally active age groups rather than a fully age-representative UK consumer sample. Monthly income levels

**TABLE 1** | Participants' demographics.

Demographic variable	Category	Frequency (n)	Percentage
Gender	Female	350	56.7
	Male	267	43.3
Age group (years)	18–24	120	19.5
	25–34	210	34.0
	35–44	150	24.3
	45–54	90	14.6
	55–65	47	7.6
Monthly income (£)	<1500	200	32.4
	1500–3000	280	45.4
	>3000	137	22.2

were relatively diverse, with 32.4% earning below £1500, 45.4% between £1500 and £3000 and 22.2% earning above £3000. This distribution reflects a varied socio-economic representation, appropriate for examining impulse spending behaviours in online contexts.

### 3.3 | Ethical Considerations

Participation in the study was voluntary, and informed consent was obtained from all respondents before completing the survey. Participants were informed about the purpose of the research, their right to withdraw at any time, and the anonymous nature of their responses. No personally identifiable information was collected, and all data were analysed in aggregated form to ensure confidentiality.

### 3.4 | Variables

The study investigates four core variables: impulse spending frequency, present bias, emotional reactivity and perceived digital advertising exposure, each selected based on theoretical relevance and empirical support in the behavioural finance and consumer psychology literature.

All measurement items were adapted from established and validated scales in prior literature, as shown in Table 2. However, as many of the original instruments were developed in general consumption or psychological contexts, minor wording modifications were introduced to ensure direct relevance to the online shopping environment, which represents the focal behavioural setting of this study. Throughout the adaptation process, the original conceptual meaning of each construct was preserved while embedding the items within digital purchasing situations.

The present bias construct was adapted from intertemporal choice and behavioural economics literature (O'Donoghue and Rabin 1999; Soman et al. 2005; Meier and Sprenger 2010; Feng et al. 2024; Asgari and Pouralimardan 2024). Original measures typically refer to abstract trade-offs between immediate and delayed rewards. In this study, the wording was contextualised

by explicitly linking these trade-offs to online purchase decisions. For example, PB2 ('I find it difficult to delay purchases, even when I know I should') and PB4 ('I prefer buying something now rather than saving for a better option later') embed present-oriented preferences directly within consumer decision-making scenarios. This ensures that respondents interpret present bias in the context of digital consumption rather than hypothetical time-preference tasks.

Items measuring emotional reactivity were adapted from established impulse and affect-driven consumption scales (Rook and Fisher 1995; Puri 1996; Nock et al. 2008; Redine et al. 2023; Faraz and Anjum 2025). To align with the study's digital context, the wording explicitly incorporates online product encounters and offers. For instance, ER1 ('I feel strong emotions when I see attractive products online') and ER3 ('I get excited easily when I encounter appealing online offers') insert online-specific cues into the items. These changes reflect the emotionally stimulating nature of digital platforms, where visual design, time-limited promotions and algorithmic recommendations often trigger affective responses.

The perceived advertising exposure scale was adapted from prior research on personalised advertising and digital marketing perceptions (Bleier and Eisenbeiss 2015; Zafar et al. 2020; Faraz and Anjum 2025). Because the original instruments were not always tied to specific consumption settings, the items were reframed to capture users' subjective perceptions of personalised ads during online browsing and shopping. For example, DAE1 ('I frequently notice personalised ads when browsing online') and DAE3 ('I feel that online platforms show me ads based on what I like or search for') explicitly refer to online activity and perceived algorithmic targeting. This ensures the construct reflects perceived, rather than objective, ad exposure in digital environments.

Impulse spending items were adapted from established scales in consumer behaviour research (Rook and Fisher 1995; Silvera et al. 2008; Iyer et al. 2020). The primary contextual modification involved inserting online-specific purchasing references. For instance, IS1 ('I often buy things online spontaneously') and IS4 ('I frequently make unplanned online purchases') directly situate

TABLE 2 | Construct operationalization and measurement items.

Construct	Source	Item code	Measurement item
<b>Present bias</b>	O'Donoghue and Rabin (1999), Soman et al. (2005), Meier and Sprenger (2010), Feng et al. (2024), Asgari and Pouralimardan (2024)	PB1	I tend to choose immediate rewards even if waiting would bring better outcomes
		PB2	I find it difficult to delay purchases, even when I know I should
		PB3	I often prioritise short-term satisfaction over long-term financial benefits
		PB4	I prefer buying something now rather than saving for a better option later
<b>Emotional reactivity</b>	Rook and Fisher (1995), Puri (1996), Nock et al. (2008), Redine et al. (2023), Faraz and Anjum (2025)	ER1	I feel strong emotions when I see attractive products online
		ER2	My mood often influences my online purchasing decisions
		ER3	I get excited easily when I encounter appealing online offers
		ER4	Emotional reactions often drive my online shopping choices
<b>Perceived digital advertising exposure</b>	Bleier and Eisenbeiss (2015), Zafar et al. (2020), Faraz and Anjum (2025)	DAE1	I frequently notice personalised ads when browsing online
		DAE2	Online ads often feel tailored to my interests or past behaviour
		DAE3	I feel that online platforms show me ads based on what I like or search for
		DAE4	I often encounter ads that seem personally relevant to me
<b>Impulse spending</b>	Rook and Fisher (1995), Silvera et al. (2008), Iyer et al. (2020)	IS1	I often buy things online spontaneously
		IS2	I sometimes make online purchases without planning to
		IS3	When I see something I like online, I tend to buy it immediately
		IS4	I frequently make unplanned online purchases

impulse behaviour within digital shopping environments. This aligns the dependent variable with the online advertising and platform context examined in the study.

All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

### 3.5 | Econometric Model

The econometric models correspond directly to the study hypotheses. Model 1 tests the direct association between present bias and impulse spending (H1), Model 2 evaluates the moderating role of emotional reactivity in the present bias–impulse spending relationship (H3), and Model 3 examines the mediating role of perceived digital advertising exposure (H2).

To empirically test the hypotheses, multiple regression-based econometric models were employed to evaluate the direct, moderating, and mediating relationships between behavioural biases,

emotional factors, perceived digital advertising exposure and impulse spending frequency.

#### Model 1: Direct Effects Model

The first model examines the direct effects of present bias, emotional reactivity and perceived digital advertising exposure on impulse spending frequency. The model is specified as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i$$

In the econometric models,  $Y_i$  represents the impulse spending frequency score for participant  $i$ , which is the dependent variable capturing how often an individual engages in unplanned purchases. The independent variables include  $X_{1i}$ , the present bias score for participant  $i$ , reflecting the tendency to prioritise immediate rewards;  $X_{2i}$ , the emotional reactivity score for participant  $i$ , indicating sensitivity to emotional stimuli; and  $X_{3i}$ , the perceived digital advertising exposure score for participant  $i$ , which measures the extent of personalised online ad exposure.

The intercept term,  $\beta_0$ , represents the baseline level of impulse spending when all predictors are zero. The regression coefficients  $\beta_1$ ,  $\beta_2$  and  $\beta_3$  estimate the respective effect sizes of present bias, emotional reactivity and perceived digital advertising exposure on impulse spending frequency. Lastly,  $\varepsilon_i$  denotes the error term, accounting for the variation in impulse spending not explained by the model predictors.

### Model 2: Moderation Model

To test whether emotional reactivity moderates the effect of present bias on impulse spending (H2), an interaction term between present bias and emotional reactivity was included:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 (X_{3i} \times X_{2i}) + \varepsilon_i$$

where  $Y_i$  denotes the impulse spending frequency for participant  $i$ ,  $X_{1i}$  is the present bias score, and  $X_{2i}$  is the emotional reactivity score. The interaction term  $\beta_3 (X_{3i} \times X_{2i})$  captures the moderation effect, indicating whether the influence of present bias on impulse spending changes depending on the level of emotional reactivity. A statistically significant  $\beta_3$  coefficient would provide evidence that emotional reactivity alters the strength or direction of the present bias effect on impulsive purchase behaviour. To reduce potential multicollinearity in the interaction model, the predictor variables involved in the moderation analysis were mean-centred prior to constructing the interaction term.

### Model 3: Mediation

Hypothesis 3 posits that perceived digital advertising exposure mediates the effect of present bias on impulse spending. This mediation was tested using a two-equation approach:

Effect of present bias on perceived digital advertising exposure (mediator):

$$X_{3i} = \alpha_0 + \alpha_1 X_{1i} + \vartheta_i$$

Effect of present bias and perceived digital advertising exposure on impulse spending:

$$Y_i = \gamma_0 + \gamma_1 X_{1i} + \gamma_2 X_{3i} + \mu_i$$

In this mediation analysis,  $X_{3i}$  represents the perceived digital advertising exposure score for participant  $i$ , which serves as the mediator variable. The first equation models the effect of present bias  $X_{1i}$  on perceived digital advertising exposure, with  $\alpha_1$  estimating how changes in present bias influence exposure to digital ads, whereas  $\alpha_0$  is the intercept and  $\vartheta_i$  captures unexplained variation in perceived digital advertising exposure.

The second equation models impulse spending frequency  $Y_i$  as a function of both present bias  $X_{1i}$  and perceived digital advertising exposure  $X_{3i}$ , where  $\gamma_1$  measures the direct effect of present bias on impulse spending,  $\gamma_2$  estimates the effect of perceived digital advertising exposure on impulse spending after accounting for present bias,  $\gamma_0$  is the intercept, and  $\mu_i$  is the residual error term capturing variance not explained by the predictors.

## 4 | Findings

Table 3 provides an overview of key variables related to impulse spending. Although participants show moderate levels of impulse spending and present bias, the relatively high mean for emotional reactivity (4.65) suggests that affective responses may play a particularly strong role in this sample. The moderate exposure to digital advertising (mean = 4.00) indicates potential variability in how marketing influences behaviour. The standard deviations reflect sufficient variability, but the clustering around midpoints may limit the detection of extreme behaviours.

Table 4 presents correlations between impulse spending frequency and the other key variables. Impulse spending is moderately correlated with present bias ( $r = 0.52$ ), indicating that individuals who prioritise immediate rewards tend to engage more frequently in impulsive purchases. Emotional reactivity is also positively associated with impulse spending ( $r = 0.45$ ), suggesting that higher emotional responsiveness may increase impulsive buying tendencies. Additionally, exposure to personalised digital advertising shows a moderate positive correlation with impulse spending ( $r = 0.48$ ), highlighting the influential role of digital marketing in facilitating impulsive purchase behaviour. These relationships support the premise that behavioural biases, emotional factors and marketing environments jointly contribute to impulse spending.

All constructs were measured using four-item scales as shown in Table 2, and the reliability analysis, reported in Table 5, is based on these final measurement items. Table 5 reports the internal consistency reliability for each of the study constructs. All scales demonstrate good-to-excellent reliability, with Cronbach's alpha values ranging from 0.82 to 0.89. Specifically, the impulse spending frequency scale showed strong reliability ( $\alpha = 0.87$ ), indicating consistent measurement of impulsive buying behaviour. The present bias score ( $\alpha = 0.84$ ), emotional reactivity index ( $\alpha = 0.89$ ) and perceived digital advertising exposure scale ( $\alpha = 0.82$ ) similarly exhibit high reliability, supporting the use of these measures for subsequent analyses. These results confirm that the instruments used in this study provide reliable assessments of the theoretical constructs.

Table 6 summarises the fit indices from the confirmatory factor analysis (CFA) conducted to assess the measurement model. The model demonstrated a satisfactory fit to the data, with a chi-square value of 345.21 ( $df = 146$ ), which is expected given the sensitivity of the chi-square statistic to sample size. More informative fit indices indicate good model fit: The CFI was 0.93, and the TLI was 0.91, both exceeding the recommended threshold of 0.90. Additionally, the RMSEA was 0.056, and the SRMR was 0.045, both below the acceptable cut-off of 0.08. Collectively, these results support the construct validity and overall adequacy of the measurement model.

Table 7 reports the AVE values for each construct, providing evidence of convergent validity. All average variance extracted (AVE) estimates exceed the commonly accepted threshold of 0.50, indicating that the majority of variance in the indicators is explained by their underlying latent constructs. Specifically, the AVE values range from 0.55 for the present bias score to 0.62 for

**TABLE 3** | Descriptive statistics.

Variable	Mean ( <i>M</i> )	Standard deviation ( <i>SD</i> )
Impulse spending frequency	4.10	1.35
Present bias score	4.25	1.12
Emotional reactivity index	4.65	1.25
Perceived digital advertising exposure	4.00	1.10

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

**TABLE 4** | Correlation matrix of key variables.

Variable	1	2	3	4
1. Impulse spending frequency	1.00			
2. Present bias score	0.52	1.00		
3. Emotional reactivity index	0.45	0.38	1.00	
4. Perceived digital advertising exposure	0.48	0.35	0.40	1.00

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

**TABLE 5** | Cronbach's alpha for scale reliability.

Construct	Number of items	Cronbach's alpha ( $\alpha$ )
Impulse spending frequency	4	0.87
Present bias score	4	0.84
Emotional reactivity index	4	0.89
Perceived digital advertising exposure	4	0.82

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

the emotional reactivity index, confirming that the measurement scales reliably capture their respective theoretical concepts. These findings support the validity of the constructs used in the study.

In Table 8, the regression model explains a substantial proportion of the variance in impulse spending ( $R^2 = 0.63$ ) and is statistically significant overall ( $F(4, 612) = 260.41, p < 0.001$ ), indicating that the predictors jointly account for meaningful variation in impulsive purchasing behaviour. Present bias shows the strongest

positive association with impulse spending ( $\beta = 0.33, p < 0.001$ ), followed by emotional reactivity ( $\beta = 0.25, p < 0.001$ ) and perceived digital advertising exposure ( $\beta = 0.23, p < 0.001$ ), suggesting that cognitive and affective factors, along with perceived marketing exposure, are significantly associated with higher levels of impulsive buying. Monthly income is also positively related to impulse spending ( $\beta = 0.07, p = 0.038$ ), although the effect size is comparatively small, indicating a modest association. Importantly, the inclusion of income as a control variable does not materially alter the magnitude or statistical significance of the

**TABLE 6** | Confirmatory factor analysis (CFA) model fit indices.

Fit index	Result	Threshold
Chi-square ( $\chi^2$ )	345.21 (df = 146)	—
CFI (comparative fit index)	0.93	>0.90
TLI (Tucker–Lewis index)	0.91	>0.90
RMSEA (root mean square error of approximation)	0.056	<0.08
SRMR (standardised root mean square residual)	0.045	<0.08

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

**TABLE 7** | Average variance extracted (AVE) for convergent validity.

Construct	AVE
Impulse spending frequency	0.58
Present bias score	0.55
Emotional reactivity index	0.62
Perceived digital advertising exposure	0.57

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

psychological predictors, supporting the robustness of the main findings.

In Table 9, the hierarchical regression results indicate that Model 1, which includes the main effects and monthly income as a control variable, explains a substantial proportion of the variance in impulse spending ( $R^2 = 0.52$ ,  $F(2, 614) = 204.66$ ,  $p < 0.001$ ). In this model, both present bias ( $\beta = 0.32$ ,  $p < 0.001$ ) and emotional reactivity ( $\beta = 0.23$ ,  $p < 0.001$ ) show significant positive associations with impulse spending, whereas monthly income has a small but significant effect ( $\beta = 0.07$ ,  $p = 0.043$ ). In Model 2, the interaction term between present bias and emotional reactivity is introduced, leading to a significant increase in explained variance ( $R^2 = 0.54$ ,  $\Delta R^2 = 0.02$ ,  $\Delta F = 8.53$ ,  $p = 0.004$ ). The interaction effect is positive and statistically significant ( $\beta = 0.12$ ,  $p < 0.001$ ), indicating that the association between present bias and impulse spending becomes stronger at higher levels of emotional reactivity. Although the main effects remain significant, the effect of monthly income becomes statistically non-significant in the full model ( $\beta = 0.06$ ,  $p = 0.053$ ), suggesting that psychological factors and their interaction account for a greater share of the variance in impulse spending than income alone.

Although the interaction term produced a modest increase in explained variance ( $\Delta R^2 = 0.02$ ), this effect is theoretically meaningful. In behavioural and psychological research, interaction effects typically account for small proportions of additional variance, particularly when examining complex cognitive–emotional mechanisms. The significant interaction indicates that the relationship between present bias and impulse spending is contingent on emotional reactivity, highlighting an important conditional process rather than a large incremental gain in predictive power.

The mediation effect was estimated using a bootstrapping procedure with 5000 resamples to generate bias-corrected confidence intervals for the indirect effect, which provides a robust test of mediation without assuming normality of the sampling distribution.

Table 10 presents the mediation analysis examining whether perceived digital advertising exposure mediates the relationship between present bias and impulse spending. The total effect of present bias on impulse spending was significant ( $c = 0.52$ ,  $p < 0.001$ ), and this effect remained significant, though slightly reduced, after including the mediator ( $c' = 0.43$ ,  $p < 0.001$ ), suggesting partial mediation. The path from present bias to advertising exposure was also significant ( $a = 0.28$ ,  $p < 0.001$ ),

as was the path from advertising exposure to impulse spending ( $b = 0.31$ ,  $p < 0.001$ ). The indirect effect ( $a \times b = 0.09$ ) was statistically significant with a 95% confidence interval of [0.04, 0.15], not crossing zero, further confirming the mediating role of perceived digital advertising exposure.

Critically, these results indicate that perceived digital advertising exposure accounts for part of the association between present bias and impulse spending, suggesting that individuals who are more present-biased also tend to report higher perceived ad exposure, which, in turn, is related to more frequent impulse purchases. The partial mediation implies that although advertising influences impulse spending, a substantial proportion of the effect remains directly attributable to present bias itself. This suggests that interventions aimed at reducing impulse spending may need to target both individual-level self-control mechanisms and broader digital marketing strategies. Importantly, this mediation reflects subjective perception rather than objective algorithmic targeting, highlighting the role of cognitive salience in impulsive consumer decision-making.

Table 11 shows that all VIF values are below 1.5, indicating no multicollinearity concerns. The Durbin–Watson statistic of 1.91 suggests no autocorrelation in residuals. These results support the validity of the regression assumptions.

Given that all constructs were measured using a self-report survey at a single point in time, the potential for common method bias (CMB) was assessed. Harman's single-factor test was conducted by entering all measurement items into an unrotated exploratory factor analysis to determine whether a single factor accounted for the majority of covariance among the measures.

Table 12 presents the results of Harman's single-factor test conducted to assess the presence of CMB. The unrotated exploratory factor analysis produced multiple factors with eigenvalues greater than 1, and the first factor accounted for 34.7% of the total variance. This value is well below the commonly accepted threshold of 50%, indicating that no single factor dominates the variance in the data. Therefore, CMB is unlikely to be a significant threat to the validity of the study's findings.

## 5 | Discussion

This study examined the factors associated with impulse spending by focusing on present bias, emotional reactivity and perceived exposure to personalised digital advertising. Because the study relies on cross-sectional survey data, the results should be interpreted as associational relationships rather than causal effects. The findings provide insight into the psychological factors associated with impulsive buying behaviour in digitally mediated environments.

Hypothesis 1, which proposed that present bias is positively associated with impulse spending, was supported. The regression results showed a significant positive relationship between present bias and impulse spending frequency ( $\beta = 0.34$ ,  $p < 0.001$ ). This finding is consistent with prior research demonstrating that individuals who prioritise short-term rewards are more likely to engage in unplanned purchases (Silvera et al. 2008;

TABLE 8 | Multiple regression analysis.

Model summary					
$R^2 = 0.63$					
$F(4, 612) = 260.41, p < 0.001$					
Predictor	Unstandardised coefficient		Standardised coefficient		
	<i>B</i>	Std. error	$\beta$	<i>t</i>	<i>p</i> value
Constant	1.12	0.15	—	7.47	<0.001
Present bias	0.44	0.07	0.33	6.29	<0.001
Emotional reactivity	0.31	0.06	0.25	5.17	<0.001
Perceived digital advertising exposure	0.28	0.06	0.23	4.67	<0.001
Income	0.06	0.03	0.07	2.08	0.038

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

TABLE 9 | Hierarchical regression—moderation of emotional reactivity.

Effect	Model 1					Model 2				
	<i>B</i>	Std. error	$\beta$	<i>t</i>	<i>p</i> value	<i>B</i>	Std. error	$\beta$	<i>t</i>	<i>p</i> value
Main effects										
Constant	1.14	0.14	—	8.14	<0.001	1.13	0.14	—	8.02	<0.001
Present bias	0.43	0.07	0.32	6.14	<0.001	0.40	0.07	0.30	5.71	<0.001
Emotional reactivity	0.29	0.06	0.23	4.83	<0.001	0.27	0.06	0.21	4.50	<0.001
Monthly income (control)	0.06	0.03	0.07	2.03	0.043	0.05	0.03	0.06	1.94	0.53
Interaction effect										
Present bias $\times$ emotional reactivity						0.11	0.03	0.12	4.10	<0.001
Model summary										
$R^2$	0.52					0.54				
$F$	204.66 (df = 2, 614)					<0.001				
$\Delta R^2$	—					0.02				
$\Delta F$	—					8.53				

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

Feng et al. 2024). Present-biased consumers appear more likely to prioritise immediate outcomes, often giving less weight to future financial consequences, such as debt accumulation or reduced savings (Asgari and Pouralimardan 2024; Mazlan 2024). In digital shopping environments, where purchasing processes are frictionless and decision times are shortened, these tendencies may be further reinforced (Feng et al. 2024; Khetarpal and Singh 2024).

Hypothesis 2, which examined whether emotional reactivity moderates the relationship between present bias and impulse spending, was supported. The hierarchical regression analysis revealed a significant interaction effect between emotional reactivity and present bias ( $\beta = 0.11, p = 0.004$ ). This indicates that the association between present bias and impulse spending becomes stronger among individuals with higher emotional

reactivity. Emotional arousal has been widely associated with reduced self-regulation and greater impulsivity in consumption behaviour (Silvera et al. 2008; Wang et al. 2022; Barboza 2018). The findings therefore suggest that cognitive biases alone may not fully explain impulse spending behaviour; rather, impulsive consumption appears to emerge from the interaction between cognitive predispositions and affective responses.

Hypothesis 3, which proposed that perceived digital advertising exposure mediates the relationship between present bias and impulse spending, received partial support. The mediation analysis revealed a significant indirect effect ( $\beta = 0.09, p < 0.001$ ), suggesting that perceived exposure to personalised advertising accounts for part of the association between present bias and impulse spending (Amasino et al. 2023; Zafar et al. 2020). Individuals with stronger present-biased tendencies reported higher

**TABLE 10** | Mediation analysis—perceived digital advertising exposure.

Path	<i>B</i>	SE	<i>t</i>	<i>p</i> value	95% CI
Present bias → Ad exposure ( <i>a</i> )	0.28	0.06	4.67	<0.001	[0.16, 0.40]
Ad exposure → impulse spending ( <i>b</i> )	0.31	0.07	4.43	<0.001	[0.17, 0.45]
Present bias → impulse spending ( <i>c</i> )	0.52	0.07	7.43	<0.001	[0.38, 0.66]
Present bias → impulse spending ( <i>c'</i> )	0.43	0.08	5.53	<0.001	[0.27, 0.59]
Indirect effect ( <i>a</i> × <i>b</i> )	0.09	0.03	—	—	[0.04, 0.15]

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

**TABLE 11** | Multicollinearity and autocorrelation diagnostics.

Predictor variable	Tolerance	VIF	Durbin–Watson statistic (model)
Present bias	0.68	1.47	
Emotional reactivity	0.71	1.41	
Perceived digital advertising exposure	0.73	1.37	
Overall model	—	—	1.91

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

**TABLE 12** | Harman's single-factor test for common method bias.

Factor	Eigenvalue	% of variance explained	Cumulative %
Factor 1	8.34	34.7	34.7
Factor 2	3.12	12.9	47.6
Factor 3	2.41	10.0	57.6
Factor 4	1.86	7.8	65.4

Note: All constructs were measured using previously validated scales adapted from the literature and assessed on a five-point Likert scale. Data were analysed using Jamovi 2.6.26.

perceived exposure to personalised ads, which was associated with more frequent impulse purchases. This finding aligns with research indicating that personalised advertising can encourage impulsive buying by aligning promotional content with consumers' preferences and past behaviours (Goel et al. 2022; Faraz and Anjum 2025). Although personalised advertising may contribute to impulsive purchasing tendencies, it can also provide benefits for consumers by improving the relevance of product recommendations and reducing information search costs. When implemented responsibly, personalised marketing may enhance user experience by helping consumers discover products that better match their preferences.

## 5.1 | Theoretical Significance

This study contributes to the literature on consumer behaviour and behavioural economics by integrating cognitive, emotional and environmental explanations of impulse spending within a unified empirical framework. First, the findings extend ICT by demonstrating that present bias is significantly associated with impulsive purchasing behaviour in digitally mediated consump-

tion contexts. Previous research suggests that present-biased individuals tend to prioritise immediate rewards over delayed benefits, which may lead to financially suboptimal decisions (O'Donoghue and Rabin 1999; Meier and Sprenger 2010; Feng et al. 2024). The results reinforce these theoretical arguments by showing that stronger present bias is associated with higher levels of impulse spending, consistent with earlier studies in behavioural finance and consumer psychology (Silvera et al. 2008; Iyer et al. 2020; Asgari and Poralimardan 2024). These findings highlight the importance of time-inconsistent preferences in explaining impulsive consumer behaviour, particularly in online environments where purchasing processes are rapid and frictionless (Feng et al. 2024; Zafar et al. 2020).

Second, the study extends insights from ART and the ELM by demonstrating that emotional reactivity and perceived exposure to personalised digital advertising shape impulse spending behaviour. Emotional arousal has been widely associated with reduced self-regulation and spontaneous purchasing behaviour (Rook and Fisher 1995; Silvera et al. 2008; Arruda and Oliveira 2023), and the findings indicate that emotional reactivity strengthens the relationship between present bias and impulse

spending (Barboza 2018; Wang et al. 2022). In addition, the mediation results suggest that perceived exposure to personalised advertising partially explains this relationship, highlighting how persuasive marketing cues in digital marketplaces may reinforce present-oriented consumption tendencies (Bleier and Eisenbeiss 2015; Amasino et al. 2023).

## 5.2 | Practical Significance

In addition to theoretical contributions, the findings provide several practical implications for consumers, marketers and policymakers operating within increasingly digitalised retail environments. For consumers, the results highlight the importance of recognising how behavioural biases and emotional responses may influence purchasing decisions. Individuals with stronger present bias may struggle with delaying gratification and maintaining long-term financial goals (Meier and Sprenger 2010; Asgari and Pouralimardan 2024), which may lead to impulsive purchases and potential financial stress (Mazlan 2024; Amasino et al. 2023). Improving financial literacy and awareness of behavioural biases may therefore help individuals adopt more deliberate consumption habits and reduce impulsive spending behaviour (Barboza 2018; Heilman et al. 2021).

For businesses and marketers, the findings indicate that personalised digital advertising can influence impulse spending by presenting highly relevant offers based on behavioural data (Bleier and Eisenbeiss 2015; Zafar et al. 2020). Strategies, such as algorithmic recommendations, scarcity cues and personalised promotions, may encourage rapid purchase decisions (Feng et al. 2024; Khetarpal and Singh 2024). Although these approaches may enhance marketing effectiveness, organisations should adopt responsible and transparent practices that avoid exploiting consumers' psychological vulnerabilities (Iyer et al. 2020; Faraz and Anjum 2025). The findings also have policy implications, suggesting that regulatory frameworks promoting transparency and greater consumer control over personalised advertising may support fair and responsible digital marketing practices (Meirezaldi 2023; Kumar et al. 2025).

## 5.3 | Broader Social and Policy Implications

Beyond individual-level behavioural mechanisms, the findings contribute to a broader understanding of how behavioural biases interact with digitally mediated consumption environments. Behavioural economics research shows that present-biased individuals prioritise immediate gratification over long-term outcomes (O'Donoghue and Rabin 1999; Meier and Sprenger 2010), whereas consumer behaviour studies emphasise the role of emotional responses and situational cues in triggering impulsive purchases (Rook and Fisher 1995; Puri 1996; Silvera et al. 2008). The present findings extend these perspectives by suggesting that such tendencies are not solely internal traits but may also be amplified within algorithmically curated digital marketplaces.

Digital platforms increasingly rely on personalised advertising systems that tailor content based on user data and behavioural patterns (Bleier and Eisenbeiss 2015; Zafar et al. 2020). Individuals with stronger present bias may therefore be more

responsive to personalised offers, creating a reinforcing cycle between behavioural predispositions and algorithmic persuasion. This suggests that impulse spending in digital environments reflects an interaction between cognitive biases and technological infrastructures rather than purely individual decision-making processes.

These dynamics raise ethical and policy concerns regarding the use of behavioural data to influence consumer choices. Persuasive digital marketing techniques, including personalised recommendations and limited-time offers, may particularly affect emotionally reactive individuals. The implications may be more pronounced for financially vulnerable consumers, who often exhibit stronger present-oriented decision-making due to economic constraints (Meier and Sprenger 2010). Consequently, impulse-oriented digital advertising has broader implications for consumer protection, social inequality and responsible platform governance. Future research could further examine how socio-economic differences shape vulnerability to impulsive spending in digitally mediated environments.

## 6 | Conclusion

This study examined the associations between present bias, emotional reactivity, perceived digital advertising exposure and impulse spending, offering insights into the psychological and marketing factors related to impulsive consumer behaviour. By examining these relationships, the study aimed to provide a comprehensive understanding of how cognitive biases, emotional triggers and digital marketing strategies intersect to influence spending patterns.

The first research question asked to what extent present bias is associated with the frequency of impulse spending. The findings revealed a positive relationship between present bias and impulse spending, indicating that individuals who report stronger tendencies toward immediate gratification also report more frequent impulsive purchases. This finding aligns with existing research on cognitive biases and impulse spending, emphasising the need for interventions that help consumers balance immediate desires with future financial well-being.

The second research question examined whether emotional states moderate the relationship between present bias and impulse spending. The findings indicated a significant interaction, showing that the positive association between present bias and impulse spending is stronger among consumers with higher emotional reactivity. This highlights the importance of emotional regulation in mitigating impulsive behaviour and suggests that emotional well-being plays a critical role in shaping consumer spending decisions.

The third research question investigated whether perceived exposure to personalised digital advertising mediates the relationship between present bias and impulse spending. The findings revealed a significant indirect effect, suggesting that part of the association between present bias and impulse spending operates through perceived advertising exposure. Individuals with stronger present bias tend to report higher perceived exposure to personalised ads, which, in turn, is related to more frequent

impulse purchases. Although advertising plays a crucial role in amplifying impulsive buying tendencies, present bias remains a strong direct predictor of such behaviour.

On the basis of the findings, several recommendations can be made for both businesses and consumers. For businesses, marketers should be mindful of the ethical implications of using personalised digital advertising that exploits cognitive biases, such as present bias. Although personalised ads can drive sales, businesses should consider strategies that promote responsible consumption, such as offering tools for budgeting and financial education to consumers. For consumers, individuals should be aware of the psychological drivers of their purchasing behaviour and practice emotional regulation to resist impulsive buying. Financial literacy programmes that educate consumers about cognitive biases like present bias and the impact of emotional reactivity could help promote more mindful spending habits.

Several limitations should be acknowledged when interpreting the findings. First, the study relies on a cross-sectional survey design, which limits the ability to draw causal conclusions. Second, the sample consists of digitally active UK consumers recruited through social media platforms, which may not fully represent the broader population. Future research using longitudinal designs or probability-based samples could provide additional insight into the causal mechanisms underlying impulse spending behaviour.

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### Ethics Statement

This ethics was obtained by the Bath Spa University. All participants provided informed consent.

### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data supporting the findings of this study are available upon request.

### Peer Review

For transparency, the peer review documents associated with this article are available at <https://doi.org/10.1111/issj.70049>.

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