International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1

Trapped by the Click: Dark Patterns, Impulsive Buying and Post-Purchase Regret among Online Shoppers

[1]Amrutha P, [2]Dr Swapna H R
[1]School of Commerce-PG Studies
JAIN (Deemed to be) University,
Bangalore, Karnataka, India.
[2]Professor
School of Commerce-PG Studies
JAIN (Deemed to be) University, Bangalore, Karnataka, India.

Abstract
Dark patterns, such as urgency prompts, scarcity claims and social-proof counters, are now routine features of e-commerce, quick-commerce and social-commerce interfaces. While they may lift short-term sales, they may also provoke unplanned purchases and later regret. This study examines whether exposure to dark patterns is associated with impulsive buying and post-purchase regret, whether impulsive buying mediates that association, and whether digital literacy moderates the effect of exposure on impulsive buying. Drawing on the Stimulus–Organism–Response (S-O-R) model and cognitive dissonance theory, a quantitative, explanatory, cross-sectional survey was administered through a 20-item online questionnaire; 83 valid responses from adult online shoppers (from 103 received) were analysed using reliability and validity tests, correlation, regression, bootstrap mediation and moderated regression. Exposure strongly predicted impulsive buying ($\beta = .64$, $p < .001$), impulsive buying predicted regret ($\beta = .51$, $p < .001$), and exposure was also associated with regret in total ($\beta = .49$, $p < .001$). The indirect effect through impulsive buying was positive but fragile (0.201; 95% bootstrap CI [0.004, 0.487]). Digital literacy weakened the exposure–impulsive buying link ($B = -0.64$, $p < .001$), yet highly literate respondents reported more impulsive buying and regret, indicating an awareness–behaviour gap. Given the small, female-majority sample, ceiling effects and common-method bias, the findings are suggestive rather than conclusive. They nevertheless point to the need for ethical interface design, practical consumer education and enforcement of dark-pattern rules.
Keywords: dark patterns; impulsive buying; post-purchase regret; digital literacy; S-O-R model; cognitive dissonance

1. Introduction

1.1 Background of the study

Digital commerce has compressed the time and effort required to search, compare and buy. Smartphones, digital wallets, instant payments, quick-commerce applications and social or live-stream shopping allow a purchase to move from discovery to payment in minutes. These environments are not neutral. Platforms collect extensive behavioural data, including browsing history, search terms, cart activity, location and responses to past promotions, and can use it to personalise recommendations and to test interface variants on large audiences. Personalisation brings convenience, but it can also be used to steer vulnerable consumers.

A prominent concern is the use of dark patterns, a term popularised by Brignull (2010) for interface tricks that lead users to do things they did not intend. The term now covers design features that push, pressure or deceive users into choices that benefit the platform or seller more than the user. Typical examples are countdown timers, "last item" messages, signals that many others are viewing or buying a product, pre-selected add-ons, drip pricing, hidden cancellation costs and guilt-inducing refusal wording. Such features can trigger impulsive buying, which is generally understood as a spontaneous, unplanned purchase made with limited deliberation and strong emotion (Rook, 1987; Stern, 1962). The immediate pleasure may be followed by the realisation that the product was not needed, cost too much or could have been obtained more cheaply, and these perceptions can generate post-purchase regret, cognitive dissonance, dissatisfaction and loss of trust in the platform.

The issue matters to consumers, firms, researchers and regulators alike. For firms, manipulative design may raise conversions but erode loyalty through returns, complaints and negative reviews. For regulators, it raises questions

of transparency, informed consent and fair pricing. India has formally recognised the problem through the Guidelines for Prevention and Regulation of Dark Patterns, 2023, which identify thirteen categories of dark pattern, including false urgency, basket sneaking, confirm shaming, drip pricing and interface interference (Government of India, 2023).

1.2 Research problem

When online consumers meet manipulative interfaces, they may buy items they did not intend to buy and feel remorse afterwards. Frictionless features such as one-click purchase, stored payment details and instant checkout reduce the need to compare alternatives, assess need or consider financial goals, while urgency and scarcity messages add emotional pressure to act quickly. Many consumers may not even recognise these cues as dark patterns, and awareness alone may not prevent impulsive responses, because fear of missing out, excitement and perceived value continue to operate even when a cue is noticed. The problem addressed here is therefore that, although dark patterns are increasingly documented in digital commerce, little is known about how exposure to them is linked to impulsive buying and how impulsive buying, in turn, is linked to regret after purchase.

1.3 Research gap

Five gaps motivate the study. First, dark patterns, impulsive buying and post-purchase regret have mostly been studied as separate constructs, and few studies test the full pathway from manipulative interface exposure to impulsive purchase and then to regret. Second, most dark-pattern research examines short-term outcomes such as click-through, consent, purchase intention and conversion, whereas downstream outcomes such as regret, dissatisfaction, returns and lost trust are far less studied. Third, evidence from fast-growing mobile, quick-commerce and social-commerce markets in India and other emerging economies is limited, even though app-based shopping, frequent notifications and convenient payments may amplify dark-pattern effects. Fourth, the role of digital literacy remains unclear: it may help consumers detect manipulation, yet knowing what to avoid does not always prevent impulsive purchasing. Fifth, AI-driven personalisation opens new and less visible routes to persuasion that existing designs of study have not yet captured.

1.4 Research objectives

1. To examine the effect of dark-pattern exposure on impulsive buying among online shoppers and the relationship between impulsive buying and post-purchase regret.
2. To analyse the mediating role of impulsive buying in the relationship between dark-pattern exposure and post-purchase regret, and the moderating role of digital literacy in the relationship between dark-pattern exposure and impulsive buying.
3. To recommend measures for promoting ethical e-commerce design, enhancing consumer awareness and strengthening the regulation of digital markets.

1.5 Research questions and hypotheses

Five research questions follow from the objectives: (RQ1) How strongly does dark-pattern exposure affect impulsive buying? (RQ2) How does impulsive buying relate to post-purchase regret? (RQ3) Does impulsive buying mediate the exposure–regret relationship? (RQ4) Does digital literacy moderate the effect of exposure on impulsive buying? (RQ5) What measures can reduce the impact of dark patterns on consumers? Table 1 sets out the hypotheses derived from the objectives and the conceptual framework presented in Section 2.9.

Table 1. Alignment of objectives, research questions and hypotheses

Objective	Question	Hypothesis
1	RQ1	H1: Exposure to dark patterns positively influences impulsive buying.
2	RQ2	H2: Impulsive buying is positively related to post-purchase regret.
3	RQ3	H3: Exposure to dark patterns positively predicts post-purchase regret (total effect). H4: Impulsive buying mediates the relationship between exposure and regret.
4	RQ4	H5: Digital literacy negatively moderates the exposure–impulsive buying relationship, which is weaker among shoppers with higher digital literacy.
5	RQ5	Addressed through the overall interpretation of results and the recommendations (Section 6.4).

1.6 Significance of the study

Theoretically, the study integrates the S-O-R model, which explains how external stimuli shape internal states and behaviour, with cognitive dissonance theory, which explains the discomfort that follows a purchase that conflicts with prior intentions, financial goals or expectations. For managers and designers, it suggests that manipulative interfaces may raise sales while damaging satisfaction, trust and long-term loyalty. For consumers and educators, it highlights cues, such as urgency messages, scarcity claims and pre-selected options, that merit scrutiny and can inform consumer-education programmes. For policymakers, it informs rules on price transparency, clear consent, easy cancellation, ethical personalisation and deceptive interface design.

2. Literature Review

2.1 Dark patterns: concept, evolution and prevalence

Dark patterns arose from the concern that interfaces can be deliberately engineered to serve the provider's interests at the user's expense. After Brignull (2010) catalogued "deceptive" practices, Gray et al. (2018) tied them to the ethics of user-experience design and classified common forms such as nagging, obstruction, sneaking, interface interference and forced action. Mathur et al. (2019) crawled roughly 11,000 shopping websites and found scarcity claims, urgency messages, social proof, misdirection, forced action and hidden information widespread, with such practices appearing on about one in ten sites, showing that manipulation is embedded in online retail rather than isolated. Narayanan et al. (2020) argued that continuous interface experimentation driven by commercial incentives sustains these practices, and Mathur et al. (2021) proposed asymmetry, covertness, information hiding and restrictiveness as attributes that make a pattern "dark". As the field expanded across human–computer interaction, law, marketing and consumer psychology (Gray et al., 2023), an ontology was proposed to reconcile academic and regulatory taxonomies (Gray et al., 2024). Consistent terminology matters for measurement; in this study, exposure is operationalised through the urgency, scarcity and social-proof cues that shoppers can observe while browsing.

Online retail is especially fertile ground because platforms can alter interface elements, test messages and observe responses at scale. The OECD (2022) defines dark commercial patterns as practices that restrict autonomy, disrupt decision-making and exploit behavioural biases, shifting attention from consumer weakness to the design of the choice environment. Experimental work supports this view. Nouwens et al. (2020) showed that consent-interface design materially shapes privacy decisions, and Luguri and Strahilevitz (2021) found that mild dark patterns more than doubled, and aggressive ones nearly quadrupled, the share of users accepting a costlier service relative to a control group. These studies concern privacy and subscriptions rather than product purchases, but they establish that presentation can shape behaviour even when alternatives formally remain available.

2.2 Consumer decision-making and susceptibility

Several mechanisms explain why dark patterns work. Urgency limits the time available to search and compare; scarcity evokes anticipated loss; social proof offers a quick quality heuristic; defaults are accepted because changing them takes effort; and drip pricing obstructs price comparison. These can be read as systematic, interface-level applications of Cialdini's (2009) persuasion principles. They also fit bounded rationality (Simon, 1955), heuristics and biases (Tversky & Kahneman, 1974) and fast, intuitive "System 1" thinking (Kahneman, 2011): under time pressure or cognitive load, consumers rely on simple rules, and dark patterns exploit this by making the preferred commercial option more prominent, more emotionally appealing or easier to select. The literature also separates legitimate nudges that help consumers pursue their own interests (Thaler & Sunstein, 2008) from dark patterns that confer asymmetric benefit on the platform. Formal freedom of choice may remain, but effective autonomy is reduced.

Who is susceptible? Zac et al. (2024) found strong susceptibility across consumer groups with few differences by income, education or age, implying that the design itself, rather than only consumer inexperience, creates vulnerability, and that friction can dampen manipulative effects. Personality-based research under the S-O-R model suggests that emotionality and other traits may shape responses to dark-pattern stimuli, raising ethical concerns about personalisation that targets inferred psychological weaknesses. This stream suggests that purchase-process design may matter more than consumer awareness, a point that bears directly on the role assigned to digital literacy in this study.

2.3 Dark patterns and impulsive buying

Impulsive buying was distinguished from planned buying by Stern (1962), who identified pure, reminder, suggestion and planned impulse types. Rook (1987) described a sudden, often powerful urge to buy immediately; Beatty and Ferrell (1998) emphasised browsing, positive affect, time availability and impulse-buying tendency; and Verplanken and Herabadi (2001) separated cognitive (little planning) from affective (excitement, loss of control) components. Online settings intensify these tendencies: recommendation engines continually surface products, flash sales, limited-time discounts, push notifications and influencer content raise arousal, and saved cards reduce the psychological pain of paying. The S-O-R model, adapted to online retail by Eroglu et al. (2001), treats digital cues as stimuli that trigger internal states such as pleasure, arousal, trust or perceived value, which then produce behavioural responses such as impulsive purchase.

Direct evidence links dark patterns to impulsivity. In an online shopping experiment, Sin et al. (2025) found that dark patterns increased purchase impulsivity relative to a control, and that behaviourally informed interventions reduced it, with effects varying by pattern type. Evidence from Indonesia points the same way in an emerging market (Uceng & Hanifah, 2024). Huber et al. (2026) reported a positive association between susceptibility to dark AI patterns and impulsive buying, and studies of quick-commerce and social-commerce settings identify urgency and social proof as predictors of unplanned purchase (Agrawal et al., 2026). Live-stream research adds that trust and emotional arousal mediate the link between streamer interaction and impulsive buying, with anticipated regret as a boundary condition ("Streamer Interaction and Consumer Impulsive Buying," 2025). Fear of missing out is central to these accounts: scarcity and limited-time cues generate anticipated inaction regret, and Li et al. (2021) showed that positive reviews lower anticipated action regret while raising anticipated inaction regret, an effect amplified by scarcity messages. A countdown timer therefore communicates not only time but possible loss.

2.4 Impulsive buying, post-purchase regret and cognitive dissonance

Post-purchase regret arises when consumers believe a different choice would have served them better, and can attach to the product, price, timing or decision process, often accompanied by guilt, disappointment and frustration. Regret regulation theory characterises it as a comparison-based cognitive–emotional state that can prompt switching or complaint (Zeelenberg & Pieters, 2007). Cognitive dissonance theory complements this account: people experience discomfort when behaviour conflicts with attitudes, beliefs or self-image (Festinger, 1957). A financially disciplined shopper who buys on impulse under a limited-time prompt experiences exactly such a conflict, and the gap between self-image and action is felt as regret. Regret is also fed by counterfactual thinking, since online shoppers readily discover cheaper or better alternatives after purchase.

Studies of young Indian consumers report joy and guilt following unplanned purchases (Jain et al., 2018), and work in Malaysia, Pakistan and Indonesia likewise links online impulse buying to regret, often through a dissonance lens (Lazim et al., 2020; Sarwar et al., 2024; "The Relationship Between Impulse Buying and Post-Purchase Regret," n.d.). Evidence on consequences is more mixed. Regret does not always lead to returns, because cumbersome return processes, perceived value or utility can keep consumers from acting ("The Role of Emotions," 2025). Beikverdi et al. (2024) catalogue the post-purchase effects of impulse buying for consumers, firms and society, while Li et al. (2025) found that regret can inhibit later impulse buying, though the effect may fade as the memory of regret weakens. Satisfaction and regret also shape later online behaviour (Tata et al., 2021). The present study concerns immediate post-purchase regret, not its downstream behavioural effects.

2.5 Digital literacy and the awareness–behaviour gap

Digital literacy may protect consumers by helping them recognise false urgency, scrutinise pre-selected options, compare prices and delay purchase; the OECD (2022) accordingly stresses empowerment and design transparency. Yet awareness is not the same as resistance. A consumer may recognise a manipulative cue and still respond because the discount appears worthwhile or the perceived cost of delay is high, and research on quick-commerce and social-commerce suggests that awareness exerts little influence on impulsive buying. Digital literacy is therefore treated here as a possible moderator rather than a complete safeguard. If interfaces keep imposing time pressure, hiding information or making refusal difficult, consumer education alone will be insufficient; neutral defaults, full price transparency, easy cancellation, removal of urgency claims and friction before high-risk purchases may also be needed.

2.6 Regulatory and ethical context

Dark patterns are now a policy concern because they undermine autonomy, informed consent and fair choice. The OECD (2022) documents hidden information, difficult cancellation, false urgency and manipulative defaults as consumer-protection risks, and instruments such as the EU Digital Services Act have increased scrutiny of deceptive interfaces. In India, the Central Consumer Protection Authority notified the 2023 Guidelines under Section 18 of the Consumer Protection Act, 2019, binding platforms, advertisers and sellers and listing thirteen specified dark patterns, the first being false urgency (Government of India, 2019, 2023). This shifts interface design from a purely marketing choice to a consumer-protection matter. Ethically, the line runs between persuasion that informs and enables genuine choice and manipulation that exploits cognitive weakness, emotional vulnerability or information asymmetry. Table 2 maps the four cues measured in this study to their psychological mechanisms and regulatory relevance; the mapping is interpretive, because the survey captures how often cues are seen, not whether they are false.

Table 2. Dark-pattern cues measured in the study

Item	Cue	Psychological mechanism	Regulatory relevance
Q5	Countdown timer beside a product or offer	Time pressure; fear of losing a deal	Possible false urgency if the timer is not genuine
Q6	"Offer ends" / "Today only" messages	Deadline framing; reduced time to compare	Possible false urgency if the offer is repeatedly renewed
Q7	"Only a few left" / "Selling fast" messages	Scarcity; anticipated inaction regret	Possible false urgency if stock claims are unsubstantiated
Q8	Messages showing how many people are viewing or have just bought	Social proof; fear of missing out	Possible false popularity claim if counts are unverifiable

Source: Compiled by the author from Cialdini (2009), Mathur et al. (2019) and Government of India (2023).

2.7 Critical analysis and identification of the research gap

Taken together, the literature supports five conclusions: dark patterns are widespread and varied; they influence decisions by creating urgency, scarcity, social validation, friction or information asymmetry; experimental evidence links them to greater purchase impulsivity; impulsive buying tends to produce regret and dissonance, although regretted purchases are not always returned and regret does not always deter repeat impulse buying; and consumer characteristics such as digital literacy, personality, price sensitivity, product involvement, fear of missing out and anticipated regret may condition these links. Critically, the methodological base is uneven. Experiments often rely on hypothetical shopping scenarios that may not reflect real spending; surveys suffer from recall bias and social desirability; cross-sectional designs cannot establish causality; and many samples are convenience samples of students or young consumers. Structural equation modelling is common for testing mediation and moderation, but rarely applied to the whole exposure–impulsivity–regret chain.

The gap is therefore twofold. The pathway from dark-pattern exposure through impulsive buying to post-purchase regret has seldom been tested in a single model, and evidence from Indian shoppers who use e-commerce, quick-commerce, social-commerce and instant-payment services is sparse. The present study addresses this gap with exposure as the independent variable, impulsive buying as the mediator, post-purchase regret as the outcome and digital literacy as the moderator.

2.8 Theoretical foundation

The S-O-R framework (Mehrabian & Russell, 1974), widely applied to online retail (Eroglu et al., 2001), explains how external stimuli act on internal states to produce behavioural responses. Here, dark-pattern exposure is the stimulus. The organism comprises internal states such as urgency, fear of missing out, arousal, perceived value, trust and anticipated regret; these were not measured directly but are treated as the mechanism underlying impulsive buying. The response has two stages: impulsive buying as the immediate behavioural response and post-purchase regret as the post-consumption outcome. Cognitive dissonance theory (Festinger, 1957) accounts for the latter stage: an unplanned purchase that conflicts with prior intentions or financial goals generates discomfort, which consumers may reduce by returning the product, rationalising the purchase, seeking supportive reviews or avoiding contrary information; when such strategies fail, dissatisfaction, complaints and lower

repurchase intention can follow. The S-O-R model thus explains the pre-purchase and purchase stages, and dissonance theory explains the post-purchase stage.

2.9 Conceptual framework

Figure 1 presents the conceptual framework. Dark-pattern exposure is the independent variable, impulsive buying the mediating variable and post-purchase regret the dependent variable. Digital literacy is the moderating variable, expected to weaken the effect of exposure on impulsive buying, since more literate consumers should better recognise and resist manipulative cues; the study does not assume that literacy eliminates the effect. Exposure is expected to raise impulsive buying (H1), impulsive buying to raise regret (H2), exposure to be related to regret in total (H3), impulsive buying to mediate that relationship (H4) and digital literacy to attenuate the first stage (H5).

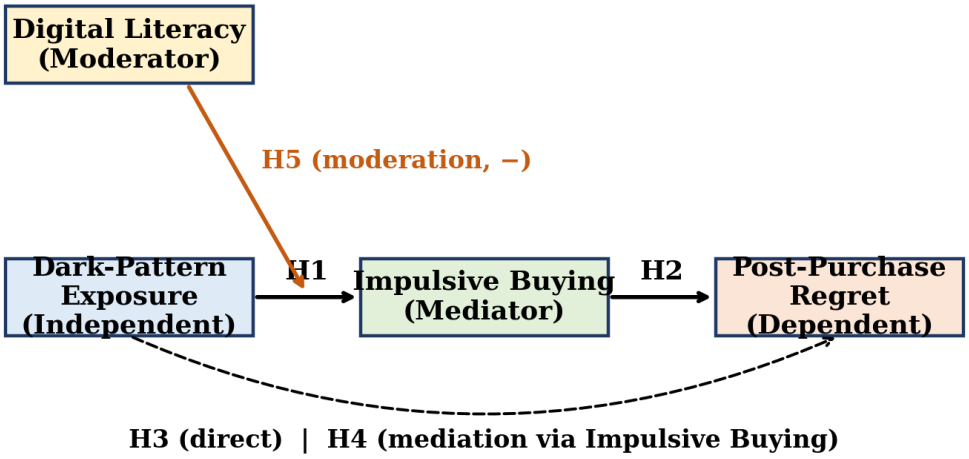

Figure 1. Conceptual framework of the study

3. Research Methodology

3.1 Research design

A quantitative, deductive approach was adopted because the study tests hypothesised relationships between established constructs. The design is explanatory (it examines how exposure relates to impulsive buying and regret), descriptive (it profiles the level of exposure and impulsive buying) and cross-sectional (respondents were measured once). Hypotheses were derived from the S-O-R framework, cognitive dissonance theory and prior empirical work.

3.2 Data sources and study population

The study relies on primary data collected through a structured online questionnaire built in Google Forms and released on 31 October 2026. The target population was active adult online shoppers who buy from e-commerce and quick-commerce platforms such as Amazon, Flipkart, Myntra, Meesho, Zepto, Blinkit, Swiggy Instamart, BigBasket or similar apps. The focus on digitally active consumers means that the sample is largely young and middle-aged adults, working professionals and postgraduates, groups that are frequently targeted by digital promotions and recommendations. Secondary sources (journal articles, OECD reports, and Indian statutes and guidelines) informed the conceptual framework.

3.3 Sampling technique and sample size

Using Cochran's (1977) formula for a large or unknown population (95% confidence, 5% margin of error, p = 0.50), the target sample was 384. Purposive sampling was used, with the survey sent by email to existing online shoppers. In total, 103 responses were received. Eligibility required at least one online purchase in the previous six months and regular use of e-commerce or quick-commerce platforms. Fifteen respondents reported no purchase in the period and were excluded; of the remaining 88, five who gave identical answers to all sixteen scale items (straight-lining) were removed. No values were missing because all items were compulsory, and no respondent was under 18. The final analytical sample was 83 (Figure 2). Because this falls well short of the 384 target, generalisability is limited (see Section 6.5).

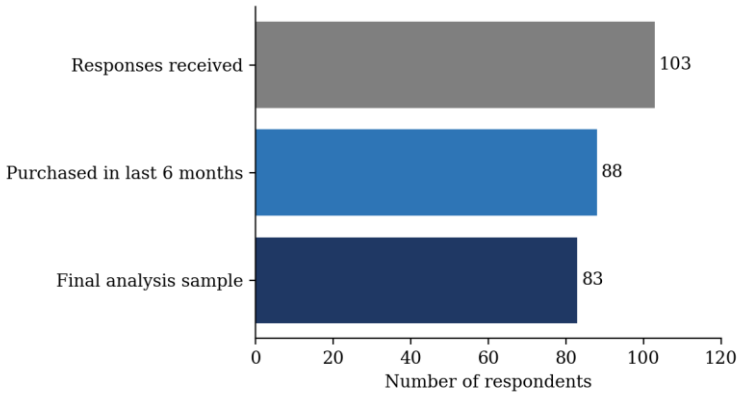

Figure 2. Derivation of the analysis sample

3.4 Data collection instrument and pilot

The questionnaire had five compulsory sections: (A) screening and demographics (Q1–Q4); (B) dark-pattern exposure (Q5–Q8); (C) impulsive buying (Q9–Q12); (D) post-purchase regret (Q13–Q16); and (E) digital literacy (Q17–Q20). Section B used a five-point frequency scale (1 = Never to 5 = Always); Sections C–E used five-point Likert items (1 = Strongly disagree to 5 = Strongly agree; Likert, 1932). Item scores were averaged to form construct scores. An earlier version with five items per construct was piloted on 87 respondents; the exposure scale failed the conventional threshold (Cronbach's α = .59 against .70; Nunnally & Bernstein, 1994). The instrument was therefore shortened to four items per construct and the exposure construct was narrowed to urgency, scarcity and social-proof cues. The results reported here come from the revised instrument administered to a new group of respondents.

3.5 Variables and measurement

Table 3 summarises the variables. Higher scores indicate more of the construct, and mean scores were classified as low (1.00–2.33), moderate (2.34–3.67) or high (3.68–5.00). Exposure was defined as how often a shopper encounters urgency, scarcity and social-proof cues. This does not imply that every such message is deceptive; the cues are measured because regulators treat them as potentially false when they cannot be substantiated. Impulsive buying is the self-reported tendency to buy unplanned or unneeded items on seeing a tempting offer or while merely browsing (Rook, 1987; Verplanken & Herabadi, 2001). Post-purchase regret is the self-reported feeling that a purchase should not have been made, that money was wasted or that a better decision was available (Zeelenberg & Pieters, 2007). Digital literacy is the shopper's self-assessed ability to identify manipulative design, understand how platforms use browsing data, detect false urgency and change pre-selected options.

Table 3. Operationalisation of constructs

Construct	Role	Items	Scale
Dark-pattern exposure (DPE)	Independent	Q5–Q8: countdown timers; "offer ends / today only"; "only a few left / selling fast"; people viewing / just bought	Never (1) to Always (5)
Impulsive buying (IB)	Mediator	Q9–Q12: buying without planning; buying before assessing need; difficulty resisting offers; buying when only browsing	Strongly disagree (1) to Strongly agree (5)
Post-purchase regret (PPR)	Dependent	Q13–Q16: regret; wishing the purchase had not been made; wasted money; could have decided better	Strongly disagree (1) to Strongly agree (5)
Digital literacy (DL)	Moderator	Q17–Q20: identify manipulative design; understand use of browsing data; detect false urgency; change pre-selected options	Strongly disagree (1) to Strongly agree (5)

Note: Item wording is reported in Table 6.

3.6 Analytical tools and techniques

Data were screened for eligibility, missing values, outliers and straight-lining, then analysed in Microsoft Excel and Python. Descriptive statistics (frequencies, means, standard deviations, skewness, kurtosis) profiled respondents and responses. Reliability was assessed with Cronbach's (1951) α and corrected item–total correlations, and construct validity with the Kaiser–Meyer–Olkin (KMO) measure, Bartlett's test and exploratory factor analysis (principal components, Varimax rotation); Harman's single-factor test checked common-method bias (Podsakoff et al., 2003). Pearson correlations were supplemented by Spearman rank correlations. H1–H3 were tested using simple and multiple regression with heteroscedasticity-consistent (HC3) standard errors as a robustness check. Mediation (H4) used a 5,000-resample percentile bootstrap equivalent to PROCESS Model 4 (Hayes, 2018; Preacher & Hayes, 2008), with the Sobel (1982) test reported for reference. Moderation (H5) used a mean-centred interaction model equivalent to PROCESS Model 1 (Aiken & West, 1991; Hayes, 2018) followed by simple-slope analysis. Group differences were examined using Welch's *t*-test, one-way ANOVA, the Mann–Whitney *U* test and the Kruskal–Wallis test.

3.7 Ethical considerations

Participation was voluntary and respondents were informed of the study's purpose and their right to withdraw at any time without penalty. No names, passwords, payment details or other unnecessary identifiers were collected; the analysis file contains only anonymous, coded responses used for academic purposes.

4. Results and Findings

All analyses use the final sample of 83 respondents unless stated otherwise. Construct scores are means of four items on five-point scales (DPE = dark-pattern exposure, IB = impulsive buying, PPR = post-purchase regret, DL = digital literacy).

4.1 Sample profile

Women made up 65.1% of the sample and men 34.9%. The largest age group was 25–34 years (34.9%), followed by 35–44 (27.7%), 18–24 (24.1%) and 45 and above (13.3%), so about 63% were aged 25–44. Platform use was frequent: 55.4% shopped "often" and 31.3% "very often" (86.7% combined), while only 3.6% shopped rarely (Table 4; Figures 3–5). The sample therefore consists mainly of young and middle-aged, digitally active shoppers, which suits the research question but limits generalisation.

Table 4. Demographic profile and platform-use frequency (N = 83)

Variable	Category	Frequency	Percentage (%)
Age group	18–24 years	20	24.1
	25–34 years	29	34.9
	35–44 years	23	27.7
	45 years and above	11	13.3
Gender	Female	54	65.1
	Male	29	34.9
Platform-use frequency	Rarely	3	3.6
	Sometimes	8	9.6
	Often	46	55.4
	Very often	26	31.3

Source: Primary data (survey).

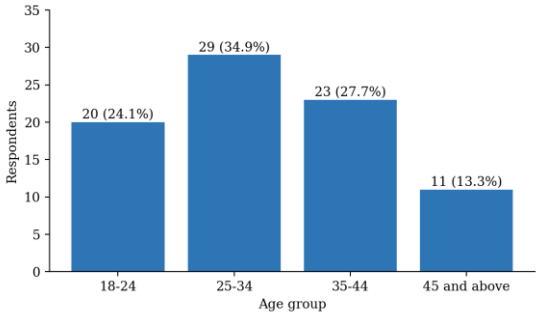

Figure 3. Age distribution of respondents



Figure 4. Gender distribution of respondents

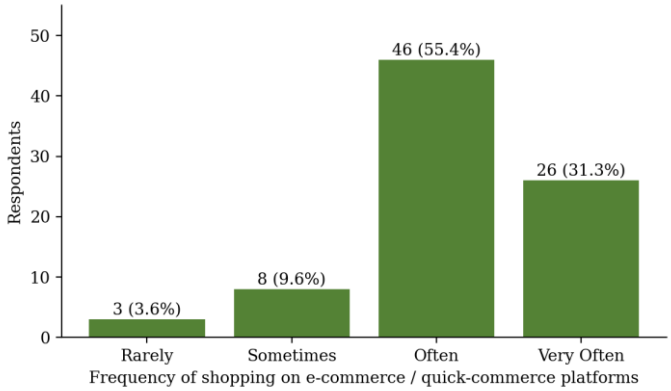

Figure 5. Frequency of shopping on e-commerce and quick-commerce platforms

4.2 Descriptive analysis

All four constructs fall in the high band (3.68–5.00) (Table 5; Figure 6). Post-purchase regret recorded the highest mean (M = 4.21, SD = 0.55), followed by exposure (M = 4.09, SD = 0.60), impulsive buying (M = 4.06, SD = 0.80) and digital literacy (M = 3.97, SD = 0.79). Distributions are negatively skewed, most strongly for impulsive buying (−2.04) and regret (−1.67), and Shapiro–Wilk tests were significant for all constructs, so responses cluster at the top of the scale; 83% of all responses to the sixteen scale items were in the top two categories. Few univariate outliers ($|z| > 3$) were found (one for exposure, three each for impulsive buying and regret); all were valid low scores and were retained.

Table 5. Descriptive statistics of the constructs (N = 83)

Construct	Mean	SD	Min	Max	Skewness	Kurtosis	Shapiro–Wilk W (p)
DPE	4.09	0.60	1.75	5.00	−0.83	1.88	.940 (.001)
IB	4.06	0.80	1.00	5.00	−2.04	4.36	.763 (<.001)
PPR	4.21	0.55	1.75	5.00	−1.67	5.22	.855 (<.001)
DL	3.97	0.79	1.75	5.00	−0.95	0.67	.912 (<.001)

Source: Primary data. Bands: low 1.00–2.33; moderate 2.34–3.67; high 3.68–5.00.

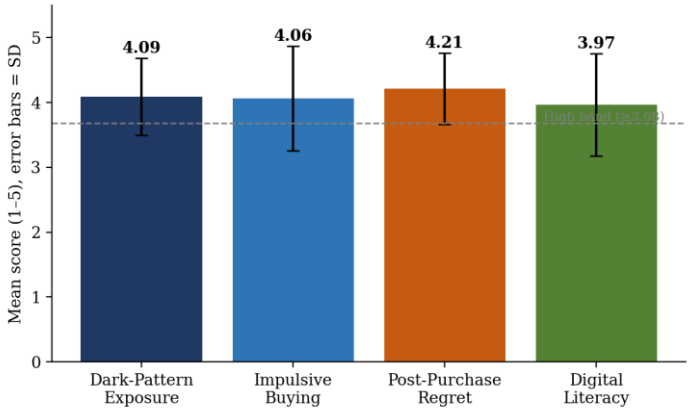

Figure 6. Mean scores of the four constructs

At item level (Table 6), "only a few left" / "selling fast" messages (Q7, *M* = 4.36) and "offer ends" / "today only" messages (Q6, *M* = 4.17) were seen most often, each reported as "often" or "always" by 90.4% of respondents; messages showing how many people were viewing or had just bought (Q8, *M* = 3.98) ranked third and countdown timers (Q5, *M* = 3.84; 65.1%) fourth. Scarcity and deadline cues were thus nearly universal in respondents' experience, although these results indicate presence, not authenticity. Agreement with impulsive-buying statements ranged from 83% to 87% (strongest for "difficult to resist attractive offers," Q11, *M* = 4.17) and with regret statements from 89% to 93% (strongest for "wasted money," Q15, *M* = 4.36; Figures 7–10). Digital-literacy confidence was highest for changing pre-selected options (Q20, *M* = 4.29) and lowest for identifying manipulative design (Q17, *M* = 3.76).

Table 6. Item-level descriptive statistics (N = 83)

Item	Statement	Mean	SD	% Top-2
Q5	Countdown timer next to a product or offer	3.84	0.83	65.1
Q6	"Offer ends" / "Today only" messages	4.17	0.71	90.4
Q7	"Only a few left" / "Selling fast" messages	4.36	0.73	90.4
Q8	Messages showing how many people are viewing / just bought	3.98	0.95	69.9
Q9	I often buy products online without planning to do so	3.99	0.90	85.5
Q10	I buy before thinking about whether I need the product	3.99	0.93	83.1
Q11	I find it difficult to resist attractive online offers	4.17	0.99	86.7
Q12	I buy even when I only intended to browse	4.11	0.90	86.7
Q13	I regret some of the products I have bought online	4.02	0.66	89.2
Q14	I often wish I had not made certain online purchases	4.23	0.80	88.0
Q15	I feel I wasted money on things I bought online	4.36	0.69	92.8
Q16	I could have made a better purchase decision	4.23	0.61	92.8
Q17	I can identify manipulative design features	3.76	0.97	69.9
Q18	I understand how platforms use my browsing behaviour	4.02	1.04	79.5
Q19	I can tell when a website is using false urgency	3.80	1.15	71.1
Q20	I know how to change preselected options	4.29	0.67	90.4

Source: Primary data. % Top-2 = share answering Often/Always (Q5–Q8) or Agree/Strongly agree (Q9–Q20).

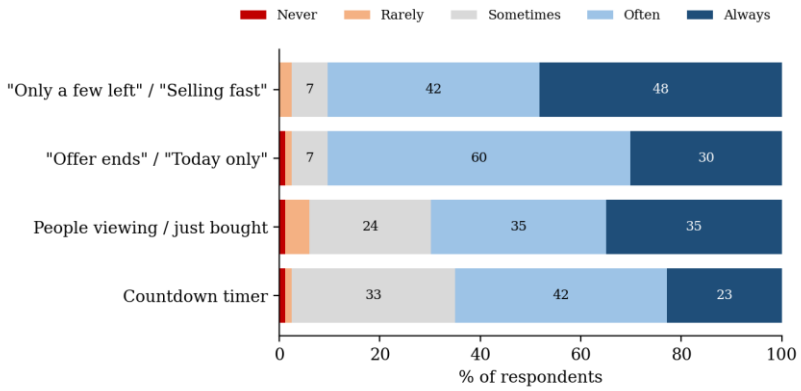

Figure 7. Response distribution for dark-pattern exposure items (%)

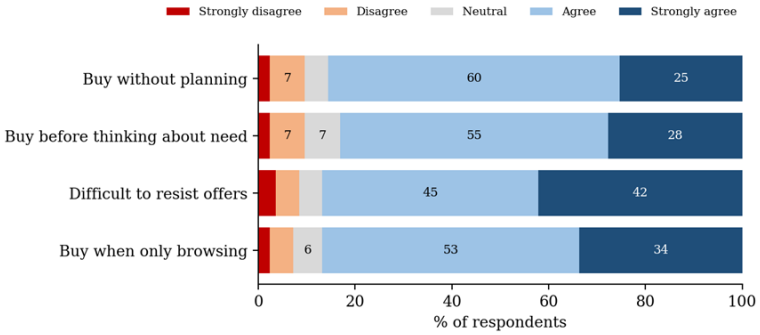

Figure 8. Response distribution for impulsive-buying items (%)

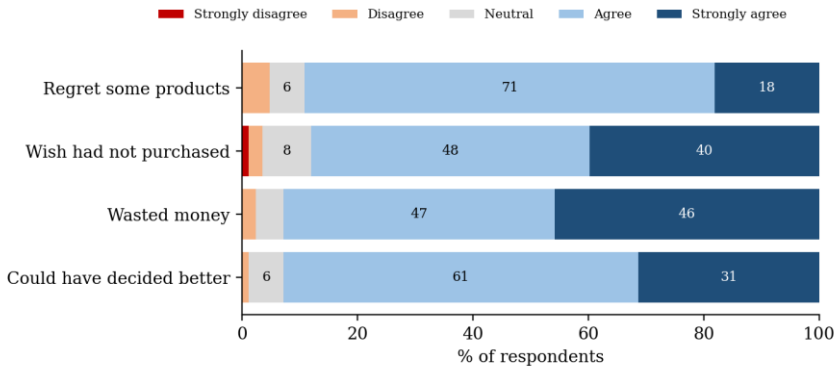

Figure 9. Response distribution for post-purchase regret items (%)

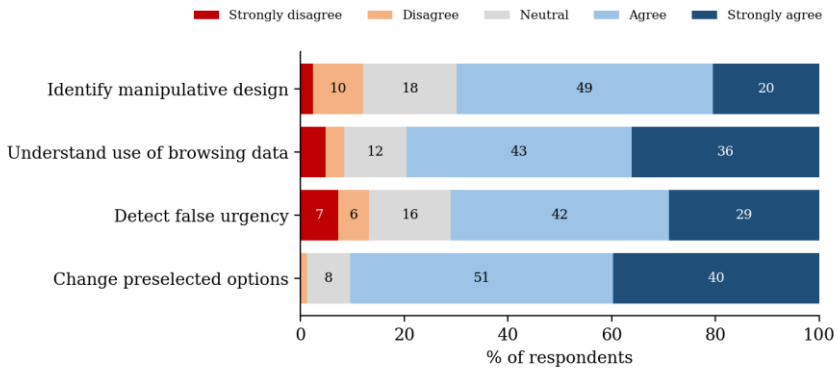

Figure 10. Response distribution for digital-literacy items (%)

4.3 Reliability and validity

All four scales exceeded the .70 threshold (Nunnally & Bernstein, 1994): impulsive buying (α = .89), digital literacy (α = .83) and regret (α = .80) were good and exposure (α = .72) acceptable (Table 7; Figure 11). The exposure scale improved markedly from α = .59 in the pilot, supporting the decision to narrow it to urgency and scarcity-type cues, although the comparison is across different respondent groups and instrument versions rather than a repeated measure. Corrected item–total correlations exceeded .30 for every item except Q20 (.29), whose removal would raise the digital-literacy α from .83 to .90; the item was retained to keep four items per construct but is a candidate for replacement. Exposure items had the lowest item–total correlations (.48–.53) but none could be dropped without lowering α.

Table 7. Reliability of the scales (Cronbach's α)

Scale	Items	α (revised)	α (pilot, 5 items)	Item–total r range	Verdict
Dark-pattern exposure	4	.715	.589	.48–.53	Acceptable
Impulsive buying	4	.887	.848	.71–.78	Good
Post-purchase regret	4	.801	.726	.57–.70	Good
Digital literacy	4	.827	.758	.29–.82	Good

Source: Primary data (revised form N = 83; pilot N = 87). Threshold: α ≥ .70.

The KMO measure was .857 ("great"; Kaiser, 1974) and Bartlett's test was significant ($\chi^2 = 742.56$, $df = 120$, $p < .001$), so the data suited factor analysis. Principal components with Varimax rotation yielded four components with eigenvalues above one (6.97, 1.61, 1.21, 1.14), jointly explaining 68.4% of variance (Figure 12). Impulsive-buying items loaded most highly on the first factor, regret items on the third, and three of four digital-literacy items on the second. Exposure items did not form a clean factor: Q5 and Q6 loaded on a separate fourth factor, Q7 on the impulsive-buying factor and Q8 on the digital-literacy factor. The constructs are therefore only partly separable in this sample. Harman's test showed the first unrotated factor explaining 43.6% of variance, below the 50% guideline (Podsakoff et al., 2003), but the high intercorrelations indicate a probable common response style, so common-method bias cannot be ruled out and relationships may be inflated.

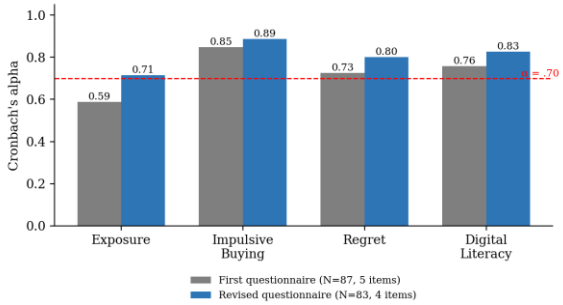

Figure 11. Cronbach's alpha: first versus revised questionnaire

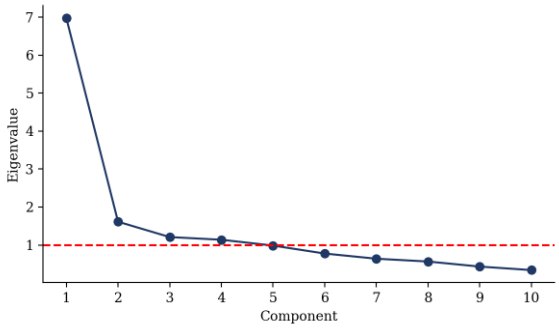

Figure 12. Scree plot of eigenvalues

4.4 Correlation analysis

Table 8 reports Pearson correlations (below the diagonal) and Spearman rank correlations (above); Figure 13 visualises the Pearson matrix. Exposure correlated strongly with impulsive buying ($r = .64$), impulsive buying with regret ($r = .51$), and exposure with regret ($r = .49$), consistent with the proposed S-O-R chain. Digital literacy was positively, not negatively, correlated with every other construct ($r = .55$ with exposure, .57 with impulsive buying and .58 with regret), so in simple bivariate terms literacy did not act as a protective factor: more literate respondents reported more exposure, more impulsive buying and more regret. Spearman coefficients were lower, notably for impulsive buying and digital literacy (.33 versus .57), which points to ceiling and tied-response effects inflating Pearson values; Spearman estimates are the more conservative.

Table 8. Correlation matrix: Pearson (below diagonal) and Spearman (above diagonal)

	DPE	IB	PPR	DL
DPE	1	.582	.446	.509
IB	.637	1	.402	.325
PPR	.488	.514	1	.538
DL	.545	.573	.579	1

Source: Primary data, N = 83. All p < .001 except Spearman IB–DL (p = .003).



Figure 13. Heat map of Pearson correlations among constructs

4.5 Hypothesis tests: regression analysis (H1–H3)

Simple regressions supported H1–H3 (Table 9). Exposure significantly predicted impulsive buying (B = 0.86, β = .64, p < .001), explaining 40.5% of its variance, a large effect by Cohen's (1988) criteria: each one-point rise in exposure was associated with a 0.86-point rise in impulsive buying (Figure 14). Impulsive buying predicted regret (B = 0.35, β = .51, p < .001; R^2 = .264; Figure 15), and exposure also predicted regret in total (B = 0.45, β = .49, p < .001; R^2 = .238). When both predictors entered the model, they explained 30.8% of the variance in regret (F(2, 80) = 17.78, p < .001); exposure (B = 0.25, p = .028) and impulsive buying (B = 0.23, p = .006) remained significant, with no multicollinearity concern (VIF = 1.68). The drop in the exposure coefficient from .45 to .25 is the basis of the mediation test.

Table 9. Regression results for H1–H3 and the combined model

Model	B	SE	β	t	p	R^2
H1: DPE → IB	0.860	0.116	.637	7.431	<.001	.405
H2: IB → PPR	0.352	0.065	.514	5.396	<.001	.264
H3: DPE → PPR (total effect)	0.451	0.090	.488	5.029	<.001	.238
Combined: DPE → PPR	0.249	0.111	.270	2.236	.028	.308
Combined: IB → PPR	0.234	0.083	.342	2.839	.006	.308

Source: Primary data, N = 83. 95% CI for B: H1 [0.630, 1.090]; H2 [0.222, 0.482]; H3 [0.272, 0.629]. Combined model F(2, 80) = 17.78, adjusted R^2 = .290.

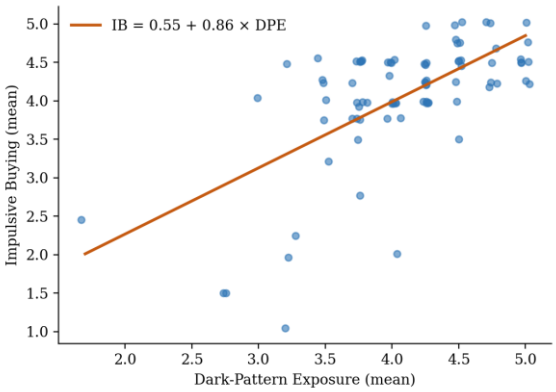

Figure 14. Dark-pattern exposure and impulsive buying

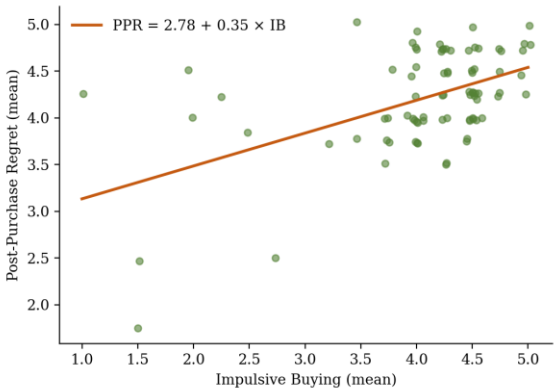

Figure 15. Impulsive buying and post-purchase regret

Diagnostics qualify these results. Durbin–Watson values (2.06–2.39) showed no autocorrelation, but residuals of the H1 and H3 models were non-normal and Breusch–Pagan tests indicated heteroscedasticity in all three models. HC3 standard errors (Table 10) left H1, H2, H3 and the H5 interaction significant, but in the combined model neither exposure (p = .055) nor impulsive buying (p = .143) remained significant, which weakens the evidence for mediation. Adding age and gender as controls raised R^2 to .479 for impulsive buying, and exposure remained a significant predictor (B = 0.83, p < .001); only respondents aged 45 and above reported less impulsive buying than the 18–24 group (B = −0.53, p = .022). In the regret model, exposure (B = 0.28, p = .017) and impulsive buying (B = 0.19, p = .032) stayed significant, with no age or gender effects, so the core relationships are not artefacts of sample composition.

Table 10. Robustness check using HC3 standard errors

Model	Predictor	B	HC3 SE	t	p
H1: IB ~ DPE	DPE	0.860	0.160	5.372	<.001
H2: PPR ~ IB	IB	0.352	0.144	2.449	.017
H3: PPR ~ DPE	DPE	0.451	0.141	3.205	.002
Combined: PPR ~ DPE + IB	DPE	0.249	0.128	1.951	.055
Combined: PPR ~ DPE + IB	IB	0.234	0.158	1.480	.143
H5: IB ~ DPE × DL	DPE × DL	−0.644	0.098	−6.568	<.001

Source: Primary data, N = 83.

To identify which cues matter most, the four exposure items were regressed jointly on impulsive buying (Table 11; Figure 16). Together they explained 49.0% of its variance (F = 18.75, p < .001). The number of people viewing or just buying (Q8, β = .48, p < .001) and "only a few left" / "selling fast" messages (Q7, β = .26, p = .010) were the only significant unique predictors; "offer ends" (Q6, β = .18, p = .071) and countdown timers (Q5, β = −.07, p = .497) added nothing once the other cues were controlled. The cues are intercorrelated (about .4–.6), and each alone relates to impulsive buying, but only social-proof and scarcity cues carry unique explanatory power.

Table 11. Impulsive buying regressed on individual dark-pattern cues

Predictor	B	SE	β	t	p	VIF
Q5 Countdown timers	−0.064	0.094	−.066	−0.682	.497	1.446
Q6 Offer ends / Today only	0.204	0.111	.181	1.830	.071	1.492
Q7 Only a few left / Selling fast	0.283	0.107	.256	2.645	.010	1.428
Q8 People viewing / just bought	0.405	0.083	.479	4.909	<.001	1.456

Source: Primary data, N = 83. R^2 = .490; adjusted R^2 = .464.

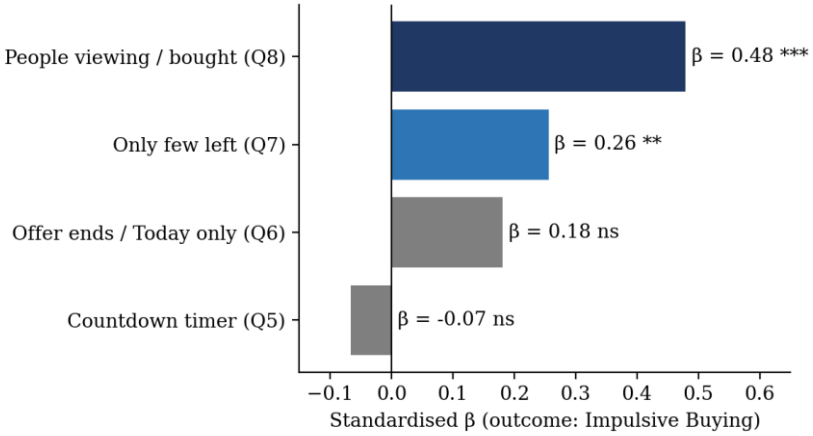

Figure 16. Standardised effect of each dark-pattern cue on impulsive buying

4.6 Hypothesis test: mediation analysis (H4)

H4 was tested with a 5,000-resample percentile bootstrap (Table 12; Figures 17 and 18). The a-path (DPE → IB) was 0.860 and the b-path (IB → PPR, controlling for exposure) was 0.234 (p = .006). The indirect effect (a × b) was 0.201 (95% CI [0.004, 0.487]), which excludes zero, and the Sobel test agreed (z = 2.652, p = .008). The direct effect remained significant (c′ = 0.249, p = .028), so mediation is partial, with about 45% of the total effect (0.451) transmitted through impulsive buying. This conclusion warrants caution: the interval's lower bound is almost zero, the direct-effect interval is also close to zero [0.005, 0.494], and the b-path is not significant under HC3 errors (p = .143). H4 is therefore accepted only tentatively.

Table 12. Mediation analysis: exposure → impulsive buying → regret

Path / effect	Estimate (B)	SE	p / 95% CI	Result
a: DPE → IB	0.860	0.116	<.001	Significant
b: IB → PPR (controlling DPE)	0.234	0.083	.006	Significant
c: Total effect, DPE → PPR	0.451	0.090	<.001	Significant
c′: Direct effect, DPE → PPR	0.249	0.111	.028; CI [0.005, 0.494]	Significant
a × b: Indirect effect	**0.201**	**0.126**	**CI [0.004, 0.487]**	**CI excludes zero**
Sobel test	z = 2.652	–	p = .008	Significant
Proportion mediated	≈ 45%	–	–	Indicative only

Source: Primary data, N = 83; 5,000 bootstrap resamples. Check: c′ + a×b = 0.249 + 0.201 = 0.451 = c.

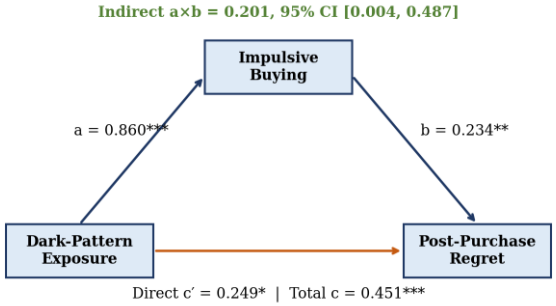

Figure 17. Mediation model with unstandardised path coefficients

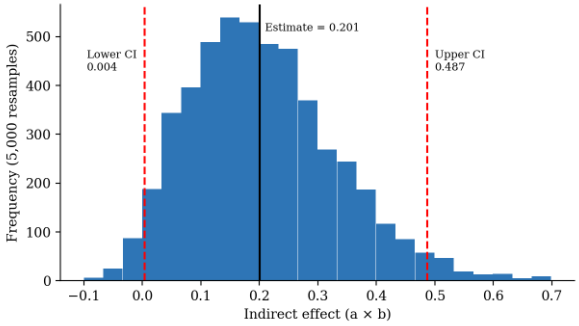

Figure 18. Bootstrap distribution of the indirect effect (5,000 resamples)

4.7 Hypothesis test: moderation analysis (H5)

The mean-centred interaction model was significant (R^2 = .629, $F(3, 79)$ = 44.56, p < .001; Table 13). The DPE × DL interaction was negative and significant (B = −0.64, p < .001) and added 15.0 percentage points of explained

variance ($\Delta R^2 = .150$). Simple slopes showed that exposure raised impulsive buying by 1.10 points at low literacy (−1 *SD*), by 0.60 at average literacy, and by only 0.09 at high literacy (+1 *SD*), which is not significantly different from zero ($p = .548$) (Figure 19). For highly literate respondents, then, no exposure–impulsive buying relationship was detected, and H5 is supported. Two cautions apply. First, the pattern partly reflects a ceiling effect: highly literate respondents already scored very high on impulsive buying (predicted values 4.27–4.37), leaving little room for exposure to add. Second, the index of moderated mediation (−0.151; 95% CI [−0.338, 0.001]) just reaches zero, and the conditional indirect effects at low, average and high literacy (0.259, 0.140, 0.021) all have intervals containing zero, so no claim that literacy conditions the whole mediation process is warranted.

Table 13. Moderation analysis: exposure → impulsive buying, moderated by digital literacy

Predictor / condition	B	SE	t	p	95% CI
Interaction model					
Intercept	4.226	0.062	68.28	<.001	[4.103, 4.349]
DPE (centred)	0.596	0.111	5.385	<.001	[0.375, 0.816]
DL (centred)	0.121	0.091	1.332	.187	[−0.060, 0.303]
DPE × DL (interaction)	**−0.644**	**0.114**	**−5.656**	**<.001**	**[−0.871, −0.417]**
Simple slopes of DPE on IB					
Low DL (−1 SD; 3.178)	1.103	0.139	7.915	<.001	–
Mean DL (3.967)	0.596	0.111	5.385	<.001	–
High DL (+1 SD; 4.755)	0.088	0.145	0.603	.548	–

Source: Primary data, N = 83. $R^2 = .629$; adjusted $R^2 = .614$; interaction $\Delta R^2 = .150$, $F = 31.99$, $p < .001$; VIFs 1.31–1.70.

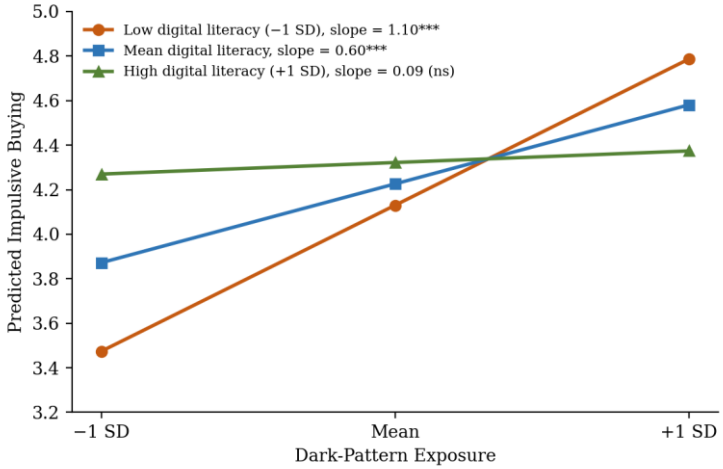

Figure 19. Interaction of dark-pattern exposure and digital literacy on impulsive buying

4.8 Group differences

Women scored higher than men on all four constructs, but gender differences were not significant (regret: 4.30 versus 4.05, $p = .085$). Age differences were significant for impulsive buying (ANOVA $F = 2.94$, $p = .038$; Kruskal–Wallis $p = .019$): respondents aged 45 and above scored lowest ($M = 3.45$) while other groups ranged from 4.01 to 4.24. Digital literacy also varied by age on the non-parametric test ($p = .016$), highest among 35–44-year-olds ($M = 4.25$) and lowest among those 45 and above (Figure 20). Exposure differed by platform-use frequency ($F = 5.60$, $p = .002$), driven by three infrequent shoppers ($M = 2.83$), and the non-parametric test was not significant ($p = .095$). Because twelve tests were run without correction for multiple comparisons, these results are exploratory; the most consistent pattern is lower impulsive buying among the oldest respondents.

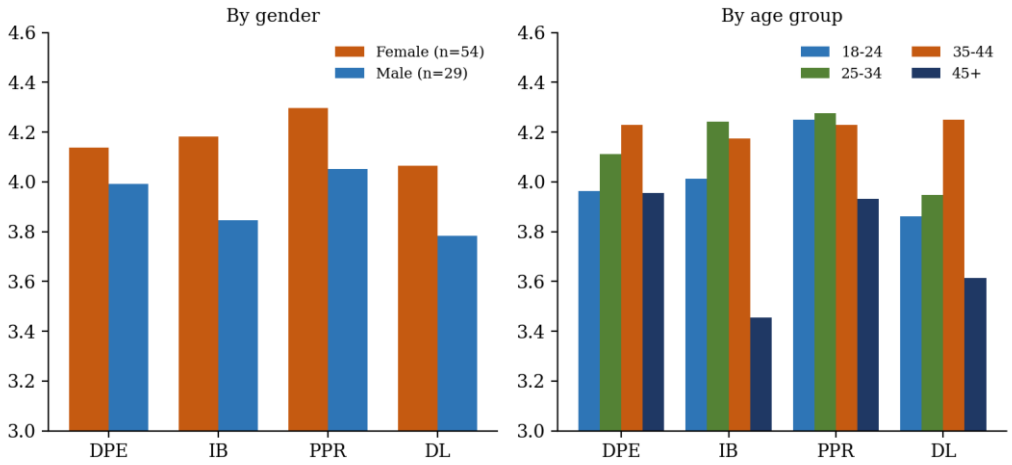

Figure 20. Mean construct scores by gender and age group

4.9 The awareness–behaviour gap

A median split on digital literacy (low: $n = 45$; high: $n = 38$) tested whether knowledge translates into resistance (Figure 21). It did not. High-literacy respondents reported more impulsive buying ($M = 4.31$ versus 3.86; Welch $t = 2.77$, $p = .007$), more regret ($M = 4.47$ versus 3.99; $t = 4.64$, $p < .001$) and more frequent exposure ($M = 4.31$ versus 3.90). A literate consumer thus appears to notice the cues yet still act on them. This is compatible with the moderation result: impulsive buying is higher at high literacy even though its relationship with exposure is weaker there.

4.10 Sensitivity to sample definition

To check whether screening decisions drove the findings, H1–H3 were re-estimated on the primary sample ($n = 83$), on all purchasers without removing straight-liners ($n = 88$) and on all responses ($n = 103$) (Figure 22). Every relationship remained significant at $p < .001$ with similar effect sizes (for example, H1 β = .64, .66 and .60 respectively), so the exclusions did not alter the conclusions.

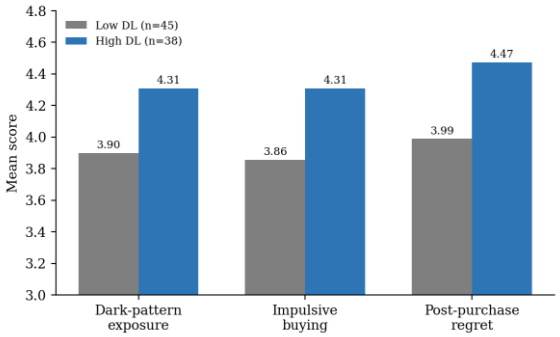

Figure 21. Construct scores of low versus high digital-literacy groups

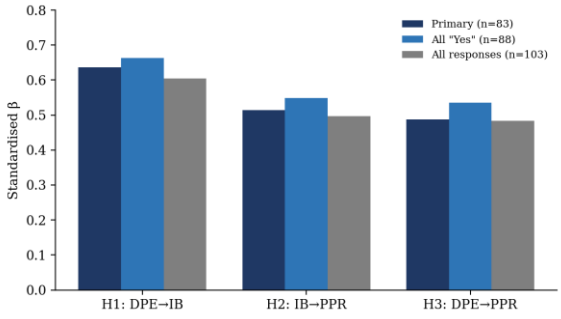

Figure 22. Standardised coefficients across sample definitions

4.11 Data-quality considerations

Several checks bear on interpretation (Table 14; Figure 23). All 103 responses arrived within 108 minutes on a single day, with a median gap of 42 seconds between submissions, which is plausible if the link was circulated in a group but suggests respondents may not have answered independently. Four of the five straight-liners submitted within one short window. Responses were concentrated at the top of the scale (83% at Agree/Often or above, against 58% in the pilot), and 27 of 83 respondents scored 4 or higher on every item. Inter-construct correlations were also much higher (.49–.64) than in the pilot (.03–.38). These indicators do not prove a problem, but they suggest acquiescence and ceiling effects that likely inflate relationships. The direction of the effects and their stability across Pearson/Spearman and robust estimates give some confidence, but the single self-report, cross-sectional design precludes causal conclusions.

Table 14. Data-integrity checks: revised versus pilot questionnaire

Check	Revised (N = 83)	Pilot (N = 87)
Collection window (minutes)	108	–
Median gap between submissions (seconds)	42	–
Share of answers at Agree/Often or above	83%	58%
Grand mean of all scale items	4.08	3.55
Correlation DPE–IB	.637	.060
Correlation DPE–PPR	.488	.180
Correlation IB–PPR	.514	.380
Correlation IB–DL	.573	.030

Source: Primary data. DPE–DL (.545 vs .300) and PPR–DL (.579 vs .310) show the same pattern.

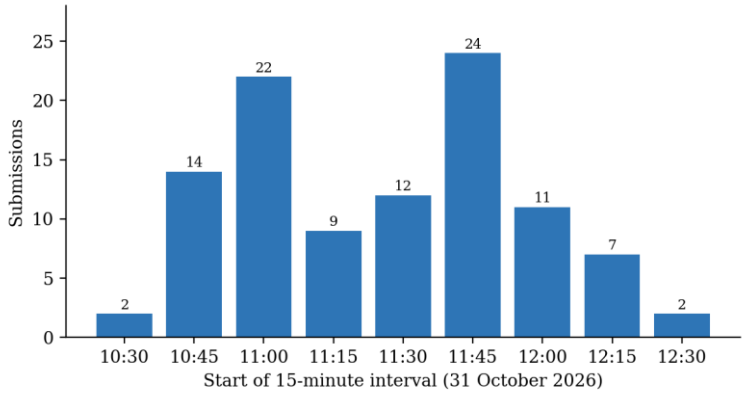

Figure 23. Number of submissions per 15-minute interval

4.12 Summary of major findings

Table 15 summarises the hypothesis tests. H1, H2, H3 and H5 are statistically supported and survive HC3 standard errors and changes to the sample definition; H4 is supported only tentatively because the indirect effect is marginal and the b-path loses significance under robust errors.

Table 15. Summary of hypothesis testing

Hypothesis	Relationship	Key estimate	p	Decision
H1	DPE → IB	β = .64; B = 0.86; R^2 = .405	<.001	Supported
H2	IB → PPR	β = .51; B = 0.35; R^2 = .264	<.001	Supported
H3	DPE → PPR (total)	β = .49; B = 0.45; R^2 = .238	<.001	Supported
H4	IB mediates DPE → PPR	Indirect = 0.201; CI [0.004, 0.487]	Bootstrap	Supported (partial; fragile)
H5	DL weakens DPE → IB	Interaction B = −0.64; ΔR^2 = .150	<.001	Supported

Source: Primary data, N = 83.

5. Discussion

5.1 Interpretation of findings

The results are consistent with the proposed S-O-R and dissonance chain. Shoppers who more often meet urgency, scarcity and social-proof cues report more impulsive buying, and those who buy more impulsively report more regret. Over nine in ten respondents agreed that they had wasted money or could have decided better, so regret appears to be a common by-product of online shopping in this sample. Cue-level results add nuance: social-proof counters and scarcity messages carried unique explanatory power, whereas countdown timers and deadline messages did not once the other cues were controlled. This fits the view that anticipated inaction regret and fear of missing out are the engine of impulsive purchase, and that cues implying that others are buying or stock is running out are more potent than time limits alone.

Mediation was only partial and fragile. Exposure was associated with regret both through impulsive buying and directly. One plausible reading is that consumers under urgency pressure regret their decisions even when they do not perceive them as impulsive; another is that the shared self-report method inflates all paths. Without data from separate sources, the mediated path cannot be asserted firmly.

5.2 Comparison with previous studies

The exposure–impulsivity link agrees with the experimental evidence of Sin et al. (2025), with findings on dark AI patterns (Huber et al., 2026), and with quick-commerce and social-media research that identifies urgency and social proof as drivers of unplanned purchase (Agrawal et al., 2026). It also supports Cialdini's (2009) account of social proof and scarcity as powerful persuasion principles. The impulsive buying–regret association matches results for Indian, Indonesian and Malaysian shoppers (Jain et al., 2018; Lazim et al., 2020; Sarwar et al., 2024) and the logic of cognitive dissonance. Unlike Zac et al. (2024), who found little demographic variation in susceptibility, we found lower impulsive buying among respondents aged 45 and above, although this was exploratory. The moderation result agrees with the OECD's (2022) emphasis on empowerment, but the follow-up analyses agree more with studies reporting that awareness has limited effect on impulsive buying.

5.3 Explanation of unexpected results

Three results were unexpected. First, digital literacy correlated positively with exposure, impulsive buying and regret, and high-literacy respondents scored higher on impulsive buying and regret than low-literacy respondents, even though literacy weakened the exposure–impulsive buying slope. Two explanations are plausible. Literate shoppers may recognise cues and understand how they were influenced, which heightens regret; or they may be heavier and more engaged platform users who are exposed more often. Alternatively, ceiling effects and acquiescence compress responses and distort the pattern, since the moderation effect arises largely because high-literacy respondents were already near the scale maximum. Second, countdown timers had no unique effect, probably because they overlap with other urgency cues. Third, the exposure scale did not load as a single factor, which suggests that its items capture related but distinct experiences, or that a shared response style blurs construct boundaries.

5.4 Theoretical implications

The findings lend initial empirical support to combining S-O-R (for the pre-purchase and purchase stages) with cognitive dissonance theory (for the post-purchase stage) in a single model. They also suggest that digital literacy functions as a boundary condition on the stimulus–response link in an Indian setting without removing the awareness–behaviour gap, which implies that models of dark-pattern effects should distinguish recognising a cue from resisting it.

6. Conclusion

This study examined how exposure to dark-pattern cues relates to impulsive buying and post-purchase regret among online shoppers, and how digital literacy conditions these relationships. Using a cross-sectional survey of 83 valid respondents and grounded in S-O-R and cognitive dissonance theory, it tested five hypotheses with regression, bootstrap mediation and moderation analysis

Four main conclusions emerge. First, urgency, scarcity and social-proof cues are experienced very frequently, particularly "only a few left" and "offer ends" messages. Second, higher exposure is strongly associated with higher impulsive buying, and impulsive buying with higher regret, consistent with the S-O-R and dissonance chain. Third, impulsive buying accounts for part of the exposure–regret relationship, but this mediation is weak. Fourth, digital literacy attenuates the effect of exposure on impulsive buying, yet literate consumers still report high impulsive buying and regret, so awareness is necessary but not sufficient. Social-proof and scarcity cues are the most influential. All findings are associational, probably inflated by response style and ceiling effects, and should be treated as indicative.

6.1 Practical and policy implications

Platforms and designers. Treat "people viewing / just bought" and "only a few left / selling fast" messages as the highest-risk cues (β = .48 and .26): use them only when verifiable and avoid fluctuating counts. Add brief confirmation steps for impulse-prone purchases, since impulsive buying had the strongest link with regret (β = .51). Avoid frequent, non-genuine "today only" prompts, and judge interface success by satisfaction, returns, complaints and trust rather than conversion alone.

Consumers and educators. Build digital-literacy teaching into schools and consumer-awareness programmes, since the exposure effect shrank at high literacy (slope 0.09 versus 1.10 at low literacy), but pair it with practical rules, such as a 24-hour waiting period, budget checks before payment and needs-based lists, because literate consumers still act impulsively. Encourage reflection on past regretted purchases; 89% of respondents regretted some online purchases.

Regulators and policymakers. Enforce the 2023 Guidelines with particular attention to false urgency, false scarcity and unverifiable social-proof counters, and require platforms to substantiate such claims on request. Treat these cues as a consumer-protection matter rather than purely a marketing choice, encourage periodic interface audits, and provide simple channels for reporting misleading urgency and scarcity messages. Because education alone appears insufficient, design-level safeguards such as neutral defaults, price transparency and friction before high-risk purchases deserve consideration.

6.2 Limitations

The sample is small (83 against a planned 384), predominantly female (65%) and aged 25–44 (63%), limiting generalisability. The cross-sectional, self-reported design supports association but not causation and is prone to recall and social-desirability bias. Common-method bias, acquiescence and ceiling effects probably inflate relationships (Harman's first factor = 43.6%), and the very short response window means independence cannot be assumed. The exposure scale is narrow, covers only urgency, scarcity and social-proof cues, and is the least reliable (α = .72) and least cleanly factored. Pre-selected add-ons, hidden charges, drip pricing and AI personalisation were not measured, the organism component of S-O-R was not measured directly, and group comparisons were uncorrected and exploratory. Findings may differ across platforms, product categories and shopper populations.

6.3 Scope for future research

- Use larger, diverse, probability-based samples with attention checks, completion-time monitoring and multiple data sources.
- Establish causality through experimental or field designs, platform audits or transaction-level data.
- Measure additional dark patterns (pre-selected options, hidden fees, drip pricing) and AI-personalised patterns.
- Measure the organism component directly (fear of missing out, arousal, anticipated regret) and test it as a mediator.
- Extend outcomes to returns, negative reviews, brand trust and repurchase intention, and compare quick commerce, social commerce and live-stream shopping across age, income and platform groups.

References

[1] Agrawal, R., Lakhwani, Y., Kumari, S., Kumar, P., & Sharma, D. (2026). Dark patterns on social media: Effect on impulse buying and consumer awareness. *Journal of Emerging Technologies and Novel Research, 4*(5), b583–b589. https://rjpn.org/jetnr/viewpaperforall.php?paper=JETNR2605191

[2] Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

[3] Beatty, S. E., & Ferrell, M. E. (1998). Impulse buying: Modeling its precursors. *Journal of Retailing, 74*(2), 161–167. https://doi.org/10.1016/S0022-4359(99)80092-X

[4] Beikverdi, L., Sipilä, J., & Tarkiainen, A. (2024). Post-purchase effects of impulse buying: A review and research agenda. *Journal of Consumer Behaviour, 23*(3), 1512–1527. https://doi.org/10.1002/cb.2287

[5] Brignull, H. (2010). *Dark patterns: Deceptive user interface design* [Website]. https://www.deceptive.design

[6] Cialdini, R. B. (2009). *Influence: Science and practice* (5th ed.). Pearson Education.

[7] Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.

[8] Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

[9] Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334.

[10] Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. *Journal of Business Research, 54*(2), 177–184.

[11] Festinger, L. (1957). *A theory of cognitive dissonance*. Stanford University Press.

[12] Government of India. (2019). *The Consumer Protection Act, 2019* (Act No. 35 of 2019). Ministry of Law and Justice.

[13] Government of India. (2023). *Guidelines for prevention and regulation of dark patterns, 2023*. Central Consumer Protection Authority, Department of Consumer Affairs.

[14] Gray, C. M., et al. (2023). *Mapping the landscape of dark patterns scholarship: A systematic literature review*. https://doi.org/10.1145/3563703.3596635

[15] Gray, C. M., Kou, Y., Battles, B., Hoggatt, J., & Toombs, A. L. (2018). The dark (patterns) side of UX design. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, Article 534. https://doi.org/10.1145/3173574.3174108

[16] Gray, C. M., Santos, C. T., Bielova, N., & Mildner, T. (2024). An ontology of dark patterns knowledge: Foundations, definitions, and a pathway for shared understanding. *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3613904.3642436

[17] Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). Guilford Press.

[18] Huber, G., Gasinski, B., Szymoniuk, M., Maciaszczyk, M., Kocot, M., Sobon, J., & Baldowski, D. (2026). The impact of dark AI patterns on consumer purchase decisions and impulsive buying. *European Research Studies Journal, 29*(1), 490–499. https://ersj.eu/journal/4324

[19] Jain, K., Gautam, S., & Pasricha, D. (2018). The pleasure and the guilt: Impulse purchase and post-purchase regret—A study of young Indian consumers. *Indian Journal of Marketing, 48*(3), 49–63.

[20] Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.

[21] Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36.

[22] Lazim, N. A. M., Sulaiman, Z., Zakuan, O., Chin, A. T., Mas'od, A., & Awang, R. S. (2020). Measuring post-purchase regret and impulse buying in online shopping experience from cognitive dissonance theory perspective. *Proceedings of the 2020 International Conference on Information Management and Technology*. https://eprints.utm.my/91094/

[23] Li, B., et al. (2025). Do consumers' post-purchase regrets reinforce or inhibit future impulse buying behavior propensity? *Current Psychology, 44*, 11036–11048. https://doi.org/10.1007/s12144-025-07873-1

[24] Li, B., Hu, M., Chen, X., & Lei, Y. (2021). The moderating role of anticipated regret and product involvement on online impulsive buying behavior. *Frontiers in Psychology, 12*, Article 732459. https://doi.org/10.3389/fpsyg.2021.732459

[25] Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 22*(140), 1–55.

[26] Luguri, J., & Strahilevitz, L. J. (2021). Shining a light on dark patterns. *Journal of Legal Analysis, 13*(1), 43–109. https://doi.org/10.1093/jla/laaa006

[27] Mathur, A., Acar, G., Friedman, M. J., Lucherini, E., Mayer, J., Chetty, M., & Narayanan, A. (2019). Dark patterns at scale: Findings from a crawl of 11K shopping websites. *Proceedings of the ACM on Human-Computer Interaction, 3*(CSCW), Article 81. https://doi.org/10.1145/3359183

[28] Mathur, A., Kshirsagar, M., & Mayer, J. (2021). What makes a dark pattern... dark? Design attributes, normative considerations, and measurement methods. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, Article 360. https://doi.org/10.1145/3411764.3445610

[29] Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.

[30] Narayanan, A., Mathur, A., Chetty, M., & Kshirsagar, M. (2020). Dark patterns: Past, present, and future. *ACM Queue, 18*(2), 67–92.

[31] Nouwens, M., Liccardi, I., Veale, M., Karger, D., & Kagal, L. (2020). Dark patterns after the GDPR: Scraping consent pop-ups and demonstrating their influence. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–13. https://doi.org/10.1145/3313831.3376321

[32] Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

[33] Organisation for Economic Co-operation and Development. (2022). *Dark commercial patterns* (OECD Digital Economy Papers). OECD Publishing. https://doi.org/10.1787/44f5e846-en

[34] Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

[35] Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891.

[36] The relationship between impulse buying and post-purchase regret in online shopping. (n.d.). *Indonesian Journal of Behavioral Studies*. https://jurnal.radenfatah.ac.id/index.php/ijobs/article/download/21296/6658/

[37] The role of emotions in the interaction between impulsive buying, regret and return behavior in online shopping. (2025). *PPAD*. https://dergipark.org.tr/en/pub/ppad/article/1728871

[38] Rook, D. W. (1987). The buying impulse. *Journal of Consumer Research, 14*(2), 189–199. https://doi.org/10.1086/209105

[39] Sarwar, M. A., Nasir, J., Sarwar, B., Hussain, M., & Abbas, A. (2024). An investigation of precursors of online impulse buying and its effects on purchase regret: Role of consumer innovation. *International Journal of Innovation Science, 16*(5), 877–897. https://doi.org/10.1108/IJIS-12-2022-0244

[40] Simon, H. A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics, 69*(1), 99–118.

[41] Sin, R., Harris, T., Nilsson, S., & Beck, T. (2025). Dark patterns in online shopping: Do they work and can nudges help mitigate impulse buying? *Behavioural Public Policy, 9*(1), 61–87. https://doi.org/10.1017/bpp.2024.49

[42] Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology, 13*, 290–312.

[43] Stern, H. (1962). The significance of impulse buying today. *Journal of Marketing, 26*(2), 59–62.

[44] Streamer interaction and consumer impulsive buying in live-stream commerce: The mediating roles of trust and emotional arousal with anticipated regret as boundary condition. (2025). *Frontiers in Communication*. https://www.frontiersin.org/journals/communication/articles/10.3389/fcomm.2025.1547639/full

[45] Tata, S. V., Prashar, S., & Parsad, C. (2021). Examining the influence of satisfaction and regret on online shoppers' post-purchase behaviour. *Benchmarking: An International Journal, 28*(6), 1987–2007. https://doi.org/10.1108/BIJ-06-2020-0332

[46] Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.

[47] Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124–1131.

[48] Uceng, A., & Hanifah, A. M. Z. (2024). Dark patterns and consumer decision making in emerging markets: Experimental evidence from Indonesia. *Data: Journal of Information Systems and Management, 2*(3), 180–192. https://journal.idscipub.com/index.php/data/article/view/919

[49] Verplanken, B., & Herabadi, A. (2001). Individual differences in impulse buying tendency: Feeling and no thinking. *European Journal of Personality, 15*(S1), S71–S83. https://doi.org/10.1002/per.423

[50] Zac, A., Huang, Y.-C., von Moltke, A., Decker, C., & Ezrachi, A. (2024). Dark patterns and online consumer vulnerability. *Behavioural Public Policy*.

[51] Zeelenberg, M., & Pieters, R. (2007). A theory of regret regulation 1.0. *Journal of Consumer Psychology, 17*(1), 3–18.