

Persuasive Digital Interfaces and Consumer Purchase Intention: The Role of Cognitive Biases in Online Retail Environments

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ABSTRACT

The evolution of technology has led to the evolution of shopping, and it's become much more persuasive and influential in the decision-making process of consumers in the digital world. This study was designed to explore the effect of scarcity cues, urgency cues, celebrity endorsement, social proof mechanisms and deceptive pricing on the purchase intention in an online shopping context. The data collected from 186 participants was analyzed quantitatively through a statistical analysis and qualitatively through a thematic analysis, thus applying a mixed-methods research design. All persuasive digital strategies were found to be effective at boosting purchase intention. Social proof ($M = 4.44$), celebrity endorsement ($M = 4.37$), and scarcity ($M = 4.27$) had the highest mean purchase intention scores, respectively; however, Bonferroni-corrected pairwise comparisons showed only the difference between social proof and scarcity was statistically significant ($p = .039$), and the differences involving celebrity endorsement did not reach significance after Bonferroni correction. Most notably, the awareness of hidden-fee pricing was related in the positive direction to purchase continuation ($\rho = 0.661$, $p < .001$), the opposite of the prediction, indicating there is no resistance to the practice of hidden-fee pricing when it is known, with important consequences for consumer protection policies. The qualitative analysis also revealed that the factors of trust, popularity, emotional appeal and perceived value significantly influenced consumer decision-making. The study focuses on how persuasive digital interfaces can affect consumer behaviour online psychologically. The results have a significant implication for designing platforms ethically, consumer protection policies, and digital literacy programs in digital retail settings.

Keywords: Cognitive biases; Consumer behaviour; Digital marketing; Social proof; Dark patterns

INTRODUCTION

Digital commerce is a major change in the way consumers search for information, consider alternatives, and make purchasing decisions (Kotler et al., 2020). The online retail platforms with which consumers interact differ from the classic offline retail stores since they present their users with a vast amount of information simultaneously: price, discount, reviews, ratings, urgency cues, subscription prompts, and

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promotional recommendations (Liu et al., 2022). Although these are all aimed at enhancing convenience and efficiency, recent studies in cognitive psychology and behavioural economics indicate that a very saturated digital environment can overwhelm consumers and drive them to engage in heuristic processing instead of careful, deliberate analysis. It is important to note that later meta-analyses (in particular, Scheibehenne, Greifeneder, and Todd, 2010) have shown that under the best of circumstances, the effects of the choice-overload phenomenon are small, averaging out to almost null across 50 replications (Iyengar & Lepper, 2000; Shah et al., 2012). Online consumers often rely on mental shortcuts when making online purchases (Kahneman, 2011).

Online shopping sites generally don't report on neutral terms. However, interface design, pricing models and enticing promotional cues shape decision-making contexts and consumer behaviour (Mathur et al., 2019). Thus, the inchoate nature of digital interfaces' psychological framing mechanisms affects purchase decisions in digital marketplaces, more than objective product quality (Hassan et al., 2021). This study is thus gaining greater significance as ecommerce is becoming ubiquitous in our society and prompting interface designers to engage in persuasive practices with a large and varied user base (Mathur et al., 2019).

Different age groups, income levels, and levels of digital literacy can have different susceptibility to manipulative design strategies (Wang et al., 2021). The literature indicates that as users are repeatedly exposed to persuasive digital environments, their dependency on heuristic decision-making processes grows, as does information overload and limited attention (Shah et al., 2012). This is also understood through the lens of dual-process theory which posits that there are two types of processing, fast and intuitive, automatic (System 1), and slower, analytical reasoning (System 2) (Kahneman, 2011). In a digital retail context, emotional appeals, visual cues and the framing of urgency are often used to capture System 1 thinking, which makes people more susceptible to behavioural manipulation (Braga & Jacinto, 2022).

Scarcity and urgency framing is one of the most common and widely used cognitive tricks in Digital Retail. Online platforms often employ countdown timers, low-stock indicators, flash sale messages, and messages of the "limited-time offer," to induce feelings of scarcity and urgency (Peng et al., 2019). They capitalize on the fear of missing out (FOMO) and create a sense of urgency on the impulse to buy things without giving them a second thought, as a result of which, the overall cognitive deliberation is reduced (Good & Hyman, 2020). Past research shows that scarcity cues that are artificially created can substantially boost purchase intention, regardless of whether a scarcity is not real (Sin et al., 2023). Results of dark pattern research also indicate that consumers often are not aware of the device-induced urgency-based manipulative techniques as it is a normal pathway in the digital commerce space (Mathur et al., 2019).

Another critical factor that can influence online consumer behaviour is social proof bias. When making purchases under uncertainty, consumers commonly use product reviews and ratings, "bestseller" labels, popularity cues, and product testimonials to assess the product (Chen et al., 2008). Social validation mechanisms are very effective heuristics that lower perceived risk and boost purchase confidence in digital spaces where physical inspection of products is not feasible (Kim & Johnson, 2016). In the larger studies, volume and rating values are highly significant in predicting the likelihood of purchase, even

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more so than the information provided in the reviews themselves (Chen et al., 2008). Social proof cues can thus be viewed as mental shorthand, which helps to alleviate information overload and thereby makes the decision making process easier (Mathur et al., 2019).

Likewise, celebrity endorsement and influencer marketing are impacting consumer choices online, to a greater degree than ever before (Kim & Johnson, 2016). Product endorsement by celebrities or popular persons that are easily recognized is viewed as more credible, attractive and socially accepted (Meyers-Levy & Loken, 2015). Celebrity endorsement can boost the purchase intention and convey credibility and aspirational value to the endorsed product (Wang et al., 2021). Celebrity-based persuasion can thus help to convince in a more emotion-driven way and limit the resistance towards promotional messages in digitally visualized and socially connected contexts (Kim & Johnson, 2016).

Another emerging issue in the digital retail landscape is the dark patterns in the user interface, also known as dark patterns (Mathur et al., 2019). This includes hidden fees, pre-selected subscription options, auto-renewal, misleading pricing transitions, and friction based checkout options that benefit platforms over consumers (Luguri & Strahilevitz, 2021). Dark patterns often activate more than one cognitive bias at a time, such as anchoring, the default bias, scarcity perception and loss aversion (Mathur et al., 2019). Experimental research indicates that consumers can be made to follow manipulative design strategies without their awareness or discomfort (Sin et al., 2023). This means that if there is a manipulation, there may be a behavioural influence that is present even after it is recognized. This taxonomy of the types of dark patterns is developed further by Gray et al. (2018) and Bongard-Blanchy et al. (2021), which categorize deceptive interface strategies into nagging, obstruction, sneaking, interface interference and forced action, and situates the hidden-fee manipulation examined in this paper.

This study's hypotheses are set in three additional theoretical frameworks. The Persuasion Knowledge Model (PKM) (Friestad and Wright, 1994) suggests that consumers form lay theories regarding the nature of persuasion attempts by marketers, and that this 'persuasion knowledge' can neutralise or mitigate persuasive efforts, but not prevent them. The PKM is directly applicable to variables studied in this research. It suggests that consumers can perceive a persuasion without engaging in a behavioural response. The dual-process framing is complemented by the Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986), which states that peripheral-route processing (e.g., motivation is low, or the ability to process information carefully is low) will dominate when motivation or ability to process information carefully is low, which is typical of fast-paced digital retail. The canonical model for analysing purchase intention as a predictor of purchase behaviour is the Theory of Planned Behaviour (Ajzen, 1991), and the theory has also shown that purchase intentions can be over-predictive of purchase behaviour; which has direct implications for the findings of the present study.

While some studies have investigated the individual cognitive biases in online shopping, little research has comparatively investigated multiple online persuasive strategies in a consolidated behavioural model (Hassan et al., 2021). Previous research tends to examine one scarcity cue, one social proof, one anchoring or one dark pattern at a time instead of investigating how multiple cues may interact to persuade consumers (Mathur et al., 2019). Moreover, little research is available on how much demographic and behavioural traits may affect persuasion by interface design (Wang et al., 2021).

This study will investigate the relationship between persuasive digital marketing strategies and cognitive bias with intention to purchase in online shopping. In particular, this study examines how scarcity cues and urgency cues, celebrity endorsements, social proof mechanisms, and price deception influence consumer choice.

In line with the aim, following hypothesis were formulated:

H1: Participants will report above-neutral purchase intention in scenarios featuring scarcity and urgency-based promotional cues.

H2: Participants will report above-neutral purchase intention in scenarios featuring celebrity endorsement.

H3: Participants will report above-neutral purchase intention in scenarios featuring social proof mechanisms, including ratings and reviews.

H4: Participants will report above-neutral awareness of deceptive pricing structures such as hidden-fee price increases.

H5: Recognition of hidden-fee price increases significantly reduces consumers' likelihood of continuing with purchase decisions.

H1 tests the dual-process theory and commodity theory prediction that scarcity cues inhibit deliberative processing, while H2 tests the social proof theory prediction that peer validation cues decrease perceived risk. H3 tests Cialdini's (2001) social proof theory prediction that peer validation cues decrease perceived risk; and H4 and H5 together test the prediction of the PKM that activated persuasion knowledge does not always result in behavioural resistance.

METHODS

Research Design

The study used mixed methods cross-sectional survey design for examining influence of cognitive biases and persuasive digital marketing strategies on the purchase intention of consumers in the online shopping environment. Given the objective of capturing self-reported self-observations of behavioural tendencies and attitudes at one point in time, across a diverse sample of online consumers, a cross sectional approach was considered appropriate (Creswell & Creswell, 2018). Given that previous behavioural studies in digital marketing had employed a mixed method was employed to systematically analyse the relationship between persuasive interface strategies and consumer decision-making (Mathur et al., 2019; Wang et al., 2021).

Participants

After removing incomplete responses, there were 186 valid responses included in the analysis. The participants were gathered using a convenience sampling method using social media and messaging apps.

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The participants had to be adults (18 years or older) with previous experience in using e-commerce platforms to meet the inclusion criteria. Incompleted responses were excluded from analysis. The sample spanned various age brackets, income levels and online shopping habits, and most of the respondents were aged between 18 and 34 years. The sample comprised 119 males (64.3%) and 67 females (35.7%). By age, the largest group was 24–34 years ($n = 72$), followed by 18–24 years ($n = 50$), 34–44 years ($n = 36$), 44–54 years ($n = 19$), and 54–64 years ($n = 9$). In terms of income, the majority earned 25–50K ($n = 91$), followed by 50–75K ($n = 47$) and below 25K ($n = 33$). Shopping frequency was predominantly monthly ($n = 81$) and weekly ($n = 63$). Participation was voluntary in nature and no incentives were given. No personal details were asked for or recorded, and responses were anonymous.

Survey Instrument

A structured self-administered questionnaire with three sections was used to collect the data. Demographic and behavioural features, such as age, sex, income level and frequency online shopping were collected in the first section. The second was overall consumer buying preference (which comprised platform preference). As an exploratory approach to the dark-patterns literature of pre-selected defaults (Mathur et al., 2019), a hypothetical tiered choice item (Basic / Plus / Pro / Elite, with features described for each tier) was added. The third part involved experimental tasks focusing on scenarios that were created to control the effect of specific cognitive biases and persuasive marketing mechanisms on purchasing intention. The scenarios included simulated online shopping situations that triggered desired cognitive cues such as urgency and scarcity cues (e.g., countdown timers, low-stock indicators), celebrity endorsements, social proof cues (e.g., star ratings, customer reviews), and deceptive pricing (e.g., hidden fees). After each scenario, a Likert scale was included and had 5 points, varying from 1 (strongly disagree) to 5 (strongly agree), for purchase intention and perceived influence. Qualitative reasoning for participants' choices was captured by appending open-ended questions. The questionnaire was piloted with a small sample of respondents before being widely implemented, with some minor changes to the wording of the scenarios made based on the pretest responses. All participants performed in all four experimental scenarios (within subjects design); the full questionnaire with all scenario texts, Likert-scale items, scale anchors and open-ended questions is reproduced in Appendix A. To avoid order effects, the order of scenarios was randomised across participants. No scenario included more than one type of cue. In the current design a control condition (an identical scenario where there is no persuasive cue) was not included, which limits the inferential scope of the cue specific tests, as discussed in the Limitations section.

Procedure

The survey was sent out online using a digital survey tool (Google Forms) and shared across social media and messaging apps to reach as many people as possible and to ensure a diverse sample. All participants were provided with a standardised introduction explaining the nature of the study, the fact that it was voluntary, and precautions regarding confidentiality of data. Participants gave electronic informed consent prior to viewing the survey items. The survey required about 5-8 minutes to complete. Responses were automatically recorded and entered into the survey platform, reducing the chances of data entry mistakes.

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Data Analysis

The data analysis used descriptive statistics, inferential testing, and qualitative thematic analysis. All outcome variables were measured by descriptive statistics, such as mean and standard deviation. One-sample t-tests were then calculated to see if there was any significant difference between purchase intention scores across each experimental condition (scarcity and urgency cues, celebrity endorsement, social proof, and hidden-fee detection) and the neutral scale midpoint ($\mu = 3$) where Cohen's d was used as a measure of effect size (Field, 2018). Spearman's rank order correlations were then calculated to explore bivariate relationships between behaviour and demographic variables; the Spearman's rho was used because the data on the Likert scales were ordinal. A one-way repeated-measures ANOVA with Bonferroni-corrected pairwise comparisons was subsequently performed to determine if there were any significant differences in the purchase intention across the three conditions of the cues: scarcity/urgency, celebrity endorsement, and social proof. All quantitative analyses were performed in R, using a significance level of $p < .05$. Since coding was done by one coder, interrater reliability was not formally evaluated, this is considered a weakness of this thematic analysis.

Thematic analysis, as outlined by Braun and Clarke (2006) was used to analyse open-ended qualitative responses. Responses were analysed in an iterative fashion, initial codes were created inductively and codes were grouped into themes for corroboration and context to the quantitative results.

Ethical Considerations

Informed consent was obtained before recruitment. Respondents were informed that they could drop out at any time without penalty. Personal data of any kind was not gathered and all data was kept on password protected systems, only accessible by the research team. No sensitive personal information was collected and data was anonymised before analysis.

RESULTS

Participant Characteristics

A total of 186 valid responses were used for analysis. The sample included respondents from different age groups, income brackets, and online shopping frequencies. The majority of respondents were in the younger age brackets (18–24 and 24–34). The majority shopped online weekly or monthly.

Regarding subscription tier preference, the Pro tier was the most popular ($n = 98$, 52.7%), followed by Elite ($n = 76$, 40.9%), Basic ($n = 6$, 3.2%), and Plus ($n = 6$, 3.2%).

Descriptive Statistics

The review/social proof condition had the highest mean purchase intention score ($M = 4.44$, $SD = 0.59$), followed by the celebrity endorsement condition ($M = 4.37$, $SD = 0.79$) and scarcity/urgency condition ($M = 4.27$, $SD = 0.71$). The condition for hidden fees resulted in a mean $M = 3.93$ ($SD = 0.88$).

One-Sample T-Tests

All four conditions had scores that were significantly different from the neutral midpoint ($\mu = 3$) when tested using one-sample t-tests. Scarcity/urgency: $t(185) = 24.46$, $p < .001$, $d = 1.79$. Celebrity endorsement: $t(185) = 23.61$, $p < .001$, $d = 1.73$. Review/social proof: $t(185) = 33.36$, $p < .001$, $d = 2.45$. Hidden-fee notice: $t(185) = 14.37$, $p < .001$, $d = 1.05$.

Table 1: Descriptive Statistics and One-Sample t Tests

Variable	M	SD	t(185)	p	Cohen's d
Scarcity/Urgency Purchase Intention	4.27	0.71	24.46	< .001	1.79
Celebrity Endorsement Purchase Intention	4.37	0.79	23.61	< .001	1.73
Review/Social Proof Purchase Intention	4.44	0.59	33.36	< .001	2.45
Hidden-Fee Notice Likelihood	3.93	0.88	14.37	< .001	1.05

Note. Effect sizes (Cohen's d) reflect distance from the scale midpoint ($\mu = 3$), not from a no-cue control condition; ; effect sizes of this magnitude are consistent with ceiling effects common in scenario-based intention measures and should not be interpreted as evidence of causal influence

Pairwise Comparisons Between Cue Conditions

Overall, the difference in purchase intention between the three purchase intention conditions was not statistically significant for the one-way ANOVA ($F(2, 555) = 2.664$, $p = .071$). The intention score in the review/social proof condition was statistically higher than the scarcity/urgency condition when using Bonferroni-corrected pairwise t-tests ($t(185) = -2.51$, $p = .039$, $d = -0.256$). There were no significant differences after Bonferroni correction between scarcity/urgency and celebrity endorsement ($t(185) = -1.93$, $p = .164$) or between celebrity endorsement and review/social proof ($t(185) = -0.89$, $p = 1.000$).

Spearman Correlations

Main variables were correlated by Spearman's rank order correlation. Notably, the direction of this relationship was positive rather than negative, constituting an inversion of H5's prediction and the study's

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most counterintuitive finding. There was a strong positive correlation between the hidden-fee notice score and purchase continuation ($\rho = 0.661$, $p < .001$). There was a significant positive relationship between age and purchase continuation ($\rho = .164$, $p = .025$). There was weak positive correlation between income and hidden-fee notice ($\rho = .140$, $p = .057$) and purchase continuation ($\rho = .155$, $p = .034$).

Table 2: Spearman Correlations Among Main Variables

Variables	ρ	p
Hidden-fee notice $\times$ Purchase continuation	.661	< .001
Age $\times$ Purchase continuation	.164	.025
Income $\times$ Hidden-fee notice	.140	.057
Income $\times$ Purchase continuation	.155	.034

Note. The income $\times$ hidden-fee notice correlation ($\rho = .140$, $p = .057$) did not reach statistical significance at $\alpha = .05$.

Qualitative Findings

The qualitative responses provided additional context for the quantitative patterns. Thematic analysis of open-ended responses revealed several recurring themes.

Appealing brand association and emotional ties was the most common theme. Language (e.g., ‘refreshing’, ‘premium’, ‘trustworthy’, ‘clean’ and ‘appealing’) was used by participants often when describing their evaluation of product and this linguistic framing and product naming had a strong influence on perceived value.

The influence of celebrities was also a key theme. Participants often pointed to the visibility, popularity, and trustworthiness of celebrity endorsement as reasons for a product gaining attention and consideration for purchase.

The third theme that arose was social proof and customer validation. This is in line with the high mean intention scores found in the review condition, where many participants reported that positive ratings, star ratings, customer experiences and perceived popularity of the product were important influences in their purchasing decisions.

A fourth theme of aesthetics and presentation quality emerged. Packaging and appearance and visual presentation of the product were often cited as influences on choice and product choice, indicating that both informational and visual heuristics are used when evaluating products online.

Other themes covered were perceived value for money, premium product attributes, limited appeal and free offer incentives. A smaller group of respondents were suspicious of a celebrity's endorsement of a product or concerned with the healthfulness of a product, suggesting the existence of more sophisticated consumer segments.

DISCUSSION

The purpose of this study was to examine the influence of persuasive digital marketing strategies and cognitive biases on consumers' purchase intention in online shopping. The five hypotheses were tested using one-sample t-tests, a repeated-measures ANOVA with Bonferroni-corrected pairwise comparisons, and Spearman rank-order correlations.

The results are presented and interpreted in relation to the organising logic of the PKM and TPB which were used as a theoretical frame for the study. The PKM states that consumers can identify that someone is trying to persuade them without resisting the persuasion behaviourally — which is directly tested by H4 and H5. Purchase intention is treated as a proximal but imperfect predictor of behaviour in the TPB, thus providing a context for the dependent variables in the five hypotheses. The remaining findings are interpreted in light of the peripheral-route processing account of the ELM (Petty and Cacioppo, 1986) which suggests that the intention resulting from cues such as scarcity, celebrity, and social proof is explained by the fact that these cues bypass the need for an analytical evaluation.

In both conditions of scarcity and urgency, the participants had a positive purchase intention, similar to what was found in H ($M = 4.27$, $t(185) = 24.46$, $p < .001$). It is important to note that there was no no-cue condition included in the design so it is not the intention that fell short of the neutral point, but the intention that surpassed the neutral point. This discovery is consistent with the theory of commodities, which leads to the conclusion that the more scarce a product is, the higher its subjective value is, and as a result, the more motivated to acquire a product one becomes. (Brock, 1968) It also supports the dual-process theory (Kahneman, 2011): availability and time-related cues activate System 1, which inhibits analytical deliberation and boosts the likelihood of impulsive decision making. The findings are aligned with Peng et al., (2019) and Good and Hyman, (2020) who reported that the purchase intentions were higher in the conditions of artificially induced scarcity, even when the consumers know that it was manipulated. This is also consistent with the findings of Sin et al. (2023) who reported that consumers' purchase intention was higher in artificially induced scarcity environment even when consumers were aware that it was manipulated.

Above neutral participant reported purchase intention for celebrity endorsement ($M = 4.37$, $t(185) = 23.61$, $p < .001$, $d = 1.73$), which supported H2. This is in line with the source credibility model (Ohanian, 1990) that suggests that the perceived expertise, trustworthiness and attractiveness of the endorser boost receptivity to the endorsed product. The match-up hypothesis (Kamins, 1990) also implies that endorsement effects are magnified if the celebrity is congruent with the product category. The qualitative results also supported this, as the association with celebrities was a recurring theme for participants as a reason to consider a purchase. The results are in line with Wang et al. (2021) and Kim and Johnson (2016).

The review/social proof condition produced the strongest above-neutral result, supporting H3 ($M = 4.44$, $t(185) = 33.36$, $p < .001$, $d = 2.45$). Bonferroni-corrected pairwise comparisons showed that social proof significantly affected intention scores compared to scarcity/urgency ($p = .039$), while, the scores of social proof were not significantly different from scores of celebrity endorsement ($p = 1.000$). This claim of

social proof being the 'most effective' cue is thus only partially supported inferentially: it is merely descriptive of its benefit over celebrity endorsement. This aligns with Cialdini's (2001) social proof theory that people tend to imitate others' behavior when they are uncertain about their own. For online retailers, who do not have the luxury of actually inspecting the goods, ratings and reviews act as a substitute for quality, and in turn minimise the perceived risk of purchase (Kim & Johnson, 2016). The results correspond to those of Chen et al. (2008), who observed that volume of reviews and numerical ratings was more likely to lead to a purchase intention than the actual text of the review and with Mathur et al. (2019) who found that social validation was one of the most consistently leveraged persuasive mechanisms on large-scale ecommerce platforms. The qualitative results also confirmed this, with ratings, reviews and perceived popularity being the key factors in people's decisions.

H4 was supported: participants reported above-neutral awareness of hidden-fee price increases ($M = 3.93$, $t(185) = 14.37$, $p < .001$, $d = 1.05$). However, it wasn't because H5 was not supported, it was because the data was contrary to the prediction. Hidden fees were not negatively associated with purchase continuation, but positively ($\rho = 0.661$, $p < .001$). This is the most counter-intuitive and theoretically important finding of this study. The model was designed to provide a direct interpretation model, the Persuasion Knowledge Model (Friestad and Wright, 1994), which distinguishes between the activated persuasion knowledge (the recognition that a persuasion attempt is being made) and behavioural resistance to the attempt, and suggests that the two do not need to occur together. The fees are typically not obvious to consumers, however, they may not be able to opt out of a transaction because the momentum and friction of the website interface, and the emotional relationship consumers feel with the product. Following the sludge concept of Thaler and Sunstein (2008) and Sin et al. (2023), sludge is defined as a by-product of a plant that results from the processing of water. The concept of sludge is that of Thaler and Sunstein 2008 and Sin et al. 2023: a by-product of a water processing plant. It is also worth noting that the number of the hidden-fee notice item is not indicative of actual attention to manipulation; high-confidence consumers might notice the fees and still use the product. In future research, these interpretations may be further elucidated using additional measures of behaviour.

Another thing to consider is the intention-behaviour gap. Throughout, the dependent variable is self-reported purchase intention in hypothetical scenarios rather than purchase behaviour. Empirical evidence from the meta analysis literature (Sheeran, 2002; Sheeran and Webb, 2016) supports this proposition, revealing that intention measures have a systematic over prediction effect on behaviour. Hassan et al. (2021) specifically investigated the intention-behaviour gap in ethical consumption and found that the gap between intention and actual behavior is significant and systematic, offering a direct point of reference for the interpretation of the results of the intention based study. In e-commerce, abandoned carts range from 60-70% meaning it's no cakewalk to convert intention to behaviour. The H5 finding can manifest in very different ways when the measure is behavioural: consumers that do notice unexpected fees may want to proceed but drop out of the car at higher rates. The assumption in the recommendation for consumer literacy programmes is that this awareness gap can be bridged if the behavioural gap is to be bridged. This assumption is questioned by the H5 finding. In this regard, the recommendations made in practice ought to be proportional to the evidence that the design supports.

This study has several limitations. First, convenience sampling via social media may introduce self-selection bias. Second, the sample was predominantly younger adults (18–34), limiting generalisability to older consumer groups. Third, the scenario-based design has limited ecological validity, as hypothetical purchase situations may not replicate the financial and emotional stakes of real purchases. Fourth, social desirability bias may have affected responses, particularly regarding awareness of manipulative design. Fifth, the cross-sectional design prevents causal inference. Sixth, because there was no no-cue control condition, the t-tests only do not only show that intention was greater than the neutral condition, but also that cues were greater than the neutral condition. Seventh, inter-rater reliability was not formally evaluated, since the coding was done by one analyst.

Future studies should use longitudinal or experimental designs with matched control conditions to establish causal links between persuasive cues and purchase intention. Incorporating actual transaction data would increase ecological validity. More culturally, demographically, and socioeconomically diverse samples would improve generalisability. Research examining how digital literacy moderates susceptibility to persuasive cues and deceptive design would also be a valuable contribution (Mathur et al., 2019).

CONCLUSION

The aim of this study was to analyse the impact of persuasive digital marketing tactics on consumer purchasing intention in e-business. The results show that each of the four conditions of persuasion (scarcity and urgency, celebrity endorsement, social proof, and hidden-fee awareness) produced above neutral intention scores. The mean purchase intention score for social proof mechanisms was significantly higher than the mean score for scarcity/urgency but not significantly different from the mean score for celebrity endorsement; it is therefore partially inferentially supported. Heuristic processing was evident as consumers relied heavily on digital retail interfaces, in line with the dual-process theory (Kahneman, 2011) and Elaboration Likelihood Model (Petty and Cacioppo, 1986). Perhaps most interestingly, there was a positive not negative relationship between the recognition of hidden-fee manipulation and purchase continuation, suggesting that the Persuasion Knowledge Model (Friestad and Wright, 1994) can be used to explain the results: activation of awareness of persuasion does not necessarily lead to behavioural resistance. The outcomes of this finding run counter to the assumption on which consumer literacy programmes are based: that increasing awareness is enough to decrease compliance with deceptive design. However, it must be noted that all the findings of this research are limited by intentional design and the practical suggestions on ethical platforms design, consumer protection policy and digital programmes of literacy presented here are theoretical suggestions reflecting hypothetical situations rather than actual purchase behaviour, and their validity in the real world is dependent on the extent to which the intention-behaviour gap can be bridged. Together, the findings demonstrate the growing psychological power of persuasive digital surfaces and the importance of designing platforms ethically, ensuring sufficient consumer protection policies, and providing digital literacy education that is grounded in critical analysis of the intensely commercialised digital retail environment.

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Appendix A: Survey Instrument

Q1. Enter your email

Open text field. Not used in analysis (no emails were recorded or stored per the study's ethics protocol).

Q2. What is your gender?

Options: Female | Male | Non-binary

Q3. What's your age?

Options: 18–24 | 24–34 | 34–44 | 44–54 | 54–64 | 64–74

Q4. What's your average monthly income?

Options: Below 25K | 25–50K | 50–75K | 75K–1 Lakh | Above 1 Lakh

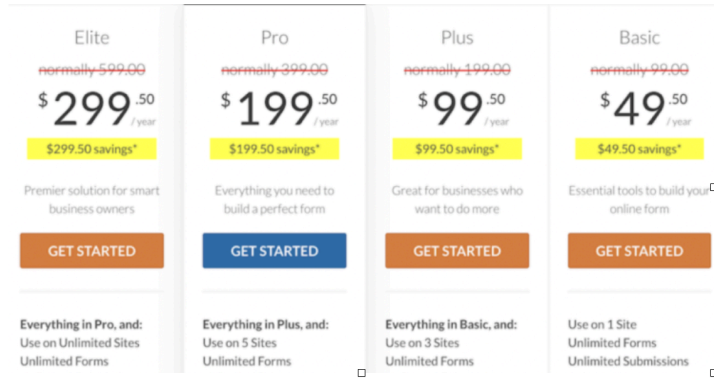
Q5. How often do you shop online?

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Options: Daily | Weekly | Monthly | Couple of times a year

Q6. Out of the 4 options given below, which subscription are you more likely to buy?



Response format: Single select.

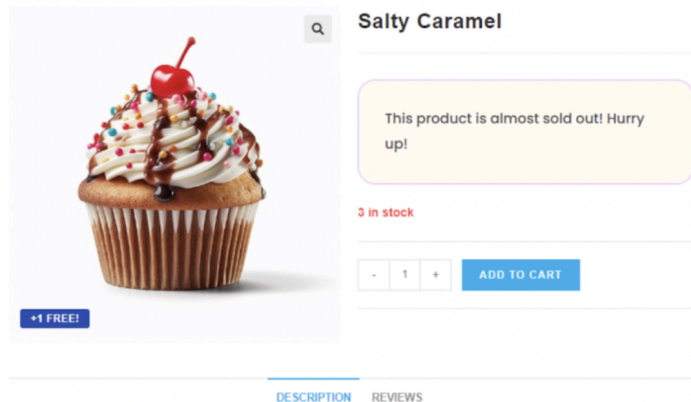
Options: Elite | Pro | Plus | Basic

Q7. Why did you choose this answer option?

Open text field. Used in qualitative thematic analysis.

Q8. How likely are you to buy the cupcake shown below?

Stimulus image shown to participants:



Response format: Five-point Likert scale.

Scale: 1 = Not likely at all | 2 = Unlikely | 3 = Neutral | 4 = Likely | 5 = Very likely

Q9. Why did you choose this answer option?

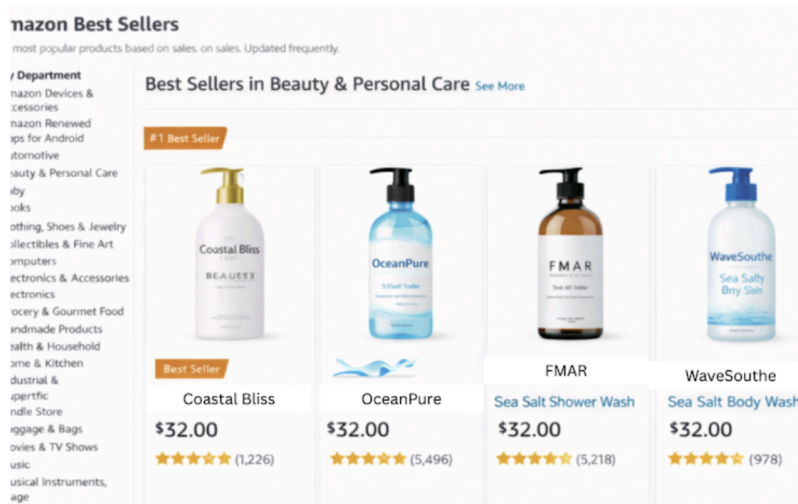
Open text field. Used in qualitative thematic analysis.

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Q10. Which product are you more likely to buy out of the 4 given below? *

Stimulus image shown to participants:



Response format: Single select.

Options: Coastal Bliss | Ocean pure | FMAR | WaveSouthe

Q11. Why did you choose this answer option?

Open text field. Used in qualitative thematic analysis.

Q12. How likely are you to buy this bottle given that Taylor Swift is promoting it?

Stimulus image shown to participants:



Response format: Five-point Likert scale.

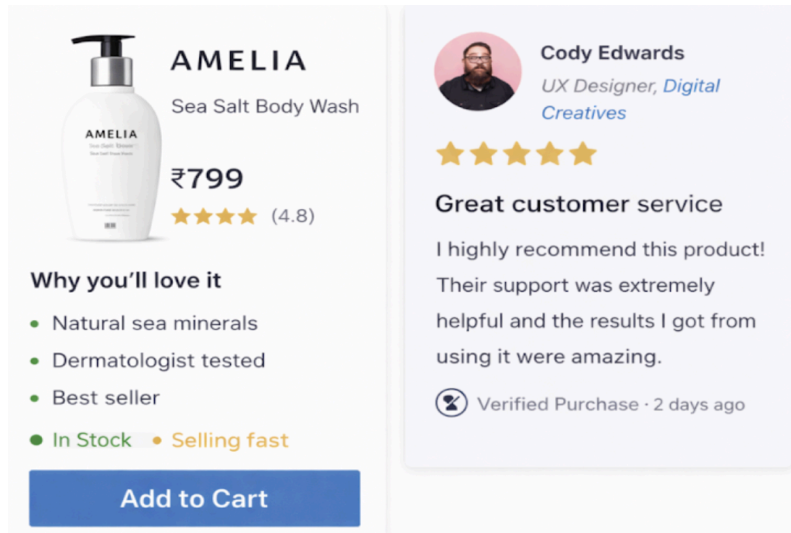
Scale: 1 = Not likely at all | 2 = Unlikely | 3 = Neutral | 4 = Likely | 5 = Very likely

Q13. Why did you choose this answer option?

Open text field. Used in qualitative thematic analysis.

Q14. Based on the review, how likely are you to buy this product?

Stimulus image shown to participants:



Response format: Five-point Likert scale.

Scale: 1 = Not likely at all | 2 = Unlikely | 3 = Neutral | 4 = Likely | 5 = Very likely

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Q15. Why did you choose this answer option?

Open text field. Used in qualitative thematic analysis.

Q16. How likely are you to notice the price increase from step 1 to step 2?

Stimulus image shown to participants:

1. Towards the start of the user's journey on stubhub.com, they are shown a price.

112

Row Y

You'll pay

\$310 each

Quantity

1 ticket

▼

2. The user proceeds through multiple steps in which they must enter their name, phone number, email and postal address. Only then are they shown the total price. In this case it is a 29% increase.

Ticket Price	1 × US\$ 310.05
Service Fee	1 × US\$ 86.13
Fulfillment Fee	1 × US\$ 4.95
TOTAL PRICE	US\$ 401.13

Response format: Five-point Likert scale.

Scale: 1 = Not likely at all | 2 = Unlikely | 3 = Neutral | 4 = Likely | 5 = Very likely

Q17. If you were to notice it, would you still go ahead and buy it? *

Response format: Single select.

Options: Yes | No | Maybe