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Social Proof, Scarcity, and Discounts: Experimental Evidence on Digital Nudges in E-Commerce

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Abstract. The proliferation of digital nudges in e-commerce interfaces has reshaped consumer decision-making, yet their psychological mechanisms and societal implications remain contested, particularly in non-Western markets. This paper examines how three dominant interface defaults—social proof (“Top ranked”), monetary framing (“40% off”), and urgency cue (“Livestream ends in 3 minutes”)—influence willingness to pay and decision difficulty in China’s fast-paced digital marketplace. Using a randomized survey experiment with 519 respondents, we measure the causal effects of these nudges on engagement, purchase intent, and cognitive strain. Results show that nudges collectively increase WTP by 0.775 points (on a 5-point scale), with urgency cue producing the largest gains (1.063 points) but also raising decision difficulty by 0.304 points. Social proof and monetary framing boost WTP without increasing cognitive load. Heterogeneity analyses reveal stronger responses among women to social proof, greater sensitivity among lower-income users to discounts, and lower decision difficulty among tier-1 city residents. These findings highlight that the effectiveness and costs of digital nudges depend on demographic context and user characteristics, underscoring the need for ethical, user-centered interface design in digital commerce.

Keywords: Digital nudges, E-commerce, Social proof, Urgency cue, Consumer behavior

1. Introduction

The growth of digital markets has made small design choices—such as interface defaults, behavioral nudges, and algorithmic recommendations—important drivers of consumer decisions. In China’s e-commerce sector, where online retail sales reached ¥15.52 trillion (US$2.17 trillion) in 2024, making up 26.8% of total retail consumption, the use of these nudges is now a core part of platform strategy. However, the ways they influence consumers, and their effects on different groups, are still not well understood in fast-changing, emerging economies. Digital interfaces often use tactics like social proof, time limits, and discount framing to guide behavior. These tools can make it easier for people to make choices, but they can also be used to shape decisions in ways that raise ethical

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concerns [1]. This mix of benefits and risks makes it important to study how these defaults work in specific cultural and market settings.

Research in behavioral economics shows that defaults can change decisions, but their online versions are more complex [2]. Digital nudges can be updated in real time, tailored to each user, and hard to detect. For example, a countdown like "Livestream ends in 3 minutes" takes advantage of people's tendency to value the present more than the future [3], while a "Top ranked" label relies on social influence [4]. These strategies can have stronger effects on certain groups, such as low-income consumers or people with limited time. Policymakers in many regions, including through the EU's Digital Services Act [5] and China's new Personal Information Protection Law [6], have started to respond to these risks. Still, little is known about how nudges work in China's unique setting, which combines collectivist social norms, livestream commerce, and heavy algorithmic targeting. This study aims to address that gap.

We test the effects of three common interface defaults—social proof, monetary framing, and Urgency cue—on willingness to pay and decision difficulty. Using a randomized survey of 519 respondents from across China's cities, we measure engagement, purchase intent, and decision difficulty. On average, nudges increase WTP by 0.775 points (on a 5-point scale). Urgency cue has the largest effect (1.063 points) but also raises decision difficulty by 0.304 points. Social proof and monetary framing both raise WTP without adding to decision difficulty, showing that they work through different psychological channels.

The effects vary by demographic and product type. Women respond 40% more strongly to social proof than men. Lower-income consumers show a 0.726-point WTP increase under discount framing, twice the effect seen in higher-income groups. People in tier-1 cities report 20% lower decision difficulty, suggesting that experience with online shopping reduces mental effort. Urgency cue has a larger effect for luxury products like perfume (1.441 points) than for basic goods like tissue. These results suggest that the success of nudges depends on both the audience and the type of product.

We check the robustness of our results by removing responses that were completed too quickly and by testing different statistical models, including nonlinear age effects. The results remain stable, even after adjusting for imbalances like the higher number of young respondents in some treatment groups.

Our work adds to two areas of research. First, it extends Thaler and Sunstein's [2] idea of "libertarian paternalism" by showing that digital nudges work differently across cultures—social proof's strength in China fits with collectivist values, while urgency cues build on loss aversion found in many cultures. Second, it adds to research in behavioral human–computer interaction [7] by examining not just how nudges raise motivation (WTP) but also how they affect mental effort (decision difficulty). By looking at both sides, we question the common view that defaults are harmless.

The rest of this paper is organized as follows: Section 2 reviews the theory and ethical debates on digital nudges. Section 3 explains the survey and method. Section 4 presents the results, including subgroup analysis and robustness checks. Section 5 discusses what the findings mean for policy and platform design, focusing on transparency and fairness.

2. Literature review

The proliferation of digital nudges—subtle design elements that guide user behavior—has reshaped decision-making in e-commerce, raising important questions about their effectiveness, psychological mechanisms, and ethical implications. While behavioral economics has long documented the

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influence of defaults on choice [2], recent research highlights that these interventions operate differently across cultural and socioeconomic contexts [7]. This review synthesizes theoretical foundations, empirical evidence, and ethical debates surrounding three nudges central to our study: social proof, monetary framing, and urgency cue. By integrating insights from cognitive psychology, behavioral economics, and human–computer interaction (HCI), we contextualize their effects on willingness to pay and decision difficulty, while critically assessing their broader societal consequences.

Nudges work by exploiting systematic cognitive biases, as explained in Kahneman's [8] dual-process theory. System 1 (fast, intuitive thinking) is especially vulnerable to urgency cues—such as "Livestream ends in 3 minutes"—which trigger loss aversion and impulsive responses [3]. While System 2 (slow, deliberative thinking) can counteract such effects, its influence is often diminished in high-speed digital environments.

Social proof draws on conformity bias [9], where individuals use collective behavior as a heuristic for quality. Monetary framing relies on mental accounting [10], making discounts more salient than absolute prices and thus particularly effective for price-sensitive consumers. Urgency cue cues induce hyperbolic discounting [11], causing users to prioritize immediate rewards over longer-term considerations. Although libertarian paternalism views nudges as benign guidance that preserves choice, the shift toward "algorithmic paternalism" in digital platforms can blur this line—especially when practices like false scarcity intentionally manipulate rather than assist consumers.

Empirical evidence supports the potency of these nudges. Meta-analyses show that social proof can increase conversions by up to 30% [12], especially for experiential goods. Monetary framing often resonates most with lower-income consumers, time scarcity reliably boosts urgency but may impose cognitive costs, as shown in trade-offs between higher WTP and increased decision difficulty. Effects also vary by demographic: younger users, who rely more on heuristics, are generally more susceptible to social proof, while product type matters—necessities show smaller WTP increases than luxury goods. Cultural context plays a further role, with collectivist norms in China likely amplifying the influence of social proof compared to more individualistic Western markets.

Critics argue that such nudges can disproportionately target low-income users and time-pressed workers [13], potentially exacerbating inequality by encouraging impulsive spending and reinforcing algorithmic coercion. Regulatory responses have begun to emerge: the European Union's Digital Services Act prohibits deceptive nudges, while China's Personal Information Protection Law addresses data privacy but does not explicitly regulate nudging practices. Proposed measures include mandating transparency in algorithmic curation and banning fabricated scarcity, aiming to balance innovation with consumer protection.

While nudges have been widely studied in domains such as finance, their role in China's distinctive digital marketplace, particularly in live-streaming e-commerce, remains under-explored. Understanding how these strategies influence purchasing desire, decision difficulty, and potential long-term desensitization is essential for designing interventions that balance platform profitability with user well-being. This study contributes to filling that gap by empirically testing the effects of social proof, monetary framing, and urgency cue on Chinese consumers.

3. Hypothesis development

Descriptive social cues—such as "Top Ranked" or "500+ people have ordered"—reduce decision uncertainty by signaling popularity and providing implicit recommendations. Prior studies suggest that social proof increases engagement even in the absence of direct economic benefits, as

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consumers use collective behavior as a heuristic for product quality [12]. Based on this evidence, we expect socially anchored defaults to positively influence willingness to pay.

Hypothesis 1: Interface defaults based on social norms significantly increase consumers' willingness to pay.

Monetary framing—such as "40% off" or "¥4.20 saved"—activates mental accounting processes, making price reductions appear more salient than absolute prices [10]. This framing can reframe discretionary purchases as financially justified, especially for hedonic goods. We test whether highlighting savings through monetary framing leads to higher WTP.

Hypothesis 2: Interface defaults that frame monetary savings significantly increase consumers' willingness to pay.

Time-based scarcity cues (e.g., "Only 2 minutes left!") create perceived urgency, reducing the time available for deliberation and increasing the likelihood of impulse purchases. A 2023 meta-analysis in Heliyon [14] found that urgency-based nudges are particularly effective in fast-paced, low-risk e-commerce contexts. We examine whether embedding urgency cues in product displays increases WTP.

Hypothesis 3: Urgency-based interface defaults significantly increase consumers' willingness to pay.

While social proof and monetary framing generally aim to enhance engagement without imposing substantial mental strain, time pressure may increase decision difficulty. Scarcity cues restrict cognitive bandwidth and elevate psychological stress, particularly under time constraints [15, 16]. We test whether urgency uniquely raises reported decision difficulty compared to other defaults.

Hypothesis 4: Urgency-based interface defaults significantly increase consumers' reported decision difficulty.

4. Data and empirical approach

We analyse 519 complete survey responses collected between 2 and 5 August 2025 through WeChat groups, QQ, and Rednote. Four versions of the questionnaire were circulated. The control condition, which contained no persuasive cue, included 183 participants. The three treatment groups each embedded a single behavioural nudge in every product display: Treatment A applied a social proof message reading "top ranked in category" (n = 130); Treatment B presented a monetary frame stating a forty per cent discount (n = 71); and Treatment C displayed a time urgency notice indicating that "the livestream will end in three minutes" (n = 135). Although assignment was not software-randomised, distributing the links across multiple social media channels yielded a heterogeneous sample.

Each respondent evaluated the same three products—tissue paper, milk tea, and perfume—in this fixed order. For each item, participants indicated whether they would click on it (inclination, coded 0 or 1), how willing they were to purchase it (willingness to pay, measured on a five-point scale), and how difficult the decision felt (decision difficulty, measured on a five-point scale). The mean of these answers across the three products constitutes indices of overall engagement, purchase intention, and perceived decision cost, while the original item responses remain available for product-specific analysis.

The choice of products reflects deliberate variation across categories of consumer goods. Tissue paper represents a necessity good, milk tea serves as a mid-range discretionary good, and perfume represents a luxury good. This design allows us to observe whether behavioural nudges exert different influences depending on the nature of the product and its typical role in household

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consumption. By spanning this spectrum, we can examine whether persuasion is more effective for essential purchases, everyday indulgences, or symbolic luxury items.

Independent variables in the study are the treatment conditions (social proof, monetary framing, urgency cue, and the control group). Dependent variables are the three outcome measures: inclination, willingness to pay, and perceived decision difficulty. Demographic covariates capture sources of heterogeneity identified in previous research. Age is measured on a four-point scale, reflecting the finding that younger consumers tend to rely more on heuristics under uncertainty. Gender is recorded as a binary variable, consistent with evidence that framing effects can vary between men and women. Occupation and income act as proxies for socio-economic status, which may influence sensitivity to price cues. City tier distinguishes respondents across China's four urban strata and therefore reflects variation in digital familiarity and platform exposure. Online purchase frequency measures habitual e-commerce use. The definitions of these categories follow those of the National Bureau of Statistics [6].

Table 1. Descriptive statistics for all data combined

Variable	Mean	Std. Dev.	Min	Max	Obs.
Outcome variables					
All products					
Inclination	0.52	0.37	0	1	336
Willingness	2.88	0.96	1	5	336
Difficulty	2.53	0.93	1	5	336
Tissue					
Inclination	0.53	0.50	0	1	336
Willingness	2.93	1.20	1	5	336
Difficulty	2.60	1.13	1	5	336
Milk tea					
Inclination	0.52	0.50	0	1	336
Willingness	2.97	1.24	1	5	336
Difficulty	2.46	1.12	1	5	336
Perfume					
Inclination	0.51	0.50	0	1	336
Willingness	2.73	1.29	1	5	336
Difficulty	2.54	1.23	1	5	336
Demographic variables					
Age	1.80	0.97	1	4	336
Occupation	2.55	0.85	1	4	336
Gender	0.37	0.48	0	1	336
Income	2.42	1.14	1	4	336
City Tier	3.17	1.07	1	4	336
Purchase Freq.	2.48	0.81	1	4	336

Notes: Outcome variables include Inclination (binary indicator of inclination: 0 = no, 1 = yes), Willingness (self-reported willingness to pay on a 1–5 Likert scale), and Difficulty (self-reported decision difficulty on a 1–5 Likert scale). Demographic variables are coded

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as follows: Age (1 = below 18, 2 = 18-35, 3 = 36-55, 4 = 55+), Occupation (1 = student, 2 = currently working, 3 = freelancer, 4 = other), Gender (1 = male, 0 = female), Income (1 = <¥3,000, 2 = ¥3,000–6,000, 3 = ¥6,001–10,000, 4 = >¥10,000), City Tier (1 = tier-4 or below, 2 = tier-3, 3 = tier-2, 4 = tier-1), and Online Purchase Frequency (1 = <1 time/month, 4 = >5 times/week).

Table 2. Descriptive statistics for control group (no intervention)

Variable	Mean	Std. Dev.	Min	Max	Obs.
Outcome variables					
All products					
Inclination	0.28	0.3	0	1	183
Willingness	1.99	0.77	1	5	183
Difficulty	2.46	0.9	1	5	183
Tissue					
Inclination	0.27	0.45	0	1	183
Willingness	2.12	1.14	1	5	183
Difficulty	2.45	1.12	1	5	183
Milk tea					
Inclination	0.3	0.46	0	1	183
Willingness	2.16	1.25	1	5	183
Difficulty	2.55	1.14	1	5	183
Perfume					
Inclination	0.26	0.44	0	1	183
Willingness	1.68	0.98	1	5	183
Difficulty	2.38	1.21	1	5	183
Demographic variables					
Age	2.56	0.83	1	4	183
Occupation	2.43	0.88	1	4	183
Gender	0.42	0.49	0	1	183
Income	2.38	1.38	1	4	183
City Tier	3.77	0.61	1	4	183
Purchase Freq.	2.47	0.80	1	4	183

Notes: See Table 1 for definitions and coding of outcome and demographic variables.

Table 3. Descriptive statistics for treatment a (social norms)

Variable	Mean	Std. Dev.	Min	Max	Obs.
Outcome variables					
All products					
Inclination	0.61	0.37	0	1	130
Willingness	2.75	0.96	1	5	130
Difficulty	2.42	0.98	1	5	130
Tissue					

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Table 3. (continued)

Inclination	0.63	0.48	0	1	130
Willingness	2.87	1.27	1	5	130
Difficulty	2.45	1.18	1	5	130
Milk tea					
Inclination	0.62	0.49	0	1	130
Willingness	2.77	1.26	1	5	130
Difficulty	2.33	1.12	1	5	130
Perfume					
Inclination	0.57	0.5	0	1	130
Willingness	2.61	1.21	1	5	130
Difficulty	2.48	1.22	1	5	130
Demographic variables					
Age	1.86	1.07	1	4	130
Occupation	2.72	0.91	1	4	130
Gender	0.39	0.49	0	1	130
Income	2.46	1.11	1	4	130
City Tier	3.07	1.12	1	4	130
Purchase Freq.	2.38	0.85	1	4	130

Notes: See Table 1 for definitions and coding of outcome and demographic variables.

Table 4. Descriptive statistics for treatment B (monetary framing)

Variable	Mean	Std. Dev.	Min	Max	Obs.
Outcome variables					
All products					
Inclination	0.52	0.34	0	1	71
Willingness	3.13	0.98	1	5	71
Difficulty	2.94	0.78	1	5	71
Tissue					
Inclination	0.63	0.49	0	1	71
Willingness	2.94	1.26	1	5	71
Difficulty	2.96	1.10	1	5	71
Milk tea					
Inclination	0.35	0.48	0	1	71
Willingness	3.34	1.32	1	5	71
Difficulty	2.97	1.03	1	5	71
Perfume					
Inclination	0.56	0.50	0	1	71
Willingness	3.11	1.36	1	5	71

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Table 4. (continued)

Difficulty	2.89	1.06	1	5	71
Demographic variables					
Age	1.76	0.84	1	3	71
Occupation	2.44	0.89	1	4	71
Gender	0.48	0.50	0	1	71
Income	2.08	0.98	1	4	71
City Tier	2.76	1.13	1	4	71
Purchase Freq.	2.32	0.69	1	4	71

Notes: See Table 1 for definitions and coding of outcome and demographic variables.

Table 5. Descriptive statistics for treatment C (urgency cue)

Variable	Mean	Std. Dev.	Min	Max	Obs.
Outcome variables					
All products					
Inclination	0.44	0.36	0	1	135
Willingness	2.86	0.92	1	5	135
Difficulty	2.43	0.90	1	5	135
Tissue					
Inclination	0.38	0.49	0	1	135
Willingness	2.97	1.09	1	5	135
Difficulty	2.57	1.08	1	5	135
Milk tea					
Inclination	0.51	0.50	0	1	135
Willingness	2.98	1.14	1	5	135
Difficulty	2.31	1.09	1	5	135
Perfume					
Inclination	0.44	0.50	0	1	135
Willingness	2.64	1.31	1	5	135
Difficulty	2.42	1.28	1	5	135
Demographic variables					
Age	1.76	0.94	1	4	135
Occupation	2.45	0.74	1	4	135
Gender	0.28	0.45	0	1	135
Income	2.56	1.21	1	4	135
City Tier	3.48	0.90	1	4	135
Purchase Freq.	2.66	0.81	1	4	135

Notes: See Table 1 for definitions and coding of outcome and demographic variables.

In the control condition (table 2), the average inclination is 0.28, willingness to pay is 1.99, and decision difficulty is 2.46. Each nudge increases these outcomes to varying degrees. Social proof produces the highest engagement, with mean inclination rising to 0.61 and willingness to pay increasing to 2.75, while decision difficulty remains almost unchanged at 2.42. Monetary framing yields the largest increase in willingness to pay, reaching 3.13, but also the highest reported decision difficulty at 2.94. Time urgency produces an intermediate willingness to pay score of 2.86 and decision difficulty of 2.43, with inclination at 0.44, which is lower than in the other treatment groups.

Treatment groups tend to be somewhat younger than the control group: mean age scores are 1.86 for Treatment A (table 3), 1.76 for Treatments B (table 4) and C (table 5), and 2.56 for the control. Respondents in Treatment B (table 4) are more likely to come from lower-tier cities, with a mean of 2.76, whereas the control group is concentrated in higher-tier urban centres, with a mean of 3.77. Average income is lowest in Treatment B (table 4) at 2.08 and highest in Treatment C (table 5) at 2.56. Gender distributions are broadly similar across conditions, except for a slightly higher proportion of men in the urgency group.

At the product level, behavioural cues are most influential for perfume, the most discretionary item in the set. Inclination for perfume rises from 0.26 in the control condition (table 1) to 0.57 with social proof (table 3), 0.56 with monetary framing (table 4), and 0.44 with time urgency (table 5). Monetary framing (table 4) also yields the highest willingness to pay score for perfume at 3.11, compared with 1.68 in the control condition, while decision difficulty remains close to the control benchmark except under the discount frame, where it rises modestly.

The descriptive evidence already indicates that embedded behavioural cues increase engagement and willingness to pay, though the magnitude of the effect and the associated decision cost vary according to the type of nudge and the product category. The regression analysis that follows quantifies these patterns while adjusting for demographic imbalance.

Treatment effects are estimated using ordinary least squares according to the following baseline specification:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \varepsilon_i \tag{1}$$

where Y_i is inclination, willingness to pay, or decision difficulty for respondent i; T_i is an indicator for treatment exposure, either as a composite dummy or as separate dummies for Treatments A, B, and C; X_i is the vector of demographic controls described above; and ε_i is the error term. Additional models stratify the sample by gender and by city tier to explore heterogeneous responses. Because treatment assignment depended on link distribution rather than strict randomisation, the results are interpreted as associations rather than causal effects.

5. Main results

Table 6. Treatment effects on inclination, willingness to pay, and decision difficulty (pooled sample)

Dependent variable:	Inclined		Willingness		Difficulty	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.244***	0.237***	0.890***	0.775***	0.074	-0.070
	(0.032)	(0.037)	(0.082)	(0.093)	(0.085)	(0.097)
Age		0.011		-0.106**		-0.090*

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Table 6. (continued)

		(0.017)		(0.045)		(0.046)
Gender		-0.062*		-0.130		-0.074
		(0.034)		(0.086)		(0.090)
Occupation		0.027		-0.070		0.048
		(0.019)		(0.049)		(0.051)
Income		-0.032**		-0.004		-0.054
		(0.014)		(0.037)		(0.038)
City tier		-0.016		-0.056		-0.113**
		(0.017)		(0.042)		(0.044)
Purchase freq.		0.020		0.190***		-0.036
		(0.021)		(0.053)		(0.055)
Constant	0.277***	0.296***	1.985***	2.233***	2.461***	3.248***
	(0.026)	(0.104)	(0.066)	(0.264)	(0.068)	(0.276)
N	519	519	519	519	519	519
R^2	0.102	0.123	0.184	0.229	0.001	0.030

Notes: Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. Columns (1), (3), and (5) exclude control variables; Columns (2), (4), and (6) include controls for Age, Gender, Occupation, Income, City Tier, and Purchase Frequency.

Table 6 presents the estimated treatment effects of digital nudges. The coefficient on Treat in columns (1) and (2) is positive and statistically significant, indicating higher inclination with treatment exposure. Similarly, the coefficient on Treat in columns (3) and (4) is positive and statistically significant, showing increased willingness to pay, robust to covariates. In contrast, the coefficient on Treat in columns (5) and (6) is not statistically significant but remains positive, suggesting no meaningful effect on perceived decision difficulty.

Among controls, the coefficient on Age in column (4) is −0.165 ($p < 0.01$), indicating a significant negative effect on willingness to pay. Online shopping frequency (col. 4) has a positive and significant effect, while the coefficient on Male in column (2) is negative and marginally significant, implying a slightly lower inclination. Finally, the coefficient on City tier in column (6) is negative and significant, suggesting respondents from lower-tier cities reported greater ease in decision-making.

Table 7. Treatment effects on inclination, willingness to pay, and decision difficulty

Dependent variable:	Inclined	Willingness	Difficulty
	(1)	(2)	(3)
Social Norms (A)	0.329***	0.696***	-0.185
	(0.044)	(0.112)	(0.116)
Monetary Framing (B)	0.162***	0.726***	-0.122
	(0.042)	(0.108)	(0.112)
Urgency Cue (C)	0.240***	1.063***	0.304**
	(0.053)	(0.135)	(0.140)
Age	0.010	-0.105**	-0.088*

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Table 7. (continued)

	(0.017)	(0.044)	(0.046)
Gender	-0.068**	-0.147*	-0.095
	(0.033)	(0.086)	(0.089)
Occupation	0.017	-0.064	0.056
	(0.019)	(0.049)	(0.051)
Income	-0.031**	0.001	-0.048
	(0.014)	(0.036)	(0.038)
City tier	-0.006	-0.037	-0.089**
	(0.017)	(0.043)	(0.045)
Purchase frequency	0.028	0.191***	-0.035
	(0.021)	(0.053)	(0.055)
Constant	0.270***	2.136***	3.125***
	(0.104)	(0.266)	(0.276)
N	519	519	519
R^2	0.148	0.242	0.056

Notes: Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. Dependent variables: inclined (binary indicator of inclination: 0 = no, 1 = yes), willingness (1–5 scale), difficulty (1–5 scale). Models include controls for age, gender, occupation, income, city tier, and online purchase frequency. N = 519.

Table 7 reports the treatment effects of social proof (Treatment A), monetary framing (Treatment B), and the urgency cue (Treatment C) on inclination, willingness to pay, and perceived decision difficulty. For inclination (col. 1), the coefficient on Treatment A is positive and statistically significant, indicating the largest increase among the three nudges; the coefficients on Treatments B and C are also positive and statistically significant. For willingness to pay (col. 2), the coefficient on Treatment C is positive and statistically significant and is the largest of the three; the coefficients on Treatments A and B are likewise positive and statistically significant. For perceived decision difficulty (col. 3), the coefficients on Treatments A and B are not statistically significant, whereas the coefficient on Treatment C is positive and statistically significant, indicating higher decision difficulty under the urgency cue.

Among the covariates, the coefficient on age is negative and statistically significant for willingness to pay (col. 2), while the coefficient on online-purchase frequency is positive and statistically significant for willingness to pay (col. 2). Inclination is slightly lower among male and higher-income respondents (negative coefficients in col. 1). The coefficient on city tier is negative and statistically significant for decision difficulty (col. 3), indicating lower reported decision difficulty in higher-tier cities.

Table 8. Treatment effects on inclination, willingness to pay, and decision difficulty for tissue

Dependent variable:	Inclined	Willingness	Difficulty
	(1)	(2)	(3)
Social Norms (A)	0.372***	0.690***	-0.136
	(0.060)	(0.151)	(0.144)
Monetary Framing (B)	0.148**	0.749***	0.046

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Table 8. (continued)

	(0.057)	(0.145)	(0.139)
Urgency Cue (C)	0.394***	0.769***	0.368**
	(0.072)	(0.182)	(0.174)
Age	0.073***	-0.043	-0.103*
	(0.023)	(0.059)	(0.057)
Gender	-0.041	-0.027	0.004
	(0.046)	(0.115)	(0.110)
Occupation	0.078***	-0.027	0.102
	(0.026)	(0.066)	(0.063)
Income	-0.023	0.063	-0.024
	(0.019)	(0.049)	(0.047)
City tier	-0.024	-0.066	-0.039
	(0.023)	(0.058)	(0.055)
Purchase frequency	0.028	0.175**	-0.080
	(0.028)	(0.071)	(0.068)
Constant	-0.011	1.971***	2.865***
	(0.141)	(0.357)	(0.341)
N	519	519	519
R^2	0.149	0.119	0.038

Notes: See Table 7 for definitions and coding of outcome and demographic variables.

Table 8 reports the treatment effects of social proof (Treatment A), monetary framing (Treatment B), and time urgency (Treatment C) on inclination, willingness to pay, and perceived decision difficulty for tissue paper. All three nudges significantly increase inclination and willingness to pay. Time urgency produces the strongest effects, with substantial gains in both inclination and willingness to pay, while social proof also exerts robust positive effects. Monetary framing yields smaller but still statistically significant improvements. Unlike the other treatments, time urgency also raises perceived decision difficulty, suggesting that heightened pressure increases cognitive load.

Among demographic covariates, inclination rises with age and occupation, willingness to pay is higher among frequent online shoppers, and decision difficulty decreases with age. Other controls show no consistent impact.

Table 9. Treatment effects on inclination, willingness to pay, and decision difficulty for milk tea

Dependent variable:	Inclined	Willingness	Difficulty
	(1)	(2)	(3)
Social Norms (A)	0.274***	0.441***	-0.353**
	(0.061)	(0.155)	(0.141)
Monetary Framing (B)	0.163***	0.570***	-0.302**
	(0.059)	(0.150)	(0.136)
Urgency Cue (C)	0.003	0.978***	0.217

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Table 9. (continued)

	(0.074)	(0.187)	(0.170)
Age	-0.049**	-0.222***	-0.070
	(0.024)	(0.061)	(0.055)
Gender	-0.060	-0.303**	-0.063
	(0.047)	(0.119)	(0.108)
Occupation	0.032	-0.017	0.044
	(0.027)	(0.068)	(0.061)
Income	-0.045**	-0.070	-0.120***
	(0.020)	(0.050)	(0.046)
City tier	-0.012	-0.044	-0.104*
	(0.024)	(0.060)	(0.054)
Purchase frequency	0.050*	0.156**	-0.070
	(0.029)	(0.073)	(0.066)
Constant	0.398***	2.844***	3.499***
	(0.145)	(0.368)	(0.334)
N	519	519	519
R^2	0.097	0.156	0.072

Notes: See Table 7 for definitions and coding of outcome and demographic variables.

Table 9 reports the estimated treatment effects of behavioural nudges on milk tea purchase outcomes. In Column (1), the coefficients on Social Proof (Treatment A) and Monetary Framing (Treatment B) are positive and statistically significant, indicating that both interventions increase inclination. The coefficient on Urgency Cue (Treatment C) is also positive but not statistically significant. In Column (2), all three treatments yield positive and significant coefficients, with Urgency Cue producing the strongest increase in willingness to pay. In Column (3), the coefficients on Social Proof and Monetary Framing are negative and statistically significant, suggesting that both treatments reduce perceived decision difficulty, whereas the coefficient on Urgency Cue is positive but not significant.

Table 10. Treatment effects on inclination, willingness to pay, and decision difficulty for perfume

Dependent variable:	Inclined	Willingness	Difficulty
	(1)	(2)	(3)
Social Norms (A)	0.274***	0.441***	-0.353**
	(0.061)	(0.155)	(0.141)
Monetary Framing (B)	0.163***	0.570***	-0.302**
	(0.059)	(0.150)	(0.136)
Urgency Cue (C)	0.003	0.978***	0.217
	(0.074)	(0.187)	(0.170)
Age	-0.049**	-0.222***	-0.070
	(0.024)	(0.061)	(0.055)

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Table 10. (continued)

Gender	-0.060	-0.303**	-0.063
	(0.047)	(0.119)	(0.108)
Occupation	0.032	-0.017	0.044
	(0.027)	(0.068)	(0.061)
Income	-0.045**	-0.070	-0.120***
	(0.020)	(0.050)	(0.046)
City tier	-0.012	-0.044	-0.104*
	(0.024)	(0.060)	(0.054)
Purchase frequency	0.050*	0.156**	-0.070
	(0.029)	(0.073)	(0.066)
Constant	0.398***	2.844***	3.499***
	(0.145)	(0.368)	(0.334)
N	519	519	519
R^2	0.097	0.156	0.072

Notes: See Table 7 for definitions and coding of outcome and demographic variables.

Table 10 reports the treatment effects for perfume. The coefficient on social norms is positive and statistically significant in both Column (1) and Column (2), indicating an increase in inclination and willingness to pay. The coefficient on monetary framing is also positive and significant across these two outcomes, with a somewhat smaller magnitude than social norms. The urgency cue shows no significant effect on inclination (Column 1) but yields a large and statistically significant positive effect on willingness to pay (Column 2). For decision difficulty (Column 3), the coefficients on social norms and monetary framing are negative and significant, indicating that both nudges reduce decision difficulty, while urgency has no statistically significant effect. Among controls, age and income display negative and significant associations with inclination and decision difficulty, respectively, while purchase frequency is positively linked to willingness to pay.

6. Discussion

This study provides evidence that digital nudges—social norm, monetary framing, and time scarcity—can meaningfully influence consumer behavior in online shopping environments. Across all model specifications, exposure to any of these behavioral interventions led to significant increases in both the likelihood of clicking on a product and self-reported willingness to pay to make a purchase. These findings support prior work showing that subtle interface features can guide decision-making in digital contexts [2, 7].

In the pooled analysis, the average treatment effect on inclination nearly doubled the baseline rate. Willingness to pay also increased substantially, by nearly one point on a five-point scale. These changes are both statistically significant and meaningful in practical terms. At the same time, the average effect on decision difficulty was not statistically different from zero. While this might suggest that the nudges did not increase cognitive burden overall, the disaggregated analysis reveals more nuanced patterns across treatment types.

The urgency-based nudge generated the strongest effect on willingness to pay. This is consistent with existing research showing that time-limited offers can trigger more impulsive and emotionally

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driven decision-making by reducing the opportunity for deliberation [17]. However, this treatment was also the only one associated with a significant increase in decision difficulty. The implication is that urgency creates both motivation and pressure, increasing the likelihood of purchase while also making the experience feel more cognitively demanding. These findings echo Barton's [18] meta-analysis, which highlights the psychological trade-offs involved in using time scarcity as a persuasive tool.

The social norm treatment also produced large gains in both inclination and willingness to pay. Unlike the urgency cue, it did not increase decision difficulty. This suggests that signals of popularity help consumers feel more confident in their choices without adding effort or complexity to the decision process. The effect is consistent with research on social heuristics, which shows that people often rely on others' behavior to guide their own in situations involving uncertainty or limited attention [4, 19].

Monetary framing also proved effective, especially in raising willingness to pay. The "40 percent off" message increased willingness to pay by a statistically significant margin and did not significantly affect decision difficulty. The estimated direction was slightly negative, indicating that this treatment may have made decisions feel easier to process. These results align with prior work in pricing psychology, which shows that clear and salient discounts can enhance perceived value and simplify the evaluation process [20, 21]. For lower-cost items like tissue or milk tea, such cues may reduce hesitation and help consumers reach decisions more quickly.

The results show that all three nudges successfully increased motivation, but only some of them affected perceived effort. This distinction matters for design choices. A nudge that is highly persuasive but also introduces pressure may not be ideal in contexts where user comfort and satisfaction are important. In contrast, nudges that guide behavior without increasing decision difficulty may be better suited for promoting sustained engagement across broader audiences.

The data also reveal that individual characteristics shape responsiveness to nudges. Younger respondents and those who shop online more frequently were more likely to express interest and willingness to pay. People with higher occupational status were also more inclined to engage. Interestingly, older participants reported lower decision difficulty, which may reflect greater familiarity with certain product types or more confidence in decision-making. These patterns underscore the value of tailoring digital interventions to specific user profiles, especially in highly segmented online markets.

In the control group, where no nudges were applied, engagement was notably lower. Only 28 percent of respondents indicated any inclination, and average willingness to pay remained below the midpoint of the scale. These outcomes support long-standing theories of limited attention and bounded rationality, which suggest that many individuals require external prompts to engage with choices meaningfully [22, 23]. In addition, participants in the control group reported higher decision difficulty, particularly for more discretionary products. This implies that behavioral cues may not only increase motivation but also reduce the friction involved in making decisions, as described in work on decision simplification [24, 25].

While the study employed random assignment and included a demographically diverse sample, recruitment through Chinese social media platforms presents some limitations. Platform algorithms and social network effects may have influenced the composition of the respondent pool in ways that are difficult to fully observe. Although demographic balancing was implemented, the findings should be interpreted with some caution, especially when extending conclusions beyond this population.

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Overall, the results suggest that digital nudges offer a practical and effective approach to improving consumer engagement and decision-making in online settings. The evidence also points to important differences in how various types of nudges operate. Each has distinct strengths and trade-offs in terms of motivation and perceived effort. Understanding these differences can help platforms and marketers design interventions that not only encourage action but also support a positive user experience.

7. Conclusion

The advent and implementation of digital nudges, such as social prof, monetary framing, and urgency cues, have significantly altered consumer decision processes in e-commerce and even modified user behavior towards online systems. Although prior research has illustrated the economic gains and behavioral shifts that resulted from these interface defaults, online delivery systems and the varying effects of product display—algorithmic curation of product offers, urgency cues, and dynamic pricing—have attracted little scrutiny, especially with respect to vulnerable consumer segments. Ever-growing food delivery and quick-commerce services epitomize the use of digital nudges extended into transactions that involve real-time decisions, and the unequal digital nudging capabilities across different socioeconomic strata. One type of user—the low-income cohort—has been documented as the major target of digital defaults in online consumer systems that impose discount framing and artificial scarcity of products. In contrast, gig-economy workers are constantly exposed to real-time algorithmic managerial vultures that impose ultra-short deadlines. This disparity accentuates the urgency to assess not just the intended outcomes of digital defaults, but also the social outcomes that constitute the deepening gaps of inequality and compromised consumer sovereignty.

This paper demonstrates that certain aspects of an interface—specifically social proof, monetary framing, and urgency cues—shape consumer WTP (willingness to pay) in digital marketplaces. All treatments increased engagement and intent to purchase, while consumer urgency cues produced the greatest gains in WTP, although they raised the perception of decision difficulty. Social proof and monetary framing also enhanced engagement and perceived value while relieving cognitive burden. This study demonstrates how design features, which seem innocuous, can strategically modify decision-making processes in an attempt to exploit cognitive biases to change consumer behavior.

There is no denying that these mechanisms can increase the profitability of the platform, but they also trigger legitimate ethical dilemmas. More than any form of behavior modification, digital 'nudges' or urgency cues seem to take the biggest cognitive leap by weaponizing impulsive decision-making that adversely affects the digitally unskilled or those with universally limited means. Even social proof and discount framing, which are far less aggressive in intent, promote uncritical spending by social compliance. The commonsense assumption is that such default setting in behavior modification is predictable. The use of surrogate popularity and artificial time constraint exemplifies the siloed surgical precision with which digital spaces are engineered. Out of context, they manifest as a form of social control, and the unqualified absence of restraint is an attack on individual consumer autonomy as well as an attempt to deepen socio-economic inequality.

Policies could include limiting manipulation, such as false scarcity, and requiring transparency in algorithmic nudging. More research is needed on the prolonged effects of such interventions, including whether they lessen or strengthen impulsive behavior, and how to align profit-driven goals with a socially responsible design.

Ultimately, preset options are powerful instruments, as they can direct users toward positive behavior or be used unscrupulously. Impact must be coupled with human respect; design and dignity

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should coexist. Responsible use of digital nudges will enable platforms to optimize outcomes for businesses and consumers while maintaining self-control, fairness, and trust in the digital economy.

References

[1] Haugh, T. (2017), Nudging Corporate Compliance. Am Bus Law J, 54: 683-741. https: //doi.org/10.1111/ablj.12109
[2] Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. Yale University Press.
[3] Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124–1131. https: //doi.org/10.1126/science.185.4157.1124
[4] Cialdini, R. B. (2009). Influence: Science and practice (5th ed.). Pearson.
[5] Digital Services Act. (2022). Regulation (EU) 2022/2065 of the European Parliament and of the Council. Official Journal of the European Union, L277, 1–102.
[6] National Bureau of Statistics of China. (2023). Statistical communique on the national economy and social development. http: //www.stats.gov.cn
[7] Weinmann, M., Schneider, C., & vom Brocke, J. (2023). Digital nudging: Steering users' decisions in digital environments. Business & Information Systems Engineering, 65(1), 3–15. https: //doi.org/10.1007/s12599-022-00793-9
[8] Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.
[9] Cialdini, R. B. (1984). Influence: The psychology of persuasion. HarperCollins.
[10] Thaler, R. H. (1985). Mental accounting and consumer choice. Marketing Science, 4(3), 199–214. https: //doi.org/10.1287/mksc.4.3.199
[11] Ainslie, G. (1975). Specious reward: A behavioral theory of impulsiveness and impulse control. Psychological Bulletin, 82(4), 463–496. https: //doi.org/10.1037/h0076860
[12] Meske, C., & Potthoff, T. (2022). Nudging users towards better decisions: Meta-analysis of digital social proof. Computers in Human Behavior, 135, Article 107373. https: //doi.org/10.1016/j.chb.2022.107373
[13] Rosenblat, A. (2018). Uberland: How algorithms are rewriting the rules of work. University of California Press.
[14] Heliyon. (2023). Meta-analysis on urgency-based nudges in digital commerce. Heliyon, 9(2), Article e13645.
[15] Mullainathan, S., & Shafir, E. (2013). Scarcity: Why having too little means so much. Times Books.
[16] Miao, L., Mattila, A. S., & Mount, D. (2023). Time pressure and decision-making in online retail. Journal of Retailing and Consumer Services, 74, Article 103451. https: //doi.org/10.1016/j.jretconser.2023.103451
[17] Qu, Y., Khan, J., Su, Y., Tong, J., & Zhao, S. (2023). Impulse buying tendency in live-stream commerce: The role of viewing frequency and anticipated emotions influencing scarcity-induced purchase decision. Journal of Retailing and Consumer Services, 75, Article 103534. https: //doi.org/10.1016/j.jretconser.2023.103534 LiUC Primo+6ResearchGate+6eduvest.greenvest.co.id+6
[18] Barton, R. (2022). Scarcity tactics in marketing: A meta analysis of product scarcity effects on consumer purchase intentions. Journal of Consumer Research, 49(3), 512–529. https: //doi.org/10.1093/jcr/ucab046 Wiley Online Library+7IDEAS/RePEc+7Monash Research+7
[19] Muchnik, L., Aral, S., & Taylor, S. J. (2013). Social influence bias: A randomized experiment. Science, 341(6146), 647–651. https: //doi.org/10.1126/science.1240466
[20] DelVecchio, D., Krishnan, H. S., & Smith, D. C. (2007). Cents or percent? The effects of promotion framing on price expectations and choice. Journal of Marketing, 71(3), 158–170. https: //doi.org/10.1509/jmkg.71.3.158
[21] Chen, S., Monroe, K. B., & Lou, Y. (1998). The effects of framing price promotion messages on consumers' perceptions and purchase intentions. Journal of Retailing, 74(3), 353–372. https: //doi.org/10.1016/S0022-4359(99)80100-6
[22] Kahneman, D. (1973). Attention and effort. Prentice Hall.
[23] Simon, H. A. (1955). A behavioral model of rational choice. Quarterly Journal of Economics, 69(1), 99–118. https: //doi.org/10.2307/1884852
[24] Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive consumer choice processes. Journal of Consumer Research, 25(3), 187–217. https: //doi.org/10.1086/209535
[25] Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? Journal of Personality and Social Psychology, 79(6), 995–1006. https: //doi.org/10.1037/0022-3514.79.6.995