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Dual-Process Model of Consumer Responses to Deceptive Patterns in E-Commerce

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Abstract

Deceptive patterns are increasingly prevalent in e-commerce interfaces, exploiting users' cognitive vulnerabilities to nudge them toward unintended actions such as subscriptions or premium upgrades. Although prior research has examined these patterns and their negative effects, it has given limited attention to the cognitive mechanisms that determine whether users succumb to manipulation or regain autonomy. This study presents the Dual Process Deceptive Pattern Response Model, which explains transitions from intuitive exploitation to reflective recovery. Drawing on qualitative approach with abductive analysis, we show that deceptive patterns primarily hijack System 1 (fast, intuitive processing), while expectation violations activate System 2 (deliberate reasoning). This transition enables reasoned recognition, protective intentions, and a reinforcing feedback loop that strengthens long-term resistance. The model advances deception-detection scholarship by shifting the focus from content-based falsehoods to interface-embedded deception. Practically, it provides levers to reduce System 1 exploitation and accelerate System 2 recovery, preserving user autonomy in e-commerce.

Keywords: Deceptive patterns, dark patterns, deceptive design, qualitative approach, abductive thematic analysis, dual-process theory, e-commerce

Introduction

The rapid expansion of e-commerce has fundamentally reshaped how consumers make purchasing decisions. Global e-commerce sales represent about 20% of total global retail sales in 2025, with projections indicating continued double-digit growth through 2030. User penetration will be around 55% in 2026 and is expected to hit approximately 59% by 2030. The number of users is expected to amount to 4.2bn users by 2030 (Emarketer, 2025; Statista, 2026). Digital interfaces now serve as the primary touchpoint between consumers and firms, influencing everything from product discovery to subscription commitments. Yet this convenience carries a hidden cost: the proliferation of deceptive patterns (also known as manipulative or dark patterns) that subtly steer users toward actions they might not otherwise choose or hinder them from taking their preferred course of action (Havinen et al., 2025; Kollmer & Eckhardt, 2023; Mathur et al., 2019). These patterns range from pre-selected premium options and color-reversed confirmation buttons to hidden cancellation paths and urgency-inducing scarcity cues (Gray et al., 2024). Their prevalence has raised serious concerns about user autonomy, informed consent, and long-term platform trust (Ahuja & Kumar, 2022; Fassiaux, 2023).

Regulatory bodies worldwide have begun to respond. The European Union's Digital Services Act (European Union, 2022) and the U.S. Federal Trade Commission's (2023) guidance explicitly target deceptive design practices (FTC, 2023), while the research community has documented thousands of deceptive-pattern instances (Mathur et al., 2019; Narayanan et al., 2020). Despite this momentum, academic understanding remains incomplete (Chang et al., 2024; Kitkowska et al., 2022). Existing research has produced valuable taxonomies (Gray et al., 2024) and demonstrated negative outcomes such as financial loss, irritation, and eroded trust (Kollmer & Eckhardt, 2023; Lu et al., 2024; Mathur et al., 2021). However, prior studies have mostly treated deceptive patterns as static design features (Gray et al., 2025), rather than dynamic cognitive phenomena. Less is known about *how* consumers cognitively process these patterns in real time. In particular, how initial intuitive reactions give way to deliberate reflection and, ultimately, protective behaviors.

This theoretical and empirical gap is particularly consequential for IS research. Digital platforms are socio-technical systems in which design decisions directly shape user cognition and behavior (Hanafizadeh & Mehrasa, 2025; Winby & Mohrman, 2018). When interfaces exploit fast, automatic thinking, they undermine the autonomy that underpins continued use and loyalty (Mik, 2016; Prunkl, 2022; Trzaskowski, 2024). Moreover, the rise of artificial intelligence and personalized interfaces is likely to intensify the sophistication of manipulative techniques, making a robust cognitive model not merely academically interesting but practically urgent (Ienca, 2023; Kitkowska et al., 2022). Therefore, deceptive patterns should be studied as a cognitive phenomenon. Drawing on Kahneman's (2003) Dual-Process Theory, we conceptualize consumer cognition as oscillating between two systems: fast, effortless, intuition-driven processing (often characterized by immediate desire and heuristic judgments or System 1) and slow, deliberate, reasoned processing (characterized by expectation analysis and intention formation or System 2).

The present study links the System 1/System 2 distinction to the Persuasion Knowledge Model (Friestad & Wright, 1994; Rahmani, 2023) and anchors this integration in Havinen et al.'s (2025) framework for how consumers acquire knowledge, recognize manipulative patterns, and react to them. In doing so, it offers a unified process model that explains both exploitation and recovery, and develop a Dual-Process Deceptive-Pattern Response Model (DP-RM).

Through abductive thematic analysis of 23 eye-tracking-informed retrospective interviews, we demonstrate that deceptive patterns reliably exploit fast intuitive processing via salient visual and layout cues. Yet these same cues frequently generate expectation violations that trigger deliberate recovery, culminating in a self-reinforcing feedback loop that strengthens future resistance.

Our findings reveal three core insights. First, recognition is cue-dependent: visual and layout elements activate rapid intuitive responses, while interaction design and text ambiguities require effortful scrutiny. Second, the transition from intuitive exploitation to reflective recovery is not random but reliably triggered by mismatches between the interface and users' stored expectations (derived from brand familiarity, service context, or self-awareness). Third, each successful recovery episode updates users' mental models, creating a feedback loop that progressively shortens future transition times and enhances long-term autonomy. These patterns were consistent across interviewees with varying digital literacy and cultural backgrounds, underscoring the model's robustness.

By illuminating this dynamic process, the DP-RM advances IS theory in three ways. It extends Dual-Process Theory (Kahneman, 2003) into the deceptive patterns domain by demonstrating both parallel and sequential rather than parallel operation of the two systems. It enriches Persuasion Knowledge Model (Friestad & Wright, 1994; Rahmani, 2023) by applying Havinen et al.'s (2025) framework with explicit cognitive mechanisms and a feedback loop. And it provides the IS community with a process model that links micro-level cognition to macro-level outcomes such as trust, continuance intention, and ethical design. Practically, the model offers platform designers concrete intervention points, such as reducing salient intuitive cues and accelerating mismatch detection, to protect user autonomy without sacrificing business objectives.

The remainder of this paper is structured as follows. The next section reviews the theoretical foundations of deceptive patterns and dual-process cognition. We then describe our abductive thematic analysis methodology. The subsequent section presents the empirical findings. The discussion chapter introduces and elaborates the Dual-Process Deceptive-Pattern Response Model. Finally, the paper concludes with a discussion of the theoretical contributions, practical implications for designers and policymakers, limitations, and directions for future research.

Literature Review and Theoretical Background

Deceptive Patterns as Interface-Level Deception in E-Commerce

Deceptive design patterns, popularly known as manipulate or deceptive or dark patterns, are user-interface techniques that steer users toward actions they might not otherwise take or hinder them from taking their preferred course of action (Havinen et al., 2025; Mathur et al., 2021). These patterns threaten the user autonomy (Kollmer & Eckhardt, 2023) and typically benefit the designer or the owner of the system on the expense of the user (Caragay et al., 2024). Common examples include pre-selected premium options, color-reversed confirmation buttons, hidden cancellation paths, and scarcity/urgency cues (Gray et al., 2024). These patterns have proliferated in e-commerce, subscription services, and mobile apps, raising concerns about user autonomy, informed consent, and long-term trust (Ahuja & Kumar, 2022; Fassiaux, 2023; Lu et al., 2024).

Within the information systems discipline, deceptive patterns represent a specific form of interface-level deception (Kollmer & Eckhardt, 2023). Deceptive patterns distinct from, yet related to, content-based deception studied in computer-mediated communication (Ho et al., 2016; Nunamaker et al., 2016). The seminal 2016 *Journal of Management Information Systems* Special Issue on "Information Systems for Deception Detection" laid foundational groundwork for understanding deception in digital environments. The editorial introduction to the special issue (Nunamaker et al., 2016) emphasized that deception is not limited to textual content but is embedded in the structures through which users interact with systems. Subsequent articles in the issue demonstrated the power of linguistic and behavioral cues for automated detection of deception (Ludwig et al., 2016), crowdfunding platforms (Siering et al., 2016), and spontaneous computer-mediated communication (Ho et al., 2016). These studies collectively highlight that deception detection in IS relies on identifying systematic deviations from expected norms—whether in language-action patterns (Ho et al., 2016) or nonverbal behaviors (Zhang et al., 2016).

The current study extends this deception-detection tradition from *content* to *design*. While literature (c.f., Benjamin et al., 2016; Ho et al., 2016; Ludwig et al., 2016; Nunamaker et al., 2016; Siering et al., 2016) focused on detecting lies in user-generated content or fraudulent behavior, deceptive patterns embed deception directly into the interface itself. This shift is critical: users are not merely reading deceptive messages; they are being *steered* by the interface architecture before conscious deliberation can occur.

Dual-Process Theory in Consumer Cognition and IS

Kahneman's (2003) Dual-Process Theory provides a robust lens for understanding these interface-level effects. The theory distinguishes two modes of thinking that shape human decision-making. System 1 operates through effortless intuition—fast, automatic, and heavily influenced by emotions and heuristics—while System 2 involves slow, deliberate, and rational reasoning. Intuitions are defined as "thoughts and preferences that come to mind quickly and without much reflection" (Kahneman, 2003, p. 697). The present study adopts "desire" (Perugini & Bagozzi, 2004) as the key System 1 mechanism, distinguishing it from "intention," which implies planning and commitment (Malle et al., 2001). The two systems frequently operate simultaneously rather than in strict sequence (Chu et al., 2015).

This two systems architecture illuminates why deceptive patterns (e.g., bad defaults, salience/contrast, urgency cues, trick questions) are effective: they exploit System 1 shortcuts (e.g., default and framing effects) and often operate under time pressure or distraction, conditions that suppress monitoring and correction by System 2 (De Neys, 2025; Kahneman & Frederick, 2002). Large-scale audits of shopping sites and mobile apps document the prevalence of such tactics (e.g., false hierarchy, pre-selection, hidden costs, misleading countdown timers), indicating that many user journeys are optimized for intuitive compliance rather than reflective choice (Di Geronimo et al., 2020; Mathur et al., 2019). In digital environments, many consumer decisions are driven by System 1, making users vulnerable to biases and heuristics. Deceptive patterns exploit this vulnerability by targeting System 1 through visual cues, scarcity, urgency, and emotional triggers (e.g., Fear of missing out), thereby bypassing rational scrutiny (Khatri et al., 2018). When users later engage System 2 and recognize the deception, trust erodes, loyalty declines, and perceptions of ethical design suffer.

In IS and consumer behavior research, Dual-Process Theory has explained misuse of information systems resources in the workplace (Chu et al., 2015), technology adoption (Khatri et al., 2018), online decision-making (Lei et al., 2025), and responses to persuasive technologies (Verma & Arora, 2025). However, while Dual-Process Theory has been acknowledged within the deceptive pattern literature, prior review research suggests that its use has remained limited (Chang et al, 2024). Most prior work treats deceptive patterns as static features (Gray et al., 2025) that produce uniform negative outcomes (Mathur et al., 2021). This outcome-oriented approach leaves under-examined the *dynamic transition* between intuitive exploitation (System 1) and reflective recovery (System 2). This study extends this perspective by illustrating that deceptive patterns may primarily hijack System 1 via salient visual and layout cues, yet reliably trigger System 2 once expectation violations occur.

Consumer Responses to Deception: Insights from Deception-Detection Literature

Scholars have studied consumer responses to deception. For example, Zhang et al. (2016) demonstrated that verbal and nonverbal cues in online reviews significantly affect users' ability to detect fake content, with linguistic anomalies serving as mismatch signals that activate deliberate scrutiny. Similarly, Ludwig et al. (2016) showed that linguistic and content-based cues on crowdfunding platforms enable detection of fraudulent behavior, particularly when static and dynamic signals are combined. Ho et al. (2016) revealed that deceivers in an online experiment use more cognitive and affective-driven words, use fewer words, and have longer response times compared to their truthful counterparts (Nunamaker et al., 2016), while Benjamin et al. (2016) highlighted how deviations from expected communication patterns trigger heightened attention.

These studies converge on a key insight: deception detection is not automatic but depends on the activation of deliberate processing when cues deviate from expectations. Applied to deceptive patterns, this suggests that visual/layout manipulations function as System 1 "hijacks," while interaction and text ambiguities serve as mismatch triggers that shift users into System 2.

Recent advances in HCI provide consolidated ontologies that classify deceptive patterns (e.g., interface interference, obstruction, social engineering) and connect them to underlying cognitive mechanisms that offer a shared vocabulary for research and regulation (Gray et al., 2024; Schäfer et al., 2025; Verma & Arora, 2025). Experimental work further shows that 'mild' manipulations reliably increase compliance without eliciting strong resistance, whereas more aggressive tactics provoke backlash (Agrawal & Narayanan, 2026; Babaei & Vassileva, 2024; Luguri & Strahilevitz, 2021). This is consistent with the idea that subtle cues steer System 1 while avoiding System 2 counter-arguing. Physiological and behavioral evidence also indicates that 'hard-to-cancel' or 'hidden subscription' flows elevate cognitive load and frustration, which can either impair monitoring or trigger resistance depending on user resources and stakes (Hampton, 2025; Jamalifard & Russell-Rose, 2025).

Finally, individual differences in deliberative engagement matter. Analytic reasoning (as measured by cognitive reflection) improves the ability to distinguish accurate from misleading content, whereas reliance on emotion increases susceptibility—implying that interventions which cue reflection can mitigate the influence of manipulative designs (Babaei & Vassileva, 2024, 2025).

Integrating Dual-Process Theory with Deceptive-Pattern Responses

Despite these foundations, no existing model explains the *interplay* between System 1 exploitation and System 2 recovery in the specific context of deceptive interface design. Havinen et al. (2025) recently proposed a tripartite framework of consumer behaviors when encountering deceptive patterns. Their framework is grounded in the Persuasion Knowledge Model (Friestad & Wright, 1994), which posits that consumers learn about agents' tactics (persuasion knowledge), agents themselves (agent knowledge), and topics (topic knowledge), and deploy this knowledge to cope with influence attempts (Friestad & Wright, 1994; Rahmani, 2023). The model includes acquisition of knowledge, recognition, and reactions to manipulative (i.e., deceptive) patterns as described as follows.

- Acquisition of knowledge on manipulative patterns (Awareness). In the acquisition stage, consumers build awareness through personal experiences (e.g., difficult cancellations), vicarious learning (peers, reviews, media), and repeated exposure to recognizable cues (e.g., repeated textual persuasion, salient color cues). Notably, survey research shows that awareness does not guarantee effective resistance: many users recognize deceptive designs yet still feel influenced (Bongard-Blanchy et al., 2021). Also, this stage is influenced by cultural background, self-awareness, context knowledge, and brand knowledge (Havinen et al., 2025).
- Recognition of manipulative patterns. This is supported by visual elements, layout elements, interaction design elements, and text content (Havinen et al., 2025). Recognition involves identifying concrete UI and interaction elements that signal manipulation, such as false hierarchy, trick questions, confirmshaming, obstructed exits, and interpreting them in context. Recognition is shaped by interface cues and user-side factors (prior knowledge, expectations, language proficiency, time pressure). Recent ontologies and audits formalize these cues, while a study on 'hard-to-cancel' workflows highlights their persistence (Gray et al., 2024; Mathur et al., 2019; Nembaware & Sousa, 2025).
- Reactions to manipulative patterns. Havinen et al. (2025) document emotional, cognitive, and behavioral reactions ranging from irritation, skepticism, and distrust to coping (e.g., seeking exits, slowing down, consulting others) or abandonment. These reactions feed back into persuasion knowledge for future encounters. Experimental evidence indicates that mild patterns increase compliance with limited backlash, whereas aggressive manipulations can provoke resistance; meanwhile, analytic-thinking interventions improve discernment, and deceptive cancellation flows increase cognitive load. This maps closely onto dual process theory's predictions about System 1 vs. System 2 engagement (Jamalifard & Russell-Rose, 2025; Luguri & Strahilevitz, 2021).

Yet Havinen et al. (2025)'s framework stops short of specifying the cognitive mechanisms driving transitions between stages. Moreover, scholars (c.f., Benjamin et al., 2016; Ho et al., 2016; Ludwig et al., 2016; Nunamaker et al., 2016; Siering et al., 2016) advanced deception detection in content but did not address deception *by design*. While prior research advances deception detection in content, its limited attention to deception by design and the cognitive mechanisms driving transitions across response stages constrains theorizing about how consumers shift from exploitation to recognition and recovery in the face of deceptive patterns.

The present study thus developed the Dual-Process Deceptive-Pattern Response Model to explain *how* deceptive patterns operate in e-commerce interfaces by exploiting System 1 while simultaneously creating the conditions for System 2 recovery. In doing so, it bridges deception-detection research (Benjamin et al., 2016; Ho et al., 2016; Ludwig et al., 2016; Nunamaker et al., 2016; Siering et al., 2016) with contemporary deceptive pattern scholarship (Chang et al., 2024) for future IS studies on ethical interface design, user autonomy, and technology-mediated decision making.

Research Methods

The study adopted a qualitative approach. This study employed an abductive thematic analysis (Braun & Clarke, 2006; Timmermans & Tavory, 2012) to examine how consumers recognize and respond to deceptive design patterns in e-commerce interfaces. Abductive reasoning was particularly appropriate because it allowed us to integrate priori theoretical constructs. In particular, we used theory-driven coding that based on Kahneman's (2003) Dual-Process Theory (System 1: fast, effortless, intuitive processing driven by desire and heuristics; System 2: slow, deliberate, reasoned processing leading to intentions) and Havinen et al.'s (2025) framework informed by the Persuasion Knowledge Model (Friestad & Wright, 1994) on the acquisition of knowledge, recognition, and reactions to manipulative patterns. Then, we also used open to data-driven refinements and emergent patterns. This approach aligns with established practices in information systems research for investigating complex user–technology interactions (e.g., (Lindberg, 2020; Rai, 2018)).

Data Collection

The dataset comprised 23 transcripts of semi-structured retrospective interviews conducted in conjunction with eye-tracking sessions (See Table 1 for participant demographics). Participants viewed realistic screenshots of e-commerce interfaces (see Appendix) known to contain deceptive design elements (e.g., pre-selected upsells, color reversals, hidden exit options, ambiguous button labels) and after that were asked to think aloud while following their gaze paths from the task, followed by in-depth probing on their perceptions, decision processes, and reactions. All interviews were audio-recorded, professionally transcribed, and anonymized, and lasted 25–60 minutes each. The sample included participants with varying levels of digital literacy, cultural backgrounds, and e-commerce experience, providing rich variation in System 1 and System 2 processing. Ethical approval was obtained prior to data collection, and informed consent for recording and analysis was secured from all participants.

Table 1. Demographic Characteristics of Participants

Characteristic	**Category**	**n**	**%**
Age	20–30 years	16	69,60
	31–40 years	7	30,40
Gender	Man	16	69,60
	Woman	7	30,40
Nationality	Finnish	7	30,40
	Nepalese	5	21,70
	Bangladeshi	4	17,40
	Other (Lithuanian, Turkish, German, Vietnamese, Indian, Nigerian, Sri Lankan)	7	30,40
Online Shopping Frequency	Less than once a month	3	13,00
	Once a month	11	47,80
	2–3 times a month	8	34,80
	1–3 times a week	1	4,30

Data Analysis

Analysis proceeded in five iterative phases, consistent with abductive thematic analysis guidelines (Braun & Clarke, 2006; Timmermans & Tavory, 2012). Each transcript was first coded individually. Coding process was assisted by NVivo and cross-checked in Excel, and complemented by traditional (paper-based) coding. After individual coding, all 23 transcripts were integrated. Frequency counts, dominance analysis, and pattern mapping were performed to identify System 1 vs System 2 prevalence and recurring transition moments.

First, we familiarized ourselves with the data through multiple holistic readings of all 23 transcripts, noting preliminary indicators of System 1 (e.g., immediate references to visual salience such as "caught my eye," "red color," or emotional reactions) and System 2 (e.g., deliberate expectation violations such as "this breaks what I expect" or reasoned problem-solving).

Second, we developed a hybrid deductive–inductive codebook. Deductive top-level codes were derived directly from the theoretical framework (concepts, definitions were defined using PowerPoint). Inductive codes were added iteratively for emergent phenomena, notably "S1→S2 transition moments" and contextual moderators (e.g., time pressure, service type):

- Level 1: (1) Acquisition of knowledge on deceptive patterns, (2) Recognition of deceptive patterns, and (3) Reactions to deceptive patterns. These followed the Havinen et al.'s framework, informed by Persuasion Knowledge Model (Friestad & Wright, 1994).
- Level 2: For (1) Acquisition of knowledge on deceptive patterns, it includes four subthemes: cultural background, self-awareness, context knowledge, brand knowledge; for (2) Recognition of deceptive

patterns, it includes four subthemes: visual elements, layout elements, interaction design elements, text content; for (3) Reactions to deceptive patterns, it includes four subthemes: emotional, behavioral, cognitive, and social reactions. These subthemes were from Havinen et al.'s framework, informed by Persuasion Knowledge Model (Friestad & Wright, 1994). Table 2 presents examples of Level 1 and Level 2 coding.

- Level 3: Every coded unit was classified as primarily System 1 (effortless intuition, desire-based heuristics, emotional salience) or System 2 (deliberate reasoning, expectation analysis, planned intentions), following Kahneman (2003) and distinctions between desire and intention (Chu et al., 2015; Malle et al., 2001; Perugini & Bagozzi, 2004).

Table 2. Level 1 and Level 2 Coding Example

Level 1	**Level 2 and Coding Example**
Acquisition of knowledge on deceptive patterns	"[...] after I see the picture, I can recall the company, it's Amazon. And when I see this offer [...]. So this kind of attracts me" (P16) (coded as "brand knowledge", Level 2) "If I really want that item and I don't see any other stores that are selling that, then I just buy it." (P23) (coded as "context knowledge", Level 2)
Recognition of deceptive patterns	"I'm more used to see like the manipulative things. So, I think at the first picture I didn't look that much about things like that" (P7) (coded as "visual elements", Level 2)
Reactions to deceptive patterns	"Like if you lose something, it's okay. But we learn from the mistakes. So like next time I try to be extra careful because I face some of those situations." (P15) (coded as "cognitive reactions", Level 2)

Third, refining definitions and resolving ambiguities were used during the coding process. Constant comparison (Bingham, 2023) was used across transcripts to identify patterns and negative cases (e.g., participants who remained predominantly in System 1).

Fourth, we collated codes into candidate themes and mapped relationships, with particular attention to the frequency and dominance of System 1 versus System 2 processing within each subtheme and the identification of recurring transition sequences.

Fifth, themes were reviewed, refined, and named to ensure coherence and distinctiveness, resulting in a final thematic structure that both validates and extends the theoretical framework. As a result, a conceptual model of dual-process deceptive-pattern response model was inductively derived from data. This systematic, theory-informed approach enabled a nuanced understanding of how deceptive design patterns interact with dual-process cognition in real-world e-commerce contexts, producing actionable insights for both theory and practice.

Findings

This section presents the results of our abductive thematic analysis. Participants consistently described deceptive patterns as both familiar ("This looked really familiar and for me that I've seen these before, and anyway, it's pretty basic for Microsoft Office that I use them like that myself" – P2) and surprising upon reflection ("[...] somehow I started to wonder that okay that I haven't even thought before that this kind of manipulative thing is so much that I saw so much of that in those designs." – P1). The data reveal a dynamic process in which deceptive patterns exploit System 1 but routinely activate System 2 once users detect a mismatch with their expectations. This process is described as in the following sections.

Role of System 1 and System 2 in the Acquisition of Knowledge on Deceptive Patterns

Participants' awareness of deceptive patterns developed primarily through repeated exposure and post-hoc reflection, with System 2 dominating through all interviewees. First, self-awareness emerged as a strong System 2 driver of knowledge acquisition as voiced of P6:

> "I really started to wonder if there is someone here, since I'm left-handed, my left-handed brain says that it makes sense that this is like this and not there [kind of deceptive patterns]. Because it could also be on the other side actually. But somehow in this note, it's like, there's more space over there, so it can somehow be found there effortlessly." (P6)

In a similar self-awareness situation, P16 answered when discussed about being generally skeptical or whether something had happened to P16 regarding deceptive patterns:

> "[..] I'm always been this kind of person. I mean, if I take some decision as well, I think a lot. I think a lot." (P16).

Second, cultural background, particularly gaming experience, provided intuitive (System 1) reference points that later fed into System 2 reflection as commented of P5:

> "I sometimes when I was younger, when I played a lot, then I got just these, that as soon as I can do it, I control the user quite well with these things. And especially so many colors. [...] when you were young, when you saw like there were a lot of colors in the games [...] they are in color boxes and stuff like that [...] they guide you to make decisions. And then there are these big discounts and all these things that guide you. The colors are made there as well, you will notice, as soon as you look at the front page of the online store, you will immediately see that [...]". (P5)

Third, context knowledge shaped expectations, such as games normalized manipulation and deception as stated by P20: "I think that at least the younger children, just the example of games, will probably use some of these games more now, so there for sure. Then maybe young people, teenagers, may not think about them [deceptive patterns] as much as adults, and then, of course, older people who are not so used to using digital services" (P20), while shopping contexts raised stakes as P23 commented, "If I really want that item and I don't see any other stores that are selling that, then I just buy it."

Fourth, brand knowledge operated as a powerful heuristic. Familiar brands triggered System 1 trust as P24 and P16 commented: "I know Microsoft 365. I know this product is going to be useful for me. So, I would go, yeah, I would go for a trial for 100 GB data cloud storage. So, it's a huge... So, I would go for them. And I know Word, Excel, PowerPoint, Note, they're all trustworthy products of Microsoft. So, I know the product well, so I would go for them." (P24); "[...] after I see the picture, I can recall the company, it's Amazon. And when I see this offer [...]. So this kind of attracts me" (P16), while unfamiliar brands activated System 2 caution as P15 stated, "[...] everything now and then they go for like online shopping and online thing, then they might encounter those things. But basically I go for trusted brands and the brand where I make sure that the brand is already there, that they are trusted." (P14).

Role of System 1 and System 2 in the Recognition of Deceptive Patterns

It is evident that visual and layout elements are System 1 dominant, while interaction design and text content are System 2 dominant across data sources. First, visual and layout cues were recognized almost instantly. Color reversals were particularly salient:

> "I would have made some kind of change to those buttons [...], the red color on the "Back" button somehow confused it a bit like, uh, like the idea of which one to press...you would somehow think that the red would be like 'Cancel'" (P1) or "for green it's like, normally like in Finland, when I don't know actually that much Finnish...in the beginning I didn't know "Kyllä" means yes, but "Kyllä" is always written in green. So, that means "Yes". Normally, I should press that one. So, that's the conscious mind working there." (P23).

Second, pre-selection and element order steered attention automatically as voiced of P13: "[...] that it automatically chooses the more expensive one. And also what is pretty confusing about those airlines anyway, but in my opinion, so often the names of those classes. They're not that clear." (P13).

Hidden or misplaced close buttons created immediate confusion as voiced by P5 and P7: "I'm more used to see like the manipulative things. So, I think at the first picture I didn't look that much about things like that" (P7) and "I don't notice it, or focus on it, but I focus on what has a lot of that content. It's guaranteed by the kind of websites that go in a logical order and at the same width all the time, that there is nothing like a certain box that is terribly informative and then some, on the side some, where something happens, but, but oh no, it's not like someone, someone might be a couple of buttons" (P5).

Third, deeper recognition required System 2 effort. This is commented from P24:

> “Even if they mention it's like 1.99 [US$] per month, but they are asking me would you like try to try for free? So, that catches my attention okay, let's...might be safe for try for free first, and then see how it goes, and might I can cancel it later on. But one thing that catch me is like they did not give any deadline of the free to try. Like okay 30 days subscriptions or whatever. It's not mentioned here. So, that back of my mind was like, okay, I was in the center. Should I try or not?” (P24)

Fourth, ambiguous text prompted careful reading and expectation violation as P10 and P3 articulated:

> “Maybe first time who doesn't know what this is a marketing technique or anything, they will go, yeah, what is there? I have a free delivery. Maybe I require this, … So, if you are like very stick to your budget and all, definitely you will not do that” (P10).

> “It says free, but they will pay money like later if you don't do other things that it doesn't say. I would say this does what I would might...I might expect. And this one, when I press, like it will probably ask me for the card details.” (P3).

Role of System 1 and System 2 in the Reaction to Deceptive Patterns

It is shown that emotional reactions were dominant by System 1, while behavioral, cognitive, and social reactions were dominant by System 2.

First, irritation and annoyance were dominant across interviewees. Examples through the voices of P20 and P1:

> “I'm so used to them that they don't wake me up much anymore. Yes, it's probably just the annoyance, if someone has clearly been made harder to reach their own goal through that manipulation, then probably the irritation is mainly there. Or it can be frustrating or something.” (P20)

> “It's like a certain kind of feeling of irritation, it's really annoying if a window pops up on the screen all the time saying "order space", "buy buy" and especially that, well yes if there is someone like that first presses "No" and then it gets in the way that they throw their credit card like that, then maybe it emphasizes the feeling of annoyance.” (P1)

Second, behavioral reactions included rapid escape or heightened caution, as P9 commented, “there is a clear color difference in that the traditional good and evil, red is evil, and then green is good. So yes, the visuals are also trying to attract here … If you make quick decisions based only on those colors, then it's somewhere else where you want to be.” (P9)

Third, cognitive reactions involved learning as P15 and P4 voiced, “Like if you lose something, it's okay. But we learn from the mistakes. So like next time I try to be extra careful because I face some of those situations.” P15 and “I previously made a couple of mistakes. I've fallen into the some of their traps in the early days.” (P4)

Fourth, social reactions included sharing warnings, as P14 articulated, “[...] I might do that one and try to share with my friends and circle. So like [the site] is trying to use our, that's trying to [manipulate] us with this interface. So I try to circulate it within my circle” (P14)

The Dual-Process Deceptive-Pattern Response Model

Building directly on the empirical patterns identified in the described above, we propose the Dual-Process Deceptive-Pattern Response Model (Figure 1) as a novel process model that integrates Kahneman’s (2003) Dual-Process Theory with Havinen et al.’s (2025) framework, informed by Persuasion Knowledge Model (Friestad & Wright, 1994) on consumer responses to deceptive design. The model is described as follows (Figure 1).

Stage 1. Consumers *learn about* deceptive patterns in general, such as *hearing about deceptive patterns*, *reading news*, *reviews, culture* or *recalling past manipulative experiences*. Consumers primarily developed knowledge of deceptive patterns through *System 2* processes, characterized by reflection, self-awareness, and deliberate evaluation. Many described themselves as naturally reflective decisionmakers; for example, P16 noted, *"I think a lot. I think a lot,"* illustrating a tendency toward analytical reasoning when encountering interface designs. Others demonstrated reflective noticing of inconsistencies, such as P6, who questioned interface placement and commented that certain design elements made them "wonder" whether something was intentionally positioned to guide their choices. Alongside this, *System 1 played a complementary yet influential role*, drawing on intuitive cues shaped by cultural and gaming experiences. P5 explained that years of gaming had trained them to recognize how colors and salience are used to guide user behavior, forming an intuitive knowledge base that later fed into more deliberate reflection. Brand familiarity also activated System 1 heuristics, with well-known brands like Microsoft and Amazon eliciting immediate trust (P24; P16), while unfamiliar brands prompted caution and a shift back into System 2 scrutiny, as illustrated by P14's emphasis on selecting only trusted providers.

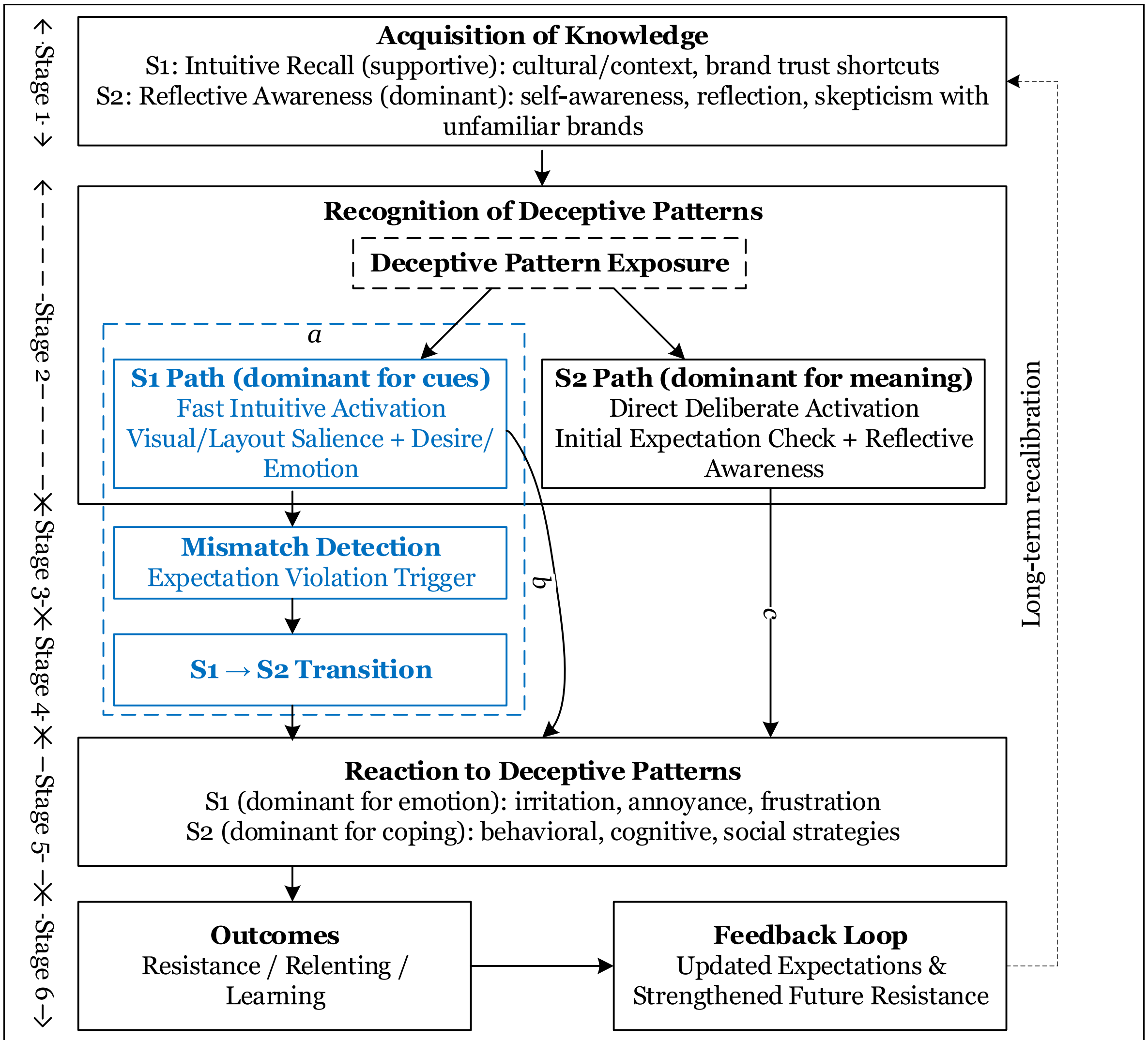

Figure 1. The Dual-Process Deceptive-Pattern Response Model (DP-RM)

Stage 2. When consumers *encounter a specific instance* of manipulation, it constitutes a *situational experience*. Exposure is the *trigger* that allows recognition to occur. Exposure happens at the moment the user encounters the deceptive pattern in the interface. A deceptive pattern is implemented through visual elements, layout elements, interaction design elements, and text elements, so exposure occurs *when the user sees or interacts with them.*

Upon deceptive pattern exposure, two paths may operate simultaneously: System 1 Path or System 2 Path. In System 1 Path, deceptive patterns engage fast, automatic processing through salient visual and layout cues that trigger immediate desire, emotion, or heuristic judgment. For example, evidenced from data that more than 75% of visual/layout units coded System 1. Examples include color reversals, e.g., P1's expectation that red signals "cancel," or P23's learned association between green and *kyllä* ("yes"), the automatic selection of premium options (P3), and hidden or misplaced close buttons (P5; P7). At this path, users experience a desire-driven pull (Kahneman, 2003; Kotabe & Hofmann, 2015) without deliberate intention formation. For the System 2 Path, deeper recognition is required for a shift into System 2 reasoning, where consumers engaged in careful reading, ambiguity resolution, and inference-making. Examples include identified expectations violating "free" messaging that likely concealed later charges, prompting them to assess what would happen after pressing a button (P10; P3). This happens for reflective users. The System 2 Path includes direct deliberate processing involving an initial expectation check and reflective awareness.

From this stage, there are three possibilities of what happens next as shown by *a*, *b*, and *c* in Figure 1. It can be going directly to the reaction (stage 5) as *b* or *c*. However, a path *a* might also be happening as shown in Figure 1. It is noted that repeated deceptive pattern exposures over time accumulate and feed back into persuasion knowledge. But this happens *after the reaction (step 5)*, not at the moment of exposure.

Stage 3. Mismatch Detection. The System 1 path frequently generates a noticeable mismatch between the interface and the user's expectations from brand knowledge, service context, cultural background, or self-awareness. The violation of stage 1 creates cognitive dissonance that interrupts the automatic process and opens the gateway to System 2.

Stage 4. The mismatch of stage 3 serves as the primary *transition trigger* that shifts processing toward stronger System 2 engagement. The direct System 1 and System 2 path (of *b* and *c* arrows, Figure 1) bypasses or accelerates this step. Four *moderators* influence S1→S2 (System 1 to System 2) transition. First, *brand knowledge* plays a role as a delayer. Empirical data indicate that familiar brands (Microsoft, Amazon) activate System 1 trust heuristics, delaying mismatch detection. Second, *service context* plays a dual role. Empirical data show that normalized contexts (e.g., games) prolong System 1 tolerance; high-stakes contexts (flight tickets, subscriptions) accelerate System 2. Third, *self-awareness* plays a role as an accelerator. Data show that participants with reflective metacognition transitioned faster. Fourth, *cultural background* (contextual) such as nationality and language experience provided richer expectation benchmarks.

Once the mismatch is detected, System 2 engages. Users shift from automatic, intuitive responses to effortful, deliberate reasoning (System 2). They scrutinize text content and interaction design, evaluate consequences, and form conscious behavioral intentions. For example, one participant reflected, "I would have made some kind of change to those buttons" (P1).

Stage 5. Reactions to deceptive patterns were shaped either by System 1 emotional responses, or by System 2 coping strategies. Immediate feelings of irritation, frustration, or annoyance were common; P20 described manipulation attempts as "annoying... frustrating," while P1 noted that repeated prompts heightened irritation. These affective reactions often preceded more deliberate behavioral or cognitive responses. Engagement with coping strategies activated System 2, enabling users to regulate their behavior, interpret their experiences, and share insights socially. Behaviorally, some exited quickly or exercised caution to avoid unintended choices, as P9 described in relation to color-driven misclick avoidance. Cognitively, participants reflected on previous mistakes to prevent repetition (P15; P4). Socially, they warned peers, as P14 noted, sharing links and cautionary experiences within their circles.

Stage 6. These reactions of stage 5 produced the outcome and formed the foundation for a feedback loop. The outcomes are (1) Resistance (most common): workarounds, avoidance, or service switching. (2) Relenting (when cognitive load or time pressure is high): compliance despite awareness. (3) Learning (long-term): updated mental models that increase future resistance. While the feedback loop accumulated experience enriched participants' future knowledge, refining their awareness and recognition of deceptive patterns.

All outcomes feed back into updated expectations and refined mental models, progressively strengthening future resistance and shortening transition times in future encounters. This loop transforms isolated incidents of manipulation into cumulative cognitive capital, progressively strengthening users' ability to detect and resist deceptive patterns more rapidly and effectively over time. In Kahneman's (2003) terms, repeated System 2 processing gradually "immunizes" System 1 by recalibrating its heuristics and expectations, thereby shortening or even pre-empting future S1 hijacks. This explains why frequent e-commerce users in the sample reported faster recognition and stronger avoidance intentions than less experienced participants.

Discussion

From System 1 Exploitation to System 2 Recovery

This study reveals a coherent dynamic process that explains how consumers move from intuitive exploitation to reflective recovery. As shown in *the acquisition of knowledge phase*, consumers entered encounters with pre-existing mental models *about* deceptive patterns in general shaped by brand familiarity, service context, and self-awareness. These models set the stage for *the recognition of deceptive patterns*, where two paths may operate simultaneously: System 1 Path and System 2 Path with three possibilities of what happens next (directly to reaction as shown by *b*, and *c,* Figure 1 Stage 2). In particular, in case of path *a* (Figure 1), salient visual and layout cues first triggered fast System 1 processing. When these cues violated stored expectations, a critical mismatch occurred, reliably activating System 2 deliberation. This transition was most evident in the shift from surface-level visual recognition to deeper interaction and text analysis. *The reactions to deceptive patterns* then illustrate the behavioral and cognitive outcomes of this shift: immediate System 1 irritation frequently gave way to System 2 strategies such as careful reading, workarounds, learning, and even social sharing. These patterns collectively demonstrate that deceptive patterns do not only operate in isolation (*path b* or *c* of Stage 2, Figure 1); rather, they initiate a predictable cognitive sequence that begins with System 1 hijack, moves through expectation-driven mismatch detection, and culminates in System 2 recovery and learning (*path a* of stage 2, Figure 1).

This dynamic process provides the empirical foundation for the Dual-Process Deceptive-Pattern Response Model. The DP-RM explains *how* deceptive patterns operate in e-commerce interfaces by exploiting System 1 while simultaneously creating the conditions for System 2 recovery. It addresses a key theoretical gap: prior deceptive pattern research has documented effects but has not modelled the *dynamic cognitive transitions* that determine whether users are successfully manipulated or regain autonomy. Specifically, in our proposed model, we leverage Havinen et al.'s (2025) three-stage framework (i.e., knowledge acquisition, recognition, and response) to illustrate *what* consumers do upon encountering deceptive (manipulate) patterns. Furthermore, we integrate Kahneman's (2003) dual-process theory—encompassing System 1 (intuitive) and System 2 (reflective) cognition—to elucidate *how* consumers think while performing these activities within digital interfaces. Contemporary dual-process accounts further assume that these systems can operate in parallel with asymmetric dominance, rather than as mutually exclusive alternatives (Chu et al., 2015; Khatri et al., 2018). This parallel operation aligns with established dual-process theories. (Epstein, 1994, p. 713) argues that the two systems "are assumed to operate in parallel and to interact with each other" at all times, even after deliberate processing is engaged. Similarly, Kahneman (2011) notes that System 2 is effortful, yet System 1 continues running in the background. Our data confirm this pattern: even after participants began deliberate reflection (System 2), they still reported quick intuitive reactions (e.g., irritation or gaze attraction) alongside analytical processing. This is why each Havinen et al.'s stage contains both S1 and S2 in parallel, but after stage 4 (the S1→S2 transition), System 2 becomes the dominant mode.

Theoretical Contributions

This study makes three primary theoretical contributions. First, we integrate and extend Dual-Process Theory into the domain of interface-embedded deception within the deceptive patterns case. While Kahneman (2003) distinguishes System 1 (effortless intuition and desire-driven heuristics) from System 2 (deliberate reasoning and intention formation) and has been applied to misuse of information systems resources in the workplace (Chu et al., 2015), technology adoption (Khatri et al., 2018), online decision-making (Lei et al., 2025), and responses to persuasive technologies (Verma & Arora, 2025), prior work has rarely modelled the sequential transition and parallel operation observed when users encounter manipulative design as it has treated these systems largely in isolation. The DP-RM demonstrates that the two systems operate sequentially and interactively: System 1 provides the initial "hijack," but expectation violations reliably trigger System 2 recovery. This addresses a key limitation in the literature, namely, the lack of process models explaining *when and why* users escape manipulation. The DP-RM addresses this by showing how deceptive patterns exploit System 1 dominance and how mismatch detection reliably triggers System 2 intervention.

Second, while Havinen et al.'s (2025) framework effectively delineates three core components—*acquisition of knowledge* concerning manipulative patterns, *recognition* of such patterns, and *adaptive reactions* to them—it stops short of elucidating the underlying cognitive mechanisms that govern transitions between these stages. In other words, the framework does not articulate the cognitive modes or temporal dynamics that facilitate movement from one stage to the next. The DP-RM enriches Havinen et al.'s framework by situating its three stages within an explicit dual-process architecture. In doing so, the DP-RM supplies the missing processual dimension, illustrating how visual and layout elements predominantly activate System 1 processing within each stage, whereas interactive and textual elements engage System 2. The model's feedback loop further enables cumulative learning across stages, thereby providing a dynamic account of progression through the framework.

Third, the model bridges content-based deception detection research from the literature (c.f., Benjamin et al., 2016; Ho et al., 2016; Ludwig et al., 2016; Nunamaker et al., 2016; Siering et al., 2016) with contemporary deceptive pattern scholarship. Particular, scholars showed that linguistic and behavioral deviations trigger deliberate scrutiny in computer-mediated communication (c.f., Ho et al., 2016). The DP-RM extends this logic to *design-level* deception, showing that visual/layout deviations function as System 1 cues while interaction/text deviations serve as System 2 triggers. In doing so, it moves the IS field from detecting deception *in* content to understanding deception *by* design. The DP-RM model is parsimonious yet powerful, explaining both why deceptive patterns often succeed in the moment and why reflective users frequently recover autonomy.

Practical and Design Implications

The DP-RM offers actionable guidance for three stakeholder groups. First, *for interface and UX designers,* the feedback loop from the findings of the study suggest that deceptive patterns are self-limiting in the long run for reflective users but highly effective against low-awareness or occasional users. Designers should therefore minimize System 1 hijacks by aligning visual and layout cues with user expectations (e.g., consistent color semantics: green = proceed, red = cancel for example; prominent, equally salient non-action options; no pre-selection of premium tiers). Make mismatch detection easier through transparent micro-copy and visible exit paths. These changes can shorten or prevent exploitative loops without sacrificing business goals.

Second, *for e-commerce platform operators and managers*, monitor deceptive-pattern prevalence through regular DP-RM audits (eye-tracking + retrospective interviews). Prioritize high-stakes flows (checkout, subscription cancellation) where System 2 engagement is critical for trust. Leverage the feedback loop by designing experiences that reward reflection rather than punish it, e.g., post-interaction explanations or "undo" options, thereby converting potential irritation into loyalty.

Third, *for policymakers and regulators*. The model supports evidence-based regulation. Requirements for "expectation-aligned defaults," mandatory prominent cancellation paths, and prohibition of color-reversed confirmation dialogs would accelerate mismatch detection at population level. Transparency tools (e.g., browser extensions that flag deceptive patterns in real time) could fast-track the feedback loop across millions of users, particularly benefiting vulnerable groups (older adults, low digital-literacy users).

Limitations and Future Research Directions

Several limitations should be noted. First, the study used retrospective interviews following controlled eye-tracking sessions with static screenshots; real-time behavior in live environments may differ under time pressure or mobile constraints. Second, we focused on recognition and immediate reactions; longer-term behavioral outcomes (actual purchase abandonment, churn, or continued use) require longitudinal designs.

Finally, although eye-tracking data were collected, they were not analyzed in the current version of the paper. Consequently, the specific attentional patterns and cognitive transitions between stages could not be directly examined. A comprehensive eye-tracking analysis is planned to investigate these mechanisms in depth and will be reported in a subsequent journal article.

These limitations open rich avenues for future research. Experimental studies (Dennis & Valacich, 2001) could manipulate specific cues (e.g., color reversal vs. neutral) and measure transition latency using process-tracing methods (Todd & Benbasat, 1987). Longitudinal field studies (Venkatesh et al., 2022) could track how the feedback loop evolves over months of real platform use. Finally, intervention research (Siponen & Baskerville, 2018) evaluating "System 2 support" features (e.g., dynamic expectation-alignment prompts) could directly inform ethical design standards.

Conclusion

The exponential growth of e-commerce has placed digital interfaces at the center of consumer decision-making. Yet these same interfaces are increasingly populated with deceptive patterns that exploit cognitive vulnerabilities to steer users toward actions they might not otherwise choose or hinder them from actions they would want to perform. This study examined how consumers cognitively process and respond to such patterns in real time by developing the Dual-Process Deceptive-Pattern Response Model.

The model indicates that upon exposure to deceptive patterns, System 1 and System 2 activate in parallel. A dominant pathway begins with System 1 hijack via salient visual and layout cues, followed by expectation violations that trigger a reliable S1→S2 transition. After the transition, System 2 becomes the dominant processing mode, while both systems continue to operate concurrently within three stages: Acquisition of knowledge, Recognition, and Reactions. The resulting feedback loop transforms isolated encounters into cumulative protective schemas, progressively strengthening future resistance and user autonomy. These patterns were consistent across participants with varying levels of digital literacy and cultural backgrounds, underscoring the model's robustness.

The Dual-Process Deceptive-Pattern Response Model demonstrates that while deceptive patterns effectively exploit System 1 in the moment, they simultaneously sow the seeds of their own long-term decline through System 2 recovery and learning. The model is parsimonious yet powerful, explaining both why deceptive patterns often succeed in the moment and why reflective users frequently recover autonomy.

The DP-RM demonstrates that good design is not merely functional, but also ethical. As digital interfaces increasingly mediate economic and social life, designing for reflective recovery rather than intuitive exploitation is both a moral responsibility and a strategic imperative for all stakeholders. In that sense, the model equips IS scholars, designers, and regulators with both a theoretical lens and practical levers to protect user autonomy while preserving the innovative potential of digital commerce. As such, this study provides a starting point for future research and contributes to the creation of more trustworthy, autonomy-respecting digital marketplaces. And this work stimulates further research at the intersection of cognitive psychology, ethical design, HCI, and information systems.

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Appendix. E-Commerce Interfaces and Deceptive Designs Used in the Interviews

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