Journal of Emerging Markets and Management
https://journals.niepublish.com/jemm

ARTICLE

Understanding Digital Nudges in E-Commerce: An Interpretative Structural Modeling-Based Analysis of Impulse Buying Behavior

Tanzila Parvez , *Hans Kaushik* *

Department of Management, Dayalbagh Educational Institute, Agra 282005, India

ABSTRACT

Online platforms have a significant influence on consumer purchase patterns, making consumer decision-making in the digital marketplace more complicated. Although there has been research on impulse buying, little is known about the ways in which various platform-related and behavioral elements combine to influence such behavior. The study addressed gaps in understanding the combined effects of these factors and provided a structured framework for analyzing online impulse buying for digital commerce stakeholders. Using Interpretive Structural Modeling (ISM), the study sought to identify important components, such as behavioral biases and platform design elements, and investigate how these interacted. The most important characteristics were identified by expert consensus using the Nominal Group Technique (NGT). These factors were then examined to create a structured framework that captured causal and hierarchical linkages. MICMAC analysis improved the ISM model by highlighting the elements that can cause more extensive behavioral reactions by classifying factors according to their influencing (Ip) and dependent power (Dp). The results showed that specific platform features and design elements produced a feeling of urgency and information overload, which in turn fueled impulsive purchasing behavior by amplifying behavioral biases through mechanisms like financial incentives and social proof. By illustrating how these elements interacted at various levels in the model, the study also demonstrates the organization of the elements to illustrate the process. From a practical viewpoint, the findings offer insights for marketers to identify the behavioral cues of the consumers that influence their purchases and offer implications for policymakers to implement rules

*CORRESPONDING AUTHOR:
Hans Kaushik, Department of Management, Dayalbagh Educational Institute, Agra 282005, India; Email: hanskaushik.dei@gmail.com

ARTICLE INFO
Received: 21 October 2025 | Revised: 23 December 2025 | Accepted: 2 January 2026 | Published Online: 10 January 2026
DOI: https://doi.org/10.63385/jemm.v2i1.341

CITATION
Parvez, T., Kaushik, H., 2026. Understanding Digital Nudges in E-Commerce: An Interpretative Structural Modeling-Based Analysis of Impulse Buying Behavior. Journal of Emerging Markets and Management. 2(1): 92–108. DOI: https://doi.org/10.63385/jemm.v2i1.341

to balance the designing of online platforms with user welfare.

Keywords: E-Commerce Platforms; Behavioral Economics; Impulse-Buying; Interpretative Structural Modelling (ISM); Consumer Decision-Making

1. Introduction

Behavioral economics draws on perspectives from psychology, sociology, and cognitive science to study how people make decisions in real-life contexts, rather than relying on the conventional notion that individuals always behave rationally [1]. It shows how everyday decisions are greatly influenced by cognitive shortcuts, biases, and limited rationality. Platforms are using nudges and customized suggestions more frequently in digital commerce to influence customer behavior. These strategies can boost user involvement and help acheive company objectives, but they also give rise to worries about higher spending, impulsive purchases, and uneven impacts on the welfare of customers. Crucially, while previous research has tended to examine behavioral biases and nudging mechanisms independently, only a small number of studies have examined how these components work together. Studies give rise to a gap that calls for a systematic approach to capture the interconnectedness and any negative consequences that arise on digital platforms. The goals of the study are as follows:

1. The study's goals are to determine and compile important factors pertaining to moderators, behavioral biases, platform nudges, and consumer outcomes in e-commerce.
2. To create a conceptual framework and analyse the interactions between these variables using Interpretive Structural Modeling (ISM).
3. To provide guidance for the creation of moral platforms and policy implications, as well as to gain an understanding of the possible negative consequences of behavioral interventions.

The purpose of this study was to identify the key behavioral and platform-related factors driving online impulse buying and to analyze their interactions using Interpretive Structural Modeling (ISM), which was employed to systematically capture the hierarchical and causal relationships among these factors. In addition to filling the indicated research gap, our methodological approach advances behavioral understanding theoretically and has useful ramifications for platforms and policymakers. Building on these ideas, researchers presented the ideas of choice architecture and nudges, highlighting how minor changes to the way options are presented can have a significant impact on choices [2]. According to research, consumer and policy-related decisions are influenced by anchoring, salience, framing effects, and defaults [3]. Digital nudging, the practice of online platforms employing design elements like reminders, prompts, or customized suggestions to systematically alter user behavior, has recently drawn the attention of researchers. The use of these tactics in corporate contexts raises serious ethical concerns about consumer autonomy and manipulation, even while they might be employed to further socially beneficial objectives. Some of the most well-known instances of digital choice architecture in action are e-commerce platforms. To influence customer behavior, businesses like Amazon, Zomato, and Blinkit use tools including push alerts, pop-up deals, recommendation engines, subscription reminders, and EMI purchasing plans. These traits often combine to entice consumers to engage in cycles of decision-making when a single action or purchase initiates a multitude of subsequent consuming triggers. An Amazon consumer adding an item to their cart might be presented with "frequently bought together" bundles, whereas a Blinkit user would see a countdown timer associated with a discount, urging an immediate purchase. These design strategies illustrate how the design of the online platforms interact with human biases to influence impulsive buying, extending the scope to behavioral economics to ascertain how customers make decisions in online marketplaces. Present bias and hyperbolic discounting theories explain the short-term incentives and instalment-based payment plans, whereas loss aversion and scarcity cues explains the time-limited offers and flash-sales. In a similar context, mental accounting reveals how consumers perceive packaged products, EMI plans, and subscription agreements for a better understanding of how platform nudges collectively influence digital consumption patterns, promoting impulsive buying, by applying these theoretical concepts to e-commerce view.

1.1. Review of Literature

Behavioral economics has altered our understanding of how decisions are made by consumers by combining psychological inferences with economic insights. Unlike traditional models that presume totally rational behavior, behavioral economics stresses that consumers make decisions under bounded rationality, using heuristics and mental shortcuts to integrate information. These inclinations are getting worsen in digital marketplaces by tailored recommendations, algorithmically selected content, and focused advertising [4]. In complicated online settings, heuristics make decision-making easier, but they also add predictable biases. Consumer decisions are frequently influenced by anchoring, availability, and representativeness heuristics, which leaves them vulnerable to interface signals like “limited stock” labels or “bestseller” tags [5]. In addition to lowering cognitive strain, platforms can use these shortcuts to boost engagement and revenue. Furthermore, research indicates how age-related cognitive decline and individual cognitive styles influence consumers’ vulnerability to biases in online decision-making [6]. Nudging, which has become more popular in online situations, is making minor adjustments to the decision environment that guide behavior without limiting freedom. Digital nudging uses interface design elements like visual framing, push alerts, defaults, and personalized prompts to sway user choices [7]. Nudges, sometimes referred to as choice architecture interventions, influence behavior by rearranging decision situations without restricting freedom. A meta-analysis of more than 200 studies (n = 2,148,439) revealed a small to medium overall effect (Cohen’s $d = 0.43$) [8]. The most successful interventions were those involving decision structures, especially when it came to behaviours involving food. In spite of moderate publication bias, the study also found robustness across settings. Through a meta-analysis (n = 17,704), study demonstrates that reflective thinking is marginally associated with improved decision accuracy and experience, while intuitive thinking tends to decrease accuracy and marginally increases enjoyment. Each style had the greatest impact when it was in line with the requirements of the task, and variables like age and time constraints also influenced results. This emphasizes how thinking types affect decision-making depending on the situation [9].

Design strategies known as “dark patterns” are intentionally developed to affect user behavior, often without the user’s awareness These patterns increase impulse-driven behavior and reinforce decision loops by taking advantage of consumers’ cognitive biases. Thousands of websites use these strategies, according to extensive assessments, and AI-driven personalization further customizes manipulative actions for specific users [10]. In order to reduce exploitative design behaviors, emerging frameworks suggest combining interface-level observations with legislative and regulatory actions, such as consumer protection regulations and directives in the EU Digital Services Act [11]. It was also demonstrated that, the frequency of dark patterns—deceptive design techniques that influence user behaviour—across digital platforms point out how information asymmetry restricts user autonomy, identify 17 prevalent kinds, and provide a taxonomy in line with the Unfair Commercial Practices Directive (UCPD), presenting the idea of “Free Choice Repression” and makes legislative recommendations to improve consumer protection and control deceptive design techniques [12]. One important behavioral result of digital nudges and dark patterns is impulse purchase. According to research, customers’ inclination to make impulsive purchases is significantly impacted by one-click buying, recommendation algorithms, flash sales, and push alerts [13]. Examining human behaviour through observation and experiments, behavioural sciences have yielded important insights for policymaking [14]. Although previous studies have examined individual aspects of online shopping behavior, the interactive and cumulative influence of these factors remains underexplored. Recognizing this gap, the current research aims to analyze their interrelationships using a structured modeling approach.

Digital nudging and choice-architecture approaches on e-commerce platforms shape consumer decisions by subtly changing how options are presented, and several recent studies highlight both their potential and risks. Interface elements (labels, defaults, prompts) can reliably steer user behaviour in digital environments, improving compliance or engagement when used transparently [15]. Choice architecture further argued that the structure and framing of online choices determine whether nudges support beneficial outcomes or create new vulnerabilities for consumers [16]. Dark patterns demonstrates that deceptive or manipulative UI tactics (fake scarcity, hidden opt-outs) increase short-term conversions but damage perceived fairness and trust, raising regulatory and reputational risks [17]. Finally, empirical work underlines how nudges, recommendation systems, and UX design interact to influence impulse purchases, while calling for more ethical design and automated detection of manipulative practices [18]. Despite extensive research on individual behavioral factors, there remains a limited understanding of how these factors interact collectively in online impulse buying, highlighting the need for a structured framework to analyze their interrelationships.

1.2. Conceptual Framework

Drawing from the theoretical foundations and prior studies, the proposed conceptual framework in **Figure 1** brings together the key determinants identified in the literature. It explains how their combined influence contributes to shaping consumers' impulsive purchase decisions in online marketplaces. In e-commerce research, platform nudges are intentional behavioral interventions in digital environments designed to subtly influence consumer decisions without restricting choice [1]. Examples include personalized recommendations, push notifications, time-limited promotions, and EMI options. These nudges act as external cues, shaping consumer attention and choice architecture. Time-limited offers, defaults, and scarcity alerts are examples of e-commerce platform nudges that subtly affect consumer decisions without restricting possibilities. Behavioral biases such scarcity bias, social proof, and anchoring amplify the effects of these nudges and often lead to higher purchase intentions [19]. Furthermore, research shows that customers can be influenced by obvious and noticeable nudges while maintaining their autonomy [20]. Reviews warn, however, that digital nudging presents moral questions about justice and openness [21]. Overall, the framework positions platform nudges as antecedents, behavioral biases as mediators, and negative outcomes as consequences, with policy and ethical considerations serving as literature-informed moderators. Based on the review of prior studies, key variables capturing these constructs have been identified, providing a foundation to link the conceptual framework with empirical investigation.

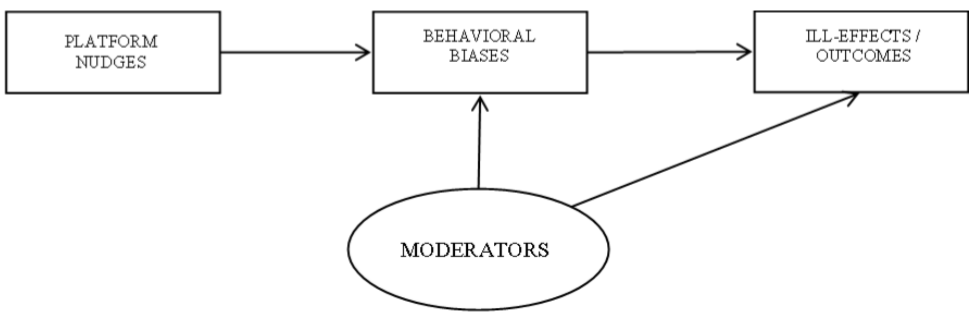

Figure 1. Conceptual Framework.

Source: Author's construct.

2. Materials and Methods

By combining structured modeling techniques with Soft Systems Methodology (SSM), the study takes a combined qualitative–analytical approach. By highlighting various viewpoints and stakeholder inputs, SSM aids in the comprehension of intricate and poorly organized issues, such as consumer decision-making in e-commerce [22]. Building on this basis, the study uses Interpretive Structural Modeling (ISM) to examine the linkages and create a conceptual framework after using the Nominal Group Technique (NGT) to identify and rank pertinent variables. The inclusion of expert perspectives and structural rigor in model building are guaranteed by this step-by-step method.

2.1. The NGT (Nominal Group Technique)

An organized approach to group discussions, the Nominal Group Technique aims to produce ideas, rank factors, and bring experts to an agreement. In contrast to unstructured brainstorming, NGT is a methodical procedure in which participants produce ideas on their own, present them in rounds, and then discuss and rank the most pertinent ideas as a group. To find important platform nudges, behavioral biases, moderators, and outcomes in e-commerce, NGT was applied in several rounds in this study, as illustrated in **Table 1**.

Table 1. NGT participants in the study.

No.	Category of Participants	Number of Participants
1	University Professors	2
2	Research Scholars	2
3	Industry Experts (E-commerce managers)	1
4	Behavioral Scientists	1
5	Policy Experts	1
6	Technology Specialists	1
Total	—	**8**

A. Criteria for Choosing Experts: The experts were selected based on their academic and professional experience in the domains of behavioral economics, consumer psychology, and e-commerce. A minimum of five years of relevant research or industry experience was considered as a criterion for inclusion.

B. Demographic Context of Experts: The expert panel consisted of 8 participants, including academicians, digital marketing professionals, and behavioral researchers. The group represented diverse age groups and both genders to ensure balanced perspectives.

C. Steps Followed in NGT (Nominal Group Technique): The Nominal Group Technique (NGT) was applied in four stages:

    (1) Identification of factors from literature,
    (2) Individual brainstorming by experts,
    (3) Group discussion and ranking of variables, and
    (4) Final consensus through structured feedback.

D. Bias Reduction Measures: To minimize bias in expert opinions, individual assessments were collected anonymously before group discussions. The facilitator has maintained neutrality and ensured equal participation of all experts during consensus formation.

E. ISM Relationship Confirmation: The contextual relationships among the variables were confirmed through iterative discussion rounds with the experts. The reachability matrix was cross-verified by at least two independent experts to ensure the logical consistency and robustness of the ISM model.

By taking these measures, NGT reduced individual dominance in group talks and guaranteed structured consensus, which strengthened and validated the results for additional modeling. The process has been illustrated in **Figure 2**, to show the methodology of how the review of literature and conceptual framework initially helped in drafting the further inclusion of NGT and ISM technique to make the final model.

2.2. Interpretive Structural Modeling (ISM)

Interpretive Structural Modeling (ISM) is used as part of the research process to methodically discover and structure the relationships among the major aspects influencing the study. By mapping both direct and indirect linkages, ISM aids in the creation of a hierarchical model, elucidating the interactions between various elements [24]. In order to validate the structural model and highlight the most significant variables, MICMAC analysis is utilized in conjunction with ISM to categorize these elements according to their driving and reliance powers [25]. This combination strategy improves the methodology's resilience and offers a verified framework for examining intricate correlations between the variables that have been found. **Figure 2** illustrates the adopted methodology applied to this research to diagnose the results.

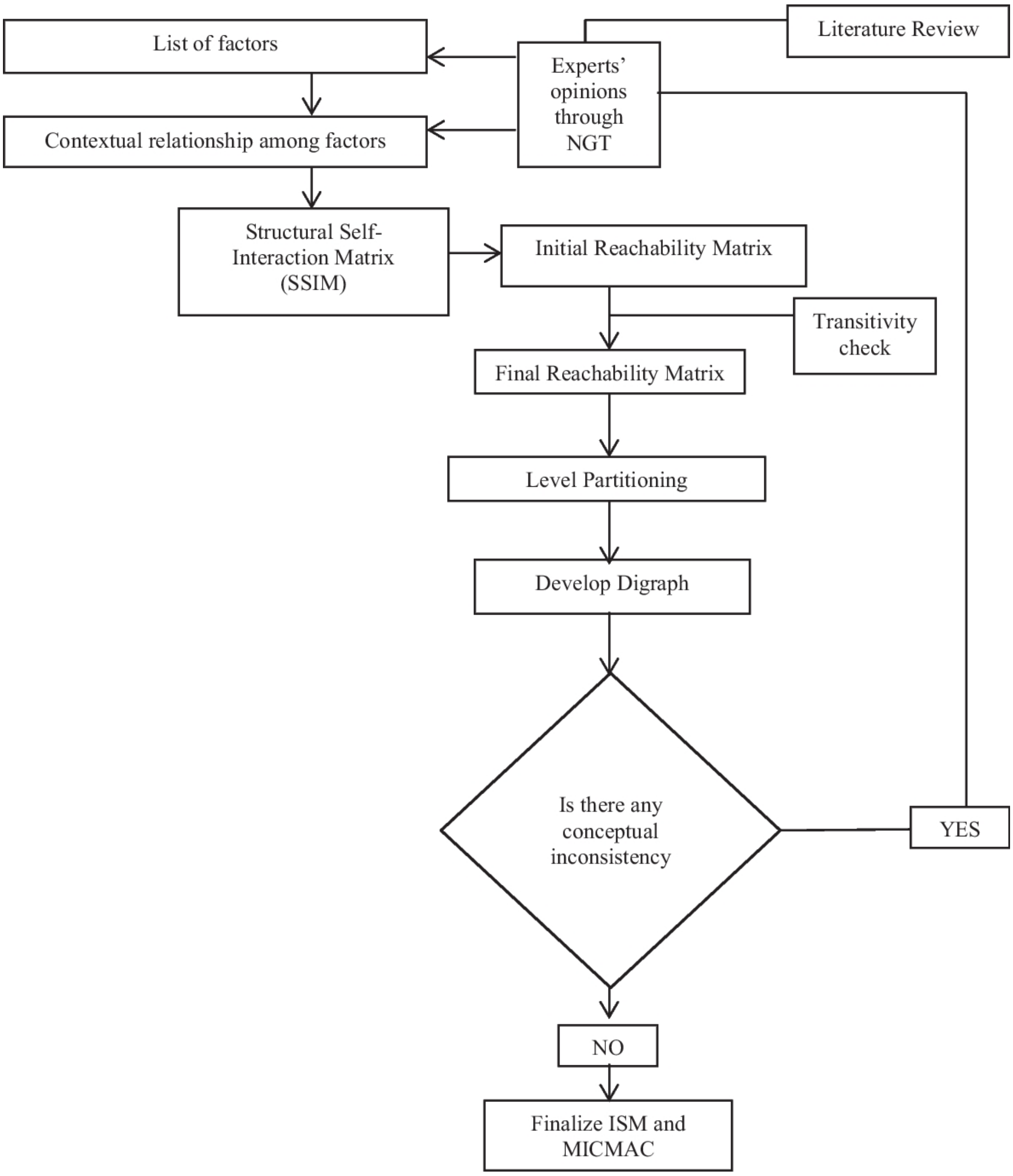

Figure 2. Methodology.

Source: Joshi et al., 2009 [23].

3. Results

3.1. Identification of Factors Influencing Impulse Buying Decisions

For the analysis, an initial set of variables was selected as possibly impacting digital purchase decisions and platform engagement based on a thorough examination of the body of existing review of literature on e-commerce, behavioral aspects of economics, and consumer behavior. These set of variables consists of variety of factors, which can be moderators, mediators, drivers, or dependent variables also related to the study. With the assistance from expert from various fields during NGT rounds, the variables were narrowed down with the consensus, reducing the list to eight important criteria named as Elements that were judged most pertinent and crucial for additional structural analysis utilizing the ISM technique in the context. The first collection of 15 criteria that have been found in the literature to influence impulsive purchases on e-commerce platforms is shown in **Table 2**. The list was whittled down and also the variables were elaborated by the experts to make them understandable in a better sense to eight essential components, as indicated in **Table 3**, after expert consensus was reached using the Nominal Group Technique

(NGT) with processing of variables. A strong basis for applying Interpretive Structural Modeling (ISM) for more in-depth analysis and moving forward with the creation of the final conceptual model was established by this revision.

Table 2. Initial list of factors/variables.

S.NO.	Factors	Authors
1.	Digital nudging through choice architecture	Weinmann et al. [26]
2.	Dark patterns in online shopping platforms	Mathur et al. [27]
3.	Countdown timers creating urgency	Tiemessen and Schraffenberger [28]
4.	Manipulative design reducing user autonomy	Sass [29]
5.	Effectiveness of nudging interventions	Mertens et al. [8]
6.	Influence of online reviews on purchases	Chen et al. [30]
7.	Information overload on e-commerce sites	Lv and Liu [31]
8.	Trust and privacy concerns in adoption	Ogut et al. [32]
9.	Delivery speed shaping satisfaction	Rashid and Rasheed [33]
10.	Financial enablers like BPNL, EMI	Wortmann et al. [34]
11.	Position bias in sponsored search results	Wang et al. [35]
12.	Deceptive design and consumer protection	Yang and Leiser [12]
13.	Personalized product recommendations	Nguyen et al. [36]
14.	Online impulse buying behavior	Anoop and Rahman [37]
15.	Social proof	Huang et al. [38]

Table 3. Final list of elements.

Element No.	Element (Factor/Variable)
E1	Digital nudging through choice architecture
E2	Dark patterns in online shopping platforms
E3	Countdown timers creating urgency
E4	Effectiveness of nudging interventions
E5	Information overload on e-commerce platforms
E6	Financial enablers like BNPL, EMI
E7	Online impulse buying behavior
E8	Social proof

1. Digital nudging through choice architecture: This refers to the architectural design of the e-commerce websites which influences the consumer decision making process while purchasing through the designs, layouts, and contours. Nudges boost engagement and encourage impulsive purchases in e-commerce. Researchers point to its expanding influence on how people consume content online.
2. Dark patterns in online shopping platforms: Sometimes, e-commerce websites use misleading design strategies like pre-checked boxes, unstated costs, or phony scarcity indications. They're referred to as "dark patterns," as they tend to incite hasty buying. Even when such measures are successful in the near term, they have the potential to erode trust over time. Because of its growing use, researchers have expressed ethical concern [27].
3. Countdown timers creating urgency: Sometimes these e-commerce platforms portray the technique of shot time deals, e.g., discounts valid till next 8 h, etc., which creates a belief of fear of missing out the deal, leading the customers to pay faster and get indulge in a false loop. These days, e-commerce advertising campaigns commonly employ these techniques.
4. Manipulative design reducing user autonomy: The way nudges are presented on e-commerce sites is directly linked to way consumers will react based on the timely offers and discounts, but too-much manipulation can cause chaos in the minds of the customers. While preserving a satisfying user experience, effective nudges boost conversions. Research indicates that well-crafted nudges have quantifiable effects on behavior [8].
5. Countdown timers creating urgency: Sometimes these

e-commerce platforms portray the technique of shot time deals, e.g., discounts valid till next 8 h, etc., which creates a belief of fear of missing out the deal, leading the customers to pay faster and get indulge in a false loop.

6. Manipulative design reducing user autonomy: The way nudges are presented on e-commerce sites is directly linked to way consumers will react based on the timely offers and discounts, but too-much manipulation can cause chaos in the minds of the customers. While preserving a satisfying user experience, effective nudges boost conversions. Research indicates that well-crafted nudges have quantifiable effects on behavior[8].
7. Information overload on e-commerce platforms: Sometimes, because of the excessive information overload on the platforms, consumers become overwhelmed and are unable to make rational decisions, rather they end up making impulsive choices. Achieving a balance between variety and simplicity is essential for online platforms. Information overload might cause impulsive or illogical behavior, according to earlier research[39].
8. Financial enablers like BNPL, EMI: Purchases appear more reasonable because to flexible payment alternatives like EMI and BNPL, which lessen the immediate financial burden. Customers are encouraged to purchase goods that they might have otherwise put off. Although it increases sales, it can also result in excessive spending and debt. Such plans are particularly well-liked by younger customers in e-commerce.
9. Online impulse buying behavior: When the customer got engaged into a purchase which was not based on rational thinking, just with the spur of the moment, the purchase thus happened is known as impulse buying. It is affected by a confluence of psychological, technological, and contextual elements. Impulsive purchases are the main focus of e-commerce consumer behavior, according to study[40].
10. Social proof: Customers are reassured of a product's popularity when they see ratings, reviews, or comments such as "X people bought this today." This social proof encourages cautious purchasers to take prompt action. It makes use of the bandwagon effect, which occurs when people copy the actions of others. Research demonstrates that social influence is a major factor in online purchasing[41].

3.2. Interaction Between Identified Elements

3.2.1. Structural Self-Interaction Matrix

In **Figure 3**, the structural self-interaction matrix is shown, which is also called as the VAXO framework is developed with the help of the ISM framework, in order to illustrate the interaction between the 8 finalized elements.

Variables	1	2	3	4	5	6	7	8
E1		O	V	V	O	O	V	V
E2			V	V	V	O	V	V
E3				V	O	V	V	O
E4					A	O	V	V
E5						V	V	V
E6							V	A
E7								A
E8								

Figure 3. Structural self-interaction matrix.

(a) Firstly, Number the elements row by row and column by column in the form of a matrix.
(b) Assessing each cell individually followed by the opinion of the experts to identify the relation between the column and row elements.
(c) Marked "V" if row elements influences column elements, "A" if column elements influence row elements, "X" if there is interdependency between the two, and "O" if there is no relation/interaction between the row and column elements.

3.2.2. Formulation of Initial and Final Reachability Matrix

Now, in **Figure 4**, the SSIM is to be converted into initial reachability matrix which is in the binary form. Because of the self-relationship, the diagonal cells from left-top to right-bottom are designated as "1". The steps are as follows:

(a) When the relation is marked as "V", place "1" in the row column position and "0" in the corresponding opposite position.

(b) When the relation is marked as "A", place "0" in the row-column position and "1" in the corresponding opposite position.

(c) When the relation is marked as "X", assign "1" in both row-column and the opposite position.

(d) When the relation is marked as "O", assign "0" to both row-column and the opposite position.

Variables	1	2	3	4	5	6	7	8	Driving Power
E1	1	0	1	1	0	0	1	1	5
E2	0	1	1	1	1	0	1	1	6
E3	0	0	1	1	0	1	1	0	4
E4	0	0	0	1	0	0	1	1	3
E5	0	0	0	1	1	1	1	1	5
E6	0	0	0	0	0	1	1	0	2
E7	0	0	0	0	0	0	1	0	1
E8	0	0	0	0	0	1	1	1	3
Dependence Power	1	1	3	5	2	4	8	5	

Figure 4. Initial reachability matrix.

Now, the methodology of the Floyd–Warshall algorithm (1962)[42] is employed in order to transform the initial reachability matrix into the final one, which is created by using the consistency rule, which guarantees that no relationships are left unfinished or in conflict. The link between the first and third elements in **Figure 5** must likewise hold if the first element is connected to a second, and the second is connected to a third. A comprehensive and logically consistent framework of contextual links among the elements is provided by updating any such ignored or missing connections in the matrix (marked with *). Once the matrix is finalized, the totals of rows and columns are calculated to identify the role of each element. The row total reflects the influencing power (Ip) of an element, while the column total represents its Dependent power (Dp). The strength of an element is based on how many factors it influences or is influenced by. These values are then applied in MICMAC analysis as shown in **Figure 6**, to cluster the elements, and the ranking of (Dp) and (Ip) helps confirm the consistency of the matrix.

Variables	1	2	3	4	5	6	7	8	Driving Power
E1	1	0	1	1	0	1*	1	1	6
E2	0	1	1	1	1	1*	1	1	7
E3	0	0	1	1	0	1	1	1*	5
E4	0	0	0	1	0	1*	1	1	4
E5	0	0	0	1	1	1	1	1	5
E6	0	0	0	0	0	1	1	0	2
E7	0	0	0	0	0	0	1	0	1
E8	0	0	0	0	0	1	1	1	3
Dependence Power	1	1	3	5	2	7	8	6	

Figure 5. Final reachability matrix.

Note: *: any such ignored or missing connections in the matrix.

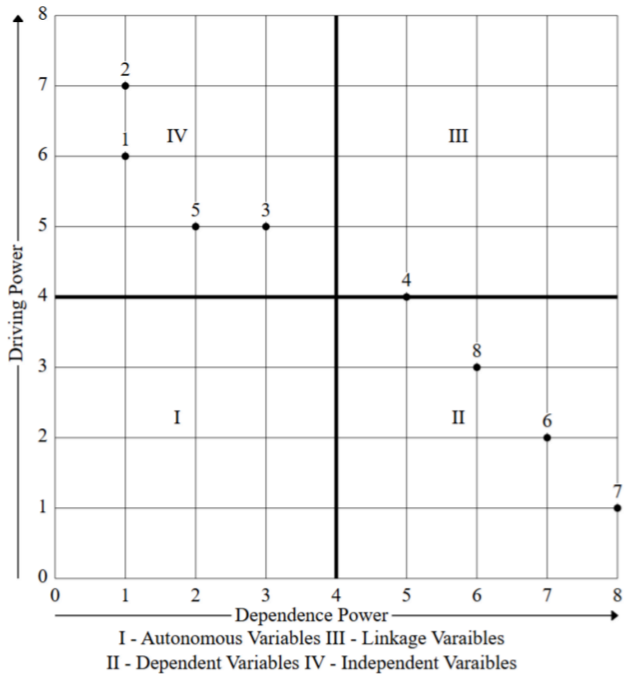

Figure 6. MICMAC framework (Cross-Impact Matrix Multiplication Applied to Classification).

In the MICMAC analysis, elements are distributed across four quadrants.

(a) Quadrant I (Autonomous); No strong drivers or dependents are here, showing limited influence.

(b) Quadrant II (Dependent); Elements 6, 7, 8 lie here, which means they are highly dependent on other factors but have low influencing power.

(c) Quadrant III (Linkage); Element 4 falls in this zone, reflecting strong influencing as well as strong dependence.

(d) Quadrant IV (Independent); Elements 1, 2, 3, 5 are positioned here, having high influencing power and low dependence. These act as the core drivers in the system.

This distribution shows that elements in Quadrant IV will play a dominant role in shaping the hierarchy, while dependent ones will settle at the lower levels during level partitioning.

3.2.3. Procedure of Level Partitioning

Level partitioning as illustrated in **Figure 7**, is the step that organizes elements into a hierarchy within ISM by identifying how many levels exist and where each element belongs[43]. This is done through four sets: the reachability set (elements influenced by a chosen factor), the antecedent set (elements influencing the chosen factor), their intersection set, and finally the assigned level. The process starts by determining the reachability of each element, then comparing it with antecedents, and placing elements into levels based on these relationships. In the initial iteration as depicted in **Figure 8**, the reachability and intersection sets are compared for each element. The elements where both sets coincide are placed at the top level. These elements are then removed from the list, so that all the elements are assigned to different levels of the hierarchy.

Elements(Mi)	Reachability Set R(Mi)	Antecedent Set A(Ni)	Intersection Set R(Mi)∩A(Ni)	Level
1	1,	1,	1,	6
2	2,	2,	2,	6
3	3,	1, 2, 3,	3,	5
4	4,	1, 2, 3, 4, 5,	4,	4
5	5,	2, 5,	5,	5
6	6,	1, 2, 3, 4, 5, 6, 8,	6,	2
7	7,	1, 2, 3, 4, 5, 6, 7, 8,	7,	1
8	8,	1, 2, 3, 4, 5, 8,	8,	3

Figure 7. Level partitioning.

Elements(Mi)	Reachability Set R(Mi)	Antecedent Set A(Ni)	Intersection Set R(Mi)∩A(Ni)	Level
1	1, 3, 4, 6, 7, 8,	1,	1,	
2	2, 3, 4, 5, 6, 7, 8,	2,	2,	
3	3, 4, 6, 7, 8,	1, 2, 3,	3,	
4	4, 6, 7, 8,	1, 2, 3, 4, 5,	4,	
5	4, 5, 6, 7, 8,	2, 5,	5,	
6	6, 7,	1, 2, 3, 4, 5, 6, 8,	6,	
7	7,	1, 2, 3, 4, 5, 6, 7, 8,	7,	1
8	6, 7, 8,	1, 2, 3, 4, 5, 8,	8,	

Figure 8. Level partitioning iteration.

Level partitioning as illustrated in **Figure 7**, is the step that organizes elements into a hierarchy within ISM by identifying how many levels exist and where each element belongs[43]. This is done through four sets: the reachability set (elements influenced by a chosen factor), the antecedent set (elements influencing the chosen factor), their intersection set, and finally the assigned level. The process starts by determining the reachability of each element, then comparing it with antecedents, and placing elements into levels based on these relationships. In the initial iteration as depicted in

Figure 8, the reachability and intersection sets are compared for each element. The elements where both sets coincide are placed at the top level. These elements are then removed from the list, so that all the elements are assigned to different levels of the hierarchy.

3.2.4. Conical and Reduced Conical Matrix Formation

Based on the level partitioning, a conical matrix as illustrated in **Figure 9**, is formed by rearranging the elements according to the levels. It re-arranges the elements based on influencing (Ip) and dependent power (Dp) to illustrate their positions in hierarchy, where E7 has the lowest Ip (1) and is placed at level 1, E6 follows with Ip (2) at level 2, while E8 is at level 3. E4 with driving power 4 is positioned at level 4. Elements E3 and E5 both show a higher driving power of 5, and hence are grouped at level 5. Finally, E1 and E2 are the strongest drivers, with the highest driving power (6 and 7), placed at level 6. Thus, the conical matrix gives a complete picture of how elements gradually rise in influence from level 1 to level 6 creating a diagraph. Thereafter, in the reduced conical matrix as depicted in **Figure 10**, the transitive links are eliminated, leaving only the most direct relationships among elements. Here again, all the elements continue to remain at their same levels as per their influencing power. This reduction refines the hierarchy, ensuring the final ISM model is simpler and highlights only the essential linkages between drivers and dependents.

Variables	7	6	8	4	3	5	1	2	Driving Power	Level
7	1	0	0	0	0	0	0	0	1	1
6	1	1	0	0	0	0	0	0	2	2
8	1	1	1	0	0	0	0	0	3	3
4	1	1*	1	1	0	0	0	0	4	4
3	1	1	1*	1	1	0	0	0	5	5
5	1	1	1	1	0	1	0	0	5	5
1	1	1*	1	1	1	0	1	0	6	6
2	1	1*	1	1	1	1	0	1	7	6
Dependence Power	8	7	6	5	3	2	1	1		
Level	1	2	3	4	5	5	6	6		

Figure 9. Conical matrix.

Note: The transitive checks represented as "*" explain that if E1 influences E2 and E2 influences E3, then the software highlights that E1 will also influence E3. These checks are considered only for MICMAC but are not taken in the Final ISM.

Variables	7	6	8	4	3	5	1	2	Driving Power	Level
E7	1	0	0	0	0	0	0	0	1	1
E6	1	1	0	0	0	0	0	0	2	2
E8	0	1	1	0	0	0	0	0	3	3
E4	0	0	1	1	0	0	0	0	4	4
E3	0	0	0	1	1	0	0	0	5	5
E5	0	0	0	1	0	1	0	0	5	5
E1	0	0	0	0	1	0	1	0	6	6
E2	0	0	0	0	1	1	0	1	7	6
Dependence Power	8	7	6	5	3	2	1	1		
Level	1	2	3	4	5	5	6	6		

Figure 10. Reduced conical matrix.

3.3. Creating the Final ISM Model and Understanding the Relationships

The hierarchical model as shown in **Figure 11**, has been derived from the reduced conical matrix which provides a structured view of how various factors interact to influence online impulse buying behaviour (E7). At the lower levels lie the influencing factors (E1, E2), while the upper most level captures the most dependent outcome (E7). The relationships across levels are explained below.

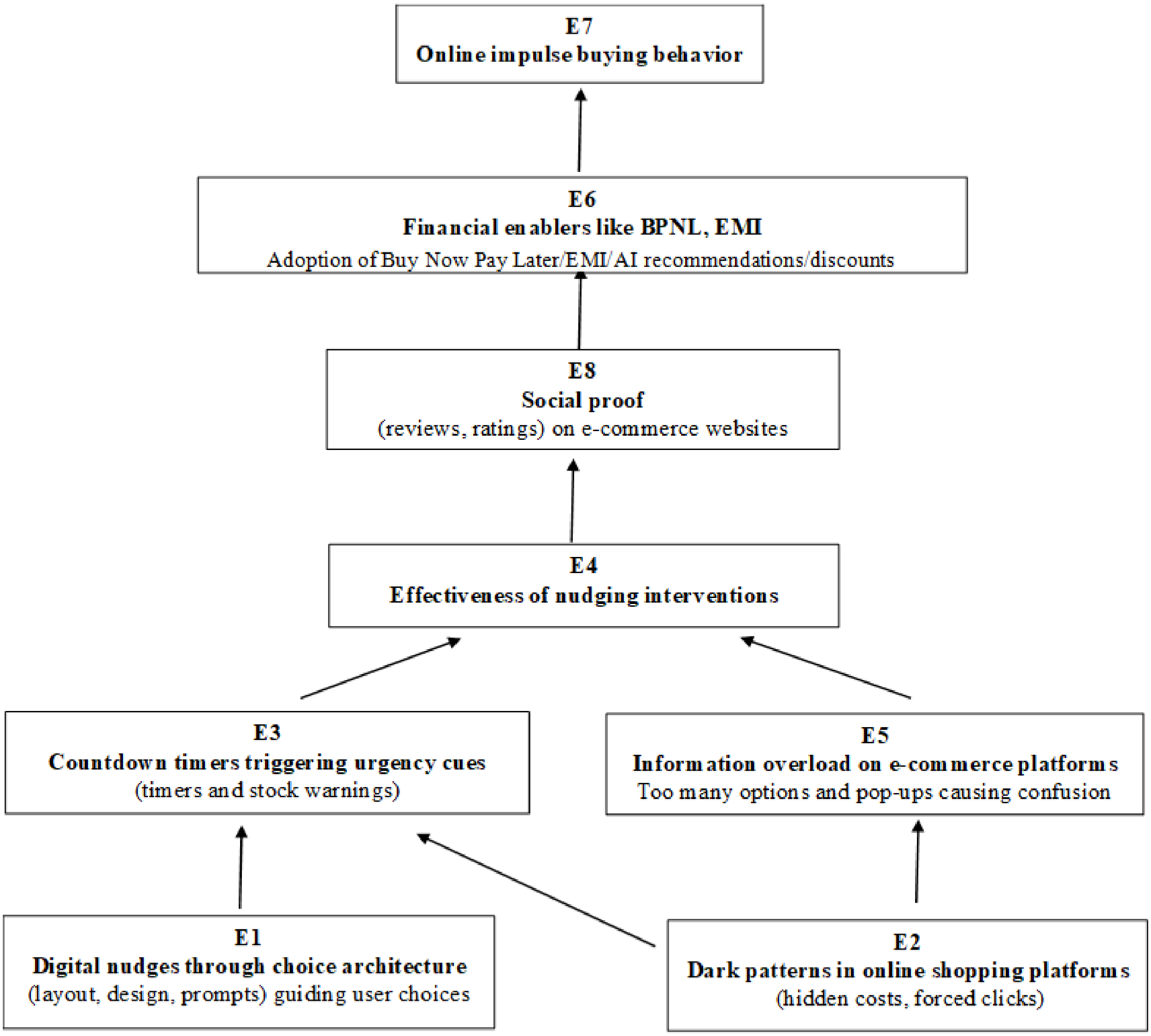

Figure 11. ISM model (Interpretative Structural Modeling).

a. Level 1: At the foundational level lie E1 and E2, which shape the digital environment within which consumers make decisions.

- E1 influence E3: Digital nudges such as "deal of the day" or "trending now" act as initial attention anchors, preparing consumers for urgency cues. Scarcity appeals are far more effective when customers are already by such framing mechanisms[2].
- E2 influence E3: Dark patterns like auto-added products or hidden defaults reinforce urgency effects.

  For instance, travel portals often present "only 2 seats left" messages alongside pre-selected insurance, combining urgency with manipulative design to accelerate decision-making.

- E2 influence E5: Dark patterns also intensify information overload. Cluttered prompts, forced add-ons, and hidden charges contribute to a crowded interface, heightening cognitive strain and reducing the consumer's ability to process information effectively [44]. Together, E1 and E2 function as the structural enablers that give rise to the psychological pressures of urgency (E3) and overload (E5) at the next level.

b. Level 2: At this level, E3 and E5 emerge as direct consumer-facing pressures, shaped by the foundational elements. E3 & E5 influences E4: The interaction of urgency and overload significantly enhances the effectiveness of nudging interventions. Under limited time offers, combined with an excess of options, consumers face both time stress and decision fatigue. This cognitive burden pushes them to rely more heavily on heuristics such as "best seller" tags or "recommended for you" suggestions. E3 and E5 therefore collectively influenced by Level 1, transforming them into behavioral vulnerabilities that can be exploited by more targeted nudging interventions.

c. Level 3: E4 integrates the foundational and intermediate elements into a cohesive mechanism. It demonstrates how structural design choices (E1, E2) and psychological pressures (E3, E5) collectively shape consumer responses. E4 drives E8: When nudges prove effective in guiding consumer choices, they enhance receptivity to social proof (E8), such as reviews and ratings. Trust in the platform's cues reduces uncertainty, making peer-generated information more influential in decision-making. E4 thus operates as a bridge, linking individual-level cognitive influence to broader social dynamics.

d. Level 4: At this stage, E8 magnifies the effects of prior nudging by providing external validation. Review, ratings, and user testimonials reinforce earlier nudging strategies by offending credibility and reassurance. E8 influences E6: Once trust is established through social proof, consumers become more open to adopting financial enablers (E6) such as BNPL, EMI schemes, or AI-driven recommendations. Empirical evidence confirms that peer validation reduces perceived risks associated with financial commitments, thereby encouraging adoption of such mechanisms [45]. Social proof therefore serves as the gateway through which psychological acceptance is converted into financial action.

e. Level 5: E6 represents the commercial dimension of the model, translating consumer trust and validation into actual purchasing power. E6 influences E7: By lowering immediate financial barriers, these enablers convert purchase intent into unplanned or impulse buying behavior (E7). Options like "Buy now Pay later" and algorithmic recommendations encourage consumers to prioritize instant gratification, reflecting present-biased decision-making patterns [46]. Financial enablers therefore act as the critical link between consumer intention and final behavioral outcomes.

f. Level 6: At the top of the hierarchy is E7, the most dependent element in the model. It represents the culmination of structural designs, manipulative tactics, psychological pressures, social influences, and financial enablers. E7 shows how these forces combine to create impulsive purchases that are frequently unrelated to logical demands. Customers show the results of nudges, scarcity cues, peer reviews, and easy EMI alternatives when they buy things they did not intend to buy. This highlights the multi-layered dependency of impulse buying on lower-level mechanisms, demonstrating the systemic progression from design strategies to consumer behavior.

4. Discussion

In some, this study began with a conceptual framework to explore digital nudges, manipulative design, urgency cues, information overload, nudging effectiveness, social proof, and financial enablers interact to produce online impulse buying behaviour. These results confirm that lower-level designs and interface mechanism exert influence upward, ultimately triggering impulsive purchases supported by extant literature that environment and interface cues play a major role in consumer impulse actions online. The framework, thus sheds light on both theoretical as well as practical interventions that need to be included, as illustrated in **Table 4**.

Table 4. Practical Implications.

Model Insight (E1–E7 Relationships)	Practical Implication
E1 & E2–E3 & E5 (Digital nudges and dark patterns create urgency and overload)	Use scarcity cues and limited-time offers carefully; avoid manipulative pop-ups that may reduce consumer trust or trigger regulation.
E3 & E5–E4 (Urgency and overload make users rely on shortcuts)	Keep interfaces simple—use "bestseller" or "trending" sections without flooding users with prompts.
E4–E8 (Effective nudges increase social proof dependence)	Highlight authentic, verified reviews and invest in fake-review detection to maintain credibility.
E8–E6 (Social proof encourages financial enabler use)	Pair popular or top-rated products with ethical EMI/BNPL offers and show clear repayment terms.
E6–E7 (Financial enablers drive impulse buying)	Promote one-click checkouts and instant credit but add consumer protection tools like spending alerts or easy cancellation options.

As per the suggested findings, it becomes necessary for digital platforms to improve accountability and transparency in their interactive design features, in order to protect consumers from being misled. Consumer protection laws (such as India's Consumer Protection [E-Commerce] Rules, 2020) should be strengthened with clear standards on dark patterns, forced continuities, hidden costs. At the same time, governments should require "Choice Architecture Audits" of E-Commerce platforms, similar to algorithmic audits, to ensure that nudges are in consumer interest and not purely manipulative. Features like push notifications, multiple discounts, and AI-driven recommendations, are frequently encouraging customers for unsustainable consumption practices. For example, Swiggy and Zomato can put users in a vicious circle of spending. Therefore, government should broaden its e-commerce clause in Consumer Protection Act by extending the awareness of how digital platforms uses algorithms to influence the choices of consumers in order to protect their personal welfare.

5. Conclusions

The research contributes to the scope of behavioral economics and to the field of e-commerce by illustrating how several behavioral biases and design of the digital platforms combine to influence online impulse buying. By combining nudges, social proof, and financial elements into the framework using ISM, the study provides a holistic view of digital persuasion and its effect on consumer behavior. The model demonstrates how multiple digital triggers interact with each other to shape impulsive buying, offering practical insights, providing guidance for policymakers, government policies, digital platform algorithms, and most importantly towards consumer awareness. Despite these noble contributions, the study has limitations as the framework relied on expert consensus, which, while being systemics, may open chances for subjectivity and biasness. It also lacks consumer-based validation, making field-based testing necessary for future research. The study may not also have captured the segment of cross-cultural context and demographics, allowing future researchers to use larger sets of data, and apply the model in different demographics and cultural context, extending it to mobile commerce and social media marketing. Such efforts would strengthen the robustness of the model, broaden its application, and will enhance the understanding of how behavioral nudges collectively drive consumer behavior in the evolving digital era.

Author Contributions

Conceptualization, methodology, software, formal analysis, and validation, T.P. and H.K.; formal analysis, investigation, resources, writing—original draft preparation, T.P.; writing—review and editing, visualization, supervision, H.K. Both authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Beatty, A., Moffitt, R., Buttenheim, A., et al. (Eds.), 2023. Implementing Behavioral Economics Approaches. In Behavioral Economics: Policy Impact and Future Directions. National Academies Press: Washington, DC, USA.

[2] Thaler, R.H., Sunstein, C.R., Balz, J.P., 2013. Choice architecture. In The Behavioral Foundations of Public Policy. Princeton University Press: Princeton, NJ, USA. pp. 428–439.

[3] Johnson, E.J., Shu, S.B., Dellaert, B.G.C., et al., 2012. Beyond nudges: Tools of a choice architecture. Marketing Letters. 23(2), 487–504. DOI: https://doi.org/10.1007/s11002-012-9186-1

[4] Hasan, M.M., Karim, F., Ripon, M.B.B., 2025. Behavioral economics and consumer decision-making: An integrative review. Business & Social Sciences. 3(1), 1–8. DOI: https://doi.org/10.25163/business.3110228

[5] Chuanlei, L., Baishu, C., Dijian, H., 2019. Effect of cognitive need and purchase involvement on information processing in the online shopping decision-making. International Journal of Computer Applications in Technology. 61(1–2), 31–36. DOI: https://doi.org/10.1504/IJCAT.2019.102091

[6] El Shamy, N., Hassanein, K., 2017. The impact of age and cognitive style on e-commerce decisions: The role of cognitive bias susceptibility. In Information Systems and Neuroscience. Springer International Publishing: Cham, Switzerland. pp. 73–83. DOI: https://doi.org/10.1007/978-3-319-67431-5_9

[7] Muda, R., Niszczota, P., Augustynowicz, P., 2020. The effect of imperfect memory recall on risk preferences. Journal of Behavioral Decision Making. 33(5), 683–690. DOI: https://doi.org/10.1002/bdm.2185

[8] Mertens, S., Herberz, M., Hahnel, U.J., et al., 2022. The effectiveness of nudging: A meta-analysis of choice architecture interventions across behavioral domains. Proceedings of the National Academy of Sciences of the United States of America. 119(1), e2107346118. DOI: https://doi.org/10.1073/pnas.2107346118

[9] Phillips, W.J., Fletcher, J.M., Marks, A.D., et al. 2016. Thinking styles and decision making: A meta-analysis. Psychological Bulletin. 142(3), 260. DOI: https://doi.org/10.1037/bul0000027

[10] Singh, N.K., Singh, P., 2022. Identifying consumer resistance of mobile payment during COVID-19: An interpretive structural modeling (ISM) approach. Business, Management and Economics Engineering. 20(2), 258–285. DOI: https://doi.org/10.3846/bmee.2022.16905

[11] Mathur, A., Mayer, J., Kshirsagar, M., 2021. What makes a dark pattern… dark? Design attributes, normative considerations, and measurement methods. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, Yokohama, Japan, 8–13 May 2021; pp. 1–27. DOI: https://doi.org/10.1145/3411764.3445610

[12] Yang, W.T., Leiser, M., 2022. Illuminating manipulative design: From "dark patterns" to information asymmetry and the repression of free choice under the Unfair Commercial Practices Directive. Loyola Consumer Law Review. 34, 484.

[13] Hadi, R., Valenzuela, A., 2020. Good vibrations: Consumer responses to technologically-mediated social touch. Journal of Consumer Research. 47(2), 256–271. DOI: https://doi.org/10.1093/jcr/ucz039

[14] Ciriolo, E., Lourenço, J.S., Almeida, S.R., 2019. The application of behavioural insights to policy in Europe. In Handbook of Behavioural Change and Public Policy. Edward Elgar Publishing: Cheltenham, UK. pp. 102–121. DOI: https://doi.org/10.4337/9781785367854.00014

[15] Sharma, K., Zhan, X., Nah, F.F.H., et al., 2021. Impact of digital nudging on information security behavior: an experimental study on framing and priming in cybersecurity. Organizational Cybersecurity Journal: Practice, Process and People. 1(1), 69–91. DOI: https://doi.org/10.1108/OCJ-03-2021-0009

[16] Dimitrova, V., 2022. Choice architecture for nudges to support constructive interactive systems. International Journal of Artificial Intelligence in Education. 32(4), 897–918. DOI: https://doi.org/10.1007/s40593-021-00263-1

[17] Kim, K.K., Kim, W.G., Lee, M., 2023. Impact of dark patterns on consumers' perceived fairness and attitude: Moderating effects of types of dark patterns, social proof, and moral identity. Tourism Management. 98, 104763. DOI: https://doi.org/10.1016/j.tourman.2023.104763

[18] Veigas, N.J., 2023. A comprehensive analysis of nudging and user experience in digital platforms. Engineering Proceedings. 59(1), 2. DOI: https://doi.org/10.3390/engproc2023059002

[19] Barton, B., Zlatevska, N., Oppewal, H., 2022. Scarcity tactics in marketing: A meta-analysis of product

scarcity effects on consumer purchase intentions. Journal of Retailing. 98(4), 741–758. DOI: https://doi.org/10.1016/j.jretai.2022.06.003

[20] Hettler, F.M., Schumacher, J.-P., Anton, E., et al., 2024. Understanding the user perception of digital nudging in platform interface design. Electronic Commerce Research. 25, 2097–2134. DOI: https://doi.org/10.1007/s10660-024-09825-6

[21] Suroto, 2025. Digital nudging strategies, applications, and ethical considerations: A systematic literature review. International Journal of Innovation in Enterprise System. 9(1), 663. DOI: https://doi.org/10.25124/ijies.v9i01.663

[22] Nakamori, Y., 2025. Decision-making with the systemic mind. In Sensible Decision-Making. Springer: Singapore. DOI: https://doi.org/10.1007/978-981-96-6811-3_3

[23] Joshi, R., Banwet, D.K., Shankar, R., 2009. Indian cold chain: modeling the inhibitors. British Food Journal. 111(11), 1260–1283. DOI: https://doi.org/10.1108/00070700911001077

[24] Goel, P., Kumar, R., Banga, H.K., et al., 2022. Deployment of interpretive structural modeling in barriers to Industry 4.0: A case of small and medium enterprises. Journal of Risk and Financial Management. 15(4), 171. DOI: https://doi.org/10.3390/jrfm15040171

[25] Ahmad, K., Islam, M.S., Jahin, M.A., et al., 2024. Analysis of Internet of Things implementation barriers in the cold supply chain: An integrated ISM-MICMAC and DEMATEL approach. PLOS ONE. 19(2), e0304118. DOI: https://doi.org/10.1371/journal.pone.0304118

[26] Weinmann, M., Schneider, C., Vom Brocke, J., 2016. Digital nudging. Business & Information Systems Engineering. 58(6), 433–436. DOI: https://doi.org/10.1007/s12599-016-0453-1

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

[28] Tiemessen, J., Schraffenberger, H., 2022. The Time Is Ticking: The Effect of Deceptive Countdown Timers on Consumers' Buying Behavior and Experience [Master's Thesis]. Radboud University: Nijmegen, The Netherlands.

[29] Sass, R., 2024. Manipulation, algorithm design, and the multiple dimensions of autonomy. Philosophy & Technology. 37(3), 108. DOI: https://doi.org/10.1007/s13347-024-00796-y

[30] Chen, T., Samaranayake, P., Cen, X., et al., 2022. The impact of online reviews on consumers' purchasing decisions: Evidence from an eye-tracking study. Frontiers in Psychology. 13, 865702. DOI: https://doi.org/10.3389/fpsyg.2022.865702

[31] Lv, J., Liu, X., 2022. The impact of information overload of e-commerce platform on consumer return intention: Considering the moderating role of perceived environmental effectiveness. International Journal of Environmental Research and Public Health. 19(13), 8060. DOI: https://doi.org/10.3390/ijerph19138060

[32] Ogut, O., Tzortzi, N.J., Bertolin, C., 2022. Vertical green structures to establish sustainable built environment: A systematic market review. Sustainability. 14(19), 12349. DOI: https://doi.org/10.3390/su141912349

[33] Rashid, D.A., Rasheed, D.R., 2024. Logistics service quality and product satisfaction in e-commerce. SAGE Open. 14(1), 21582440231224250. DOI: https://doi.org/10.1177/21582440231224250

[34] Wortmann, L., Lippold, K.C., Kaufmann, R., 2023. The Buy Now, Pay Later Model of the Fintech Industry in the Commercial Banking Sector. Copenhagen Business School: Copenhagen, Denmark.

[35] Wang, Y., Xue, Y., Liu, B., et al., 2023. Click-conversion multi-task model with position bias mitigation for sponsored search in e-commerce. In SIGIR '23: Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval. Association for Computing Machinery: New York, NY, USA. pp. 1884–1888. DOI: https://doi.org/10.1145/3539618.3591963

[36] Nguyen, D.N., Nguyen, V.H., Trinh, T., et al., 2024. A personalized product recommendation model in e-commerce based on retrieval strategy. Journal of Open Innovation: Technology, Market, and Complexity. 10(2), 100303. DOI: https://doi.org/10.1016/j.joitmc.2024.100303

[37] Anoop, T.S., Rahman, Z., 2025. Online impulse buying: A systematic review of 25 years of research using meta-regression. Journal of Consumer Behaviour. 24(1), 363–391. DOI: https://doi.org/10.1002/cb.2418

[38] Huang, W., Wang, X., Zhang, Q., et al., 2025. Beyond likes and comments: How social proof influences consumer impulse buying on short-form video platforms. Journal of Retailing and Consumer Services. 84, 104199. DOI: https://doi.org/10.1016/j.jretconser.2024.104199

[39] Jacoby, J., 1984. Perspectives on information overload. Journal of Consumer Research. 10(4), 432–435. DOI: https://doi.org/10.1086/208981

[40] Verhagen, T., van Dolen, W., 2011. The influence of online store beliefs on consumer online impulse buying: A model and empirical application. Information & Management. 48(8), 320–327. DOI: https://doi.org/10.1016/j.im.2011.08.001

[41] Chen, Y., Wang, Q., Xie, J., 2011. Online social interactions: A natural experiment on word of mouth versus observational learning. Journal of Marketing Research. 48(2), 238–254. DOI: https://doi.org/10.1509/jmkr.48.2.238

[42] Floyd, R.W., 1962. Algorithm 97: Shortest path. Com-

munications of the ACM. 5(6), 345. DOI: https://doi.org/10.1145/367766.368168

[43] Kaushik, H., Rajwanshi, R., 2025. Exploring technology adoption in dairy farms: Interactive management perspective. Journal of Science and Technology Policy Management. DOI: https://doi.org/10.1108/JSTPM-06-2024-0229

[44] 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. DOI: https://doi.org/10.1037/0022-3514.79.6.995

[45] Yadav, R., Mohan, H., Yadav, A., 2025. Examining the impact of BNPL integration on conversion rate and customer retention in e-commerce. Journal of Informatics Education and Research. 5(4), 472.

[46] Verplanken, B., Sato, A., 2011. The psychology of impulse buying: An integrative self-regulation approach. Journal of Consumer Policy. 34(2), 197–210. DOI: https://doi.org/10.1007/s10603-011-9158-5