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DIGITAL MANIPULATION VERSUS RESPONSIBLE CONSUMPTION: EXAMINING DARK PATTERNS THROUGH THE LENS OF SDG 12

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ABSTRACT

Dark patterns in digital platforms manipulate user behavior, undermining consumer autonomy and trust thus hampering sustainable consumption. Literature reveals how Generative artificial intelligence (GAI) personalizes deceptive designs, exploiting psychological vulnerabilities in real-time for profit, directly conflicting with UN SDG-12. This study uses an integrated Best-Worst Method (BWM), Total Interpretive Structural Modelling (TISM), and MICMAC analysis with insights from 20 digital platform experts to identify and model 10 key barriers to detect GAI-enhanced dark patterns, such as cognitive biases, emotional triggers, market manipulation, and user fatigue,. The researchers used TISM which partitioned the barriers into three levels: foundational (market manipulation driving others), intermediate (cognitive/emotional enablers like user awareness as mitigators) and surface (design complexity, digital literacy gaps). MICMAC analysis further confirms high driving power of market manipulation, creating self-reinforcing cycles amplified by GAI. Findings urge ethical AI management to foster informed digital consumption, aligning with SDG acceleration by empowering users against manipulation.

KEYWORDS: AI, Dark, Patterns, SDG, Digital Economy.

1. INTRODUCTION

Users on the digital platforms face various manipulative contents on a daily basis (Adams and Jansson, 2023). It is an enduring and intensifying issue, often referred to as dark patterns, designed to hoax the users into taking unwanted decisions. Dark patterns refer to user interface design elements that benefit organizations by deceiving and manipulating users (Brignull, 2011; Narayanan et al., 2020). The term "dark patterns" denotes a manipulative user interface pattern (Narayanan et al. 2020), that is used to direct the user behaviour in a manner beneficial to the service provider, but in effect it is potentially detrimental to the user's interest (Kollmer & Eckhardt 2022; Mathur et al. 2019). Dark patterns are employed by mixing deceptive language, phrases, and aesthetic designs often camouflaged as innocuous acts and user-friendly attributes.

Dark patterns usually transpire in virtual spaces and may affect the users negatively (Limbeck, 2023). Occasionally, firms employ a decoy effect by presenting a less appealing alternative in order to enhance the desirability of another product (Özdemir 2020). They manipulate the user's cognitive bias (Gunawan et al. 2022) by employing various techniques, such as capitalising on the user's inclination to seek confirmation of information that aligns with their existing beliefs (Chadwick et al., 2025). Several researches affirmed that if users become knowledgeable about dark patterns, they are more likely to reject the services offered in the marketplace (Gray et al., 2023; Brenncke, 2024; Oyibo, 2025). Dark patterns promote overconsumption by nudging consumers into unnecessary purchases, thus directly contradict SDG 12 (Responsible consumption). The sustainability goal (SDG 12) is focused on ensuring sustainable consumption patterns. However, businesses are currently setting digital barriers, which is harming consumer empowerment (Kitkowska et al., 2022). A sustainable digital economy refers to a well-functioning digital market focusing on consumer well-being in the economic and social sense (Rosario and Dias, 2023). According to United Nations (2021), "Digital sustainability" is achieved by focusing on the end user (consumer) empowerment. Aligning with sustainability for promoting user autonomy and their long-term welfare, the current study focused on extant literature related to dark patterns and identified the barriers users face in overcoming these dark patterns.

2. LITERATURE REVIEW

2.1. Dark Patterns

Dark pattern is a term coined by Brignull (2011) that refers to the manipulative design strategies businesses employ to persuade users to buy or sign up for something they didn't intend to. Lukoff et al. (2022) further elaborated dark pattern and focussed on websites and apps that design their user interface not to trick them but to exploit their psychological tendencies. This led to the enhancement of the definition of dark pattern by several authors (Kollmer and Eckhardt, 2022; Mathur et al, 2021) as "user interface design elements that compromise user autonomy by preventing informed choices and that may lead to adverse outcomes for the user, such as invasion of privacy, financial loss, and technology addiction." Dark patterns are used to undermine user autonomy by hindering their decision-making capacity through digital dark nudging and digital sludging (Kollmer and Eckhardt, 2022) (Figure 1). The term digital nudging refers to the architecture of websites and apps that alters the behaviour of the user in a way that the businesses want without hindering their choices and forbidding any options for them (Weinmann et al., 2016). Digital dark nudging refers to the design principles that affects the user autonomy. Digital dark nudging explains the unethical nature of websites that complicates, fabricates and omits information to manipulate the users. Activities like presenting travel insurance while booking flight tickets or chatbots sending messages like "Still interested? Your items are saved in the cart" when you leave shopping midway on online websites are examples of nudging

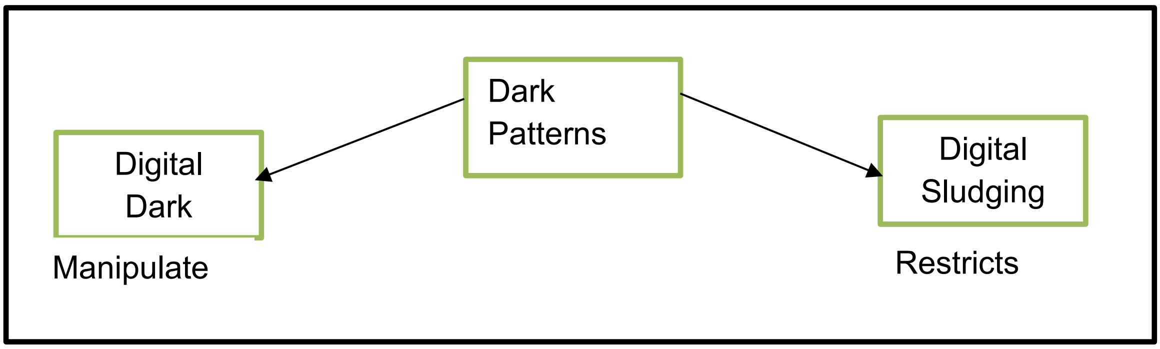

Figure 1: Dark Pattern composition (Created by authors).

Another evil twin of digital dark nudging is digital sludging. While nudging is used to alter the behaviour of the consumers, digital sludging is used by websites and chatbots to complicate the task completion process of the users (Kollmer and Eckhardt, 2023). Digital sludging refers to the excessive hurdles or barriers that complicate the user's task completion (Kollmer, 2022). Dark patterns use sludging to intentionally increase the search cost for users by misdirecting them, increasing their evaluation costs by concealing the information and choices from them, which increases the psychological costs for the users as it leads to anxiety brought by events like scarcity bias (Sin et al., 2025). Examples of sludging are visible in strategies employed by companies like Amazon which has more than six steps for cancelling their prime membership or booking sites like MakeMyTrip which shows messages like "Only 1 room left at this price" or "Limited time deal", thus creating unnecessary panic buying for the users.

Mills (2020) identified that businesses employ digital nudging and digital sludging simultaneously, where they nudge a user to favour one option, thus sludging them for other choices or vice versa. For instance, when a user wants to unsubscribe from any newsletter or subscription, digital sludging creates a series of checks for a user asking them if they want to unsubscribe, thus creating digital dark nudge by favouring the option to subscribe (Soman, 2020).

2.2 Generative Artificial Intelligence

The advertising ecosystem is rapidly evolving due to technological advancements which has led to a paradigm shift from traditional advertisement to more data driven advertisement (Ford et al., 2023). Artificial Intelligence is used in modern advertising to enhance the effectiveness of advertisements and for dynamic content generation (Park et al., 2024). Generative Artificial Intelligence (GAI) is a new emerging category of Artificial Intelligence (AI) which is capable of producing personalised text, images and high-quality written material (Susarla et al., 2023). GAI is growing exponentially in advertising and marketing for communicating and interacting with customers (Khatri et al., 2025) (Figure 2). GAI has a more powerful impact than other digital technologies while creating personalised and relevant information for customer engagement (Kshetri et al., 2024). GAI is used by businesses to offer one-to-one personalised and customised experiences, which were not previously possible by humans using other digital technologies (Kshetri et al., 2024) e.g. the use of GAI by Heinz is their award winning "A.I. Ketchup" campaign which has earned more than 850 million impressions (Hartmann et al., 2023). GAI is used for real-time imagery, personalised texts and predictive recommendations which can help to increase customer engagement in a cost-effective way (Bernard, 2023).

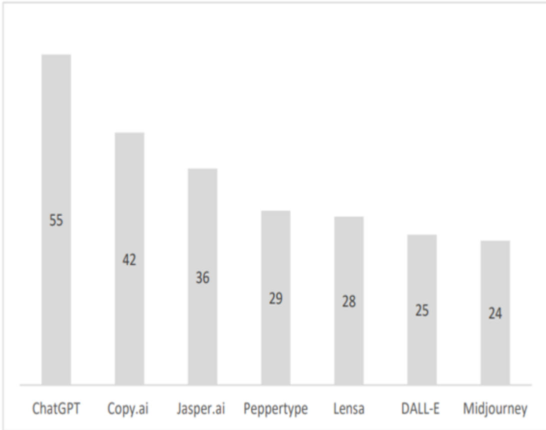

Figure 2: Percentage of Businesses using different GAI tools (Khetri et al., 2025).

GAI is considered by marketers as a major productivity booster tool. GAI uses an advanced algorithm to detect patterns in the content and generate new output after learning the patterns in the content (Yoo et al., 2023). GAI uses reinforcement learning to learn about customer problems and create the right ads to best cater to their problems. Advertisers optimise their advertising effectiveness by creating personalised ads on the spot using GAI (Nah et al., 2023).

2.3 Resource Advantage Theory

Resource Advantage Theory (RAT) was developed and conceptualised by Hunt and Morgan (2017), which provides a robust understanding of how organisations can get a competitive edge through better usage of their resources. RAT emphasises that organisations can outperform their competitors by strategically deploying their resources, thus aligning with the use of AI in predictive marketing (Naz and Kashif, 2024). However, dominant organisations use their superior resources and AI capabilities to control the market and manipulate consumer choices (Athey and Imbens, 2017). Organisations use AI-powered predictive marketing to alter behaviour of consumers into purchasing something which they don't wish to buy (Moews et al., 2019).

2.4 Generative AI and Dark Patterns

The nexus of Generative AI and Dark Patterns is proving to be a concerning development in the modern data-driven advertisement and predictive marketing (Luger and Sellen, 2016). While GAI can enhance the personalised customer experiences, concerns are rising against the potential use of GAI in creating and deploying deceptive marketing practices, also known as dark patterns (Kshetri et al., 2024). Generative AI can customise the dark pattern according to the browsing history of the users and their engagements on social media (Brunelle & Dömötörfy, 2022). Currently, Generative AI can enhance dark patterns by analysing user data in real-time and making swift changes to the digital interface, thus rendering it more manipulative and dangerous (Reicin, 2021) (Table 1). Generative AI is trained to mimic any sound, emotion, voice and behaviour, which can be used to automate and personalise design strategies to manipulate user behaviour in a much better way than traditional UX dark pattern have been able to do (Karagoz, 2024).

Table 1: Nexus of Dark patterns and GAI.

Type of Dark Pattern	Example	Companies using such Dark Pattern
Hyper-Personalization using AI	AI notices you often act impulsively at night. It sends you special "limited time" shopping offers exactly at a specific time and thus triggering the behavioural pattern of the customers.	Amazon, Shein
Roach Motel	A customer service AI "pretends" to help you cancel your subscription but keeps taking the user back to offers and delays, as they are constructed for customer retention.	Amazon, Spotify
Fake Social Proof	AI writes fake reviews, chats, or testimonials to stimulate decision-making by making the user believe that the product is popular and reliable.	Shein, Temu
Privacy Zuckering	AI dynamically adjusts privacy prompts to nudge you toward sharing more personal data, making it more difficult to proceed with accepting the conditions	Meta, Google
Emotional Targeting	AI uses sentiment analysis to detect the vulnerable emotional state of customer and suggests comfort-buying products ("Treat yourself!")	Snapchat, Spotify

3. RESEARCH METHODOLOGY

The study uses an integrated methodological approach comprising of TISM and MICMAC. TISM is used to identify the key relationships among the barriers in overcoming dark patterns generated by AI. TISM is an advanced version of ISM, which is used to identify the relationships among the factors and also explains their interdependence (Dhir and Dhir, 2020). TISM is a quantitative and qualitative technique used to analyze casual relationships after gathering insights from the experts and domain experts (Singh et al., 2024). This study uses the TISM model to develop the hierarchical structure among the identification barriers of Dark Patterns. Further MICMAC analysis is used to study the indirect relationships among the identification barriers in Dark Patterns (Figure 3).

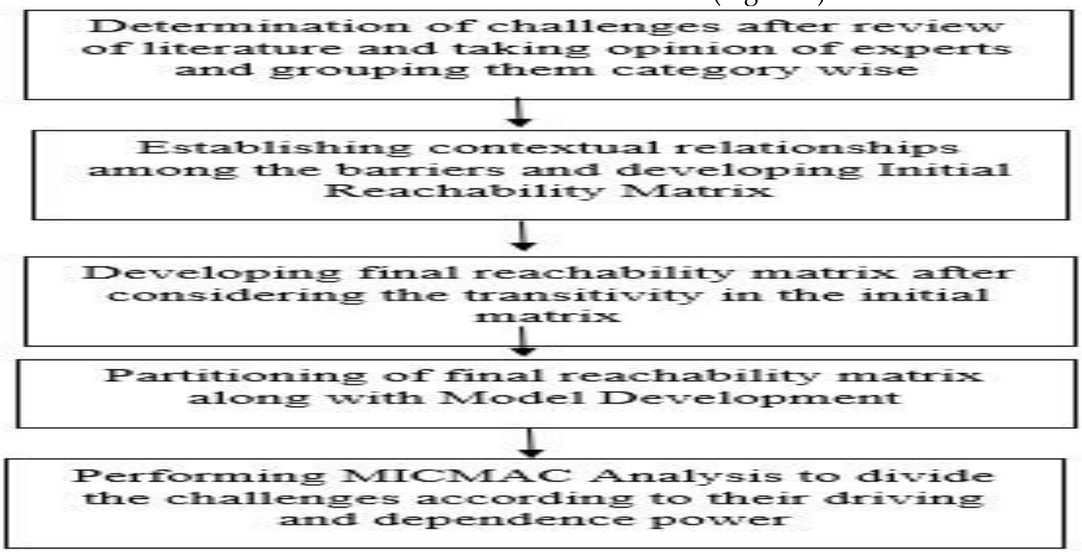

Figure 3: An Integrated phased approach TISM-MICMAC analysis (Created by authors).

3.1. Total Interpretive Structural Modelling

Total Interpretive Structural Modelling (TISM) is a structural modelling method that identifies and prioritises the relationships among the identified criteria. TISM is an advanced version of Interpretive Structural Modelling (ISM) that uses pairwise comparison to identify the relationships (Sushil and Dinesh, 2022). TISM consists of the following steps:

1. Identifying interpretive knowledge: The authors identified 10 barriers users face in identifying dark patterns after conducting an extensive review of literature. The authors initially consulted two IT experts working with more than 10 years of experience to validate the barriers identified after the literature review. Subsequently, the authors adopted snowball sampling by asking the experts to suggest more experts with at least 5 years of experience dealing with online services. Thus, 20 professionals with rich online customer engagement experience were considered for validating the barriers to dark pattern detection.
2. Determining the contextual relationships between the barriers: The next step after validating the barriers involves developing contextual relationships among the barriers in the form of an initial reachability matrix. The experts were asked to enter the value '1' where there is any relationship (direct or indirect) between the barriers and value '0' where there is no relationship between the barriers. The initial reachability matrix is created by considering the cumulative response from all the experts. If at least 15 (75%) experts have given a value '1', then the corresponding entry in the matrix is marked '1', else '0'. The matrix is shown in Table 2.

Table 2: Initial Reachability Matrix.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
C1	1	1	1	0	1	0	0	0	1	1
C2	0	1	1	0	0	0	0	0	0	1
C3	0	0	1	0	1	0	0	0	0	0
C4	1	1	1	1	1	0	0	0	1	1
C5	1	1	1	0	1	0	0	0	0	1
C6	1	1	1	0	1	1	0	0	1	1
C7	1	1	1	0	1	1	1	0	0	1
C8	1	1	1	0	1	0	0	1	0	0
C9	0	1	1	0	1	0	0	0	1	1
C10	0	1	0	0	0	0	0	0	0	1

3) Developing the final reachability matrix: This step involves developing a final reachability matrix. This is done after determining transitive relationships among the barriers using interpretive logic. The single level relationship is denoted by 1* (if P Q; and Q R; it implies that P R). The results have been summarised in Table 3.

Table 3: Final Reachability Matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	1	1	1	0	1	0	0	0	1	1
C2	0	1	1	0	0	0	0	0	0	1
C3	0	0	1	0	1	0	0	0	0	0
C4	1	1	1	1	1	0	0	0	1	1
C5	1	1	1	0	1	0	0	0	1*	1
C6	1	1	1	0	1	1	0	0	1	1
C7	1	1	1	0	1	1	1	0	0	1
C8	1	1	1	0	1	0	0	1	0	0
C9	1*	1	1	0	1	0	0	0	1	1
C10	1*	1	1*	0	0	0	0	0	0	1

4) Final reachability matrix partitioning: This step involves partitioning of the final reachability matrix into three sets: reachability set (RS), antecedent set (AS), and intersection set (IS). The reachability matrix contains all the individual barriers, along with the other barriers that have any relationship with them, respectively (row-wise). The antecedent matrix (AS) contains all the individual barriers and the other barriers that have any relationship with them, respectively (column-wise). The intersection matrix (IS) is created with all the common barriers between RS and AS. The identical elements in each barrier of the intersection set (IS) are then identified and labeled "Level 1" which are then eliminated. This step is again repeated until all the levels are defined. Thus, four levels of the partition reachability matrix

are identified (Table 4).

Table 4: Reachability Matrix Partitioning.

Delay Factor	Reachability Set	Antecedents set	Interaction set	Level
C1	C1,C2,C3,C5,C9,C10	C1,C4,C5,C6,C7,C8,C9,C10	C1,C5,C9,C10	0
C2	C2, C3, C10	C1, C2, C4, C5, C6, C7, C8, C9, C10	C2, C10	0
C3	C3, C5	C1, C2, C3, C4, C5, C6, C7, C8, C9, C10	C3, C5	1
C4	C1, C2, C3, C4, C5, C9, C10	C4	C4	1
C5	C1, C2, C3, C5, C9, C10	C1, C3, C4, C5, C6, C7, C8, C9	C1, C3, C5, C9	0
C6	C1, C2, C3, C5, C6, C9, C10	C6, C7	C6	0
C7	C1, C2, C3, C5, C6, C7, C10	C7	C7	1
C8	C1, C2, C3, C5, C8	C8	C8	1
C9	C1, C2, C3, C5, C9, C10	C1, C4, C5, C6, C9	C1, C5, C9	0
C10	C1, C2, C3, C10	C1, C2, C4, C5, C6, C7, C9, C10	C1, C2, C10	0

5) Constructing a diagraph from the final reachability matrix: The authors consulted 5 senior IT professionals to further validate the transitive relationships discovered in the final reachability matrix. A five-point Likert scale was used to measure the significance of the transitive relationships. An average score of more than 80% is adequate to identify the transitive relationship. Thus, an average Likert score of greater than or equal to 4 (80%) is considered adequate to accept the transitive links between the barriers. Figure 4 shows the direct links and the transitive links between the barriers having more than 80% score. The level partition (Table 4) developed is used to partition the levels in the diagraph.

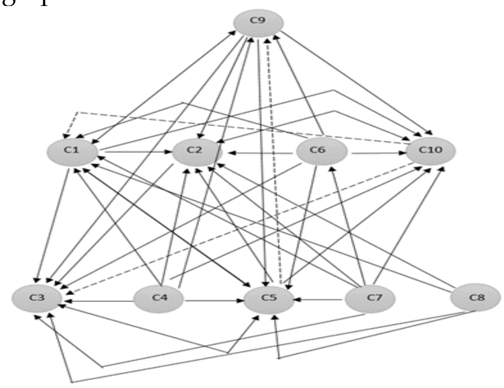

Figure 4: Diagraph.

C1- COGNITIVE BIAS; C2- EMOTIONAL TRIGGERS; C3-CONFIRM SHAMING
C4-DESIGN COMPLEXITY; C5- USER FATIGUE; C6-USER AWARENESS;
C7-DIGITAL LITERACY; C8-DESIGNER BIAS; C9-MARKET MANIPULATION;
C10- SHORT TERM USER BENEFITS.

6) MICMAC Analysis: MICMAC analysis measures the driving power and the dependency power among the barriers in overcoming dark patterns. TISM analysis was used to rank and identify the relationships among the barriers while MICMAC is used to identify the independence among the barriers and plot them according to their driving and dependence power. The driving power of the relationships is calculated by aggregating the transitive relationships of the respective barriers row-wise while the dependence power is calculated by aggregating the transitive relationships of the respective barrier column-wise. The barriers are plotted into 4 quadrants where X-axis shows the dependence power of the barriers and Y-axis shows the driving power of the barriers (Figure 5).

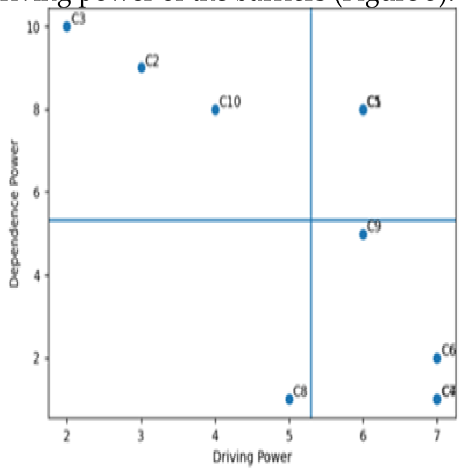

Figure 5: MICMAC Analysis.

4. RESULTS AND DISCUSSIONS

The authors initially identified 10 barriers that hinder users from overcoming dark patterns. The identified barriers are C1 (cognitive bias), C2 (Emotional triggers), C3 (Confirm shaming), C4 (Design complexity), C5 (User fatigue), C6 (User awareness), C7 (Digital literacy), C8 (Designer bias), C9 (Market manipulation) and C10 (Short-term user benefit) (Table 5). Level partitioning was used to group the barriers into three levels, while the interaction matrix represented the direct and transitive relationships between the challenges that users face in overcoming dark patterns created by generative AI using the TISM model.

Table 5: Barriers in Dark Pattern detection

Challenge	Description
Cognitive biases	Mental shortcuts lead to flawed decision-making.
Emotional triggers	Exploits fear, urgency, or other emotions to influence actions.
Confirm shaming	Guilt-tripping users into making certain choices.
Design complexity	Overly complex interfaces hide real choices or mislead users.
User fatigue	Repeated exposure leads to reduced critical thinking and poor decisions.
User awareness	Lack of recognition or understanding of dark patterns.
Digital literacy	Inability to evaluate or understand digital interactions critically.
Designer bias	Designers' assumptions or incentives embed manipulation.
Market manipulation	Platforms nudge behaviour subtly for profit, reducing autonomy.
Short-term user benefit	Immediate rewards encourage compliance despite long-term harm.

4.1. Level 3 Barriers (C3, C4, C5, C7, C8)

C3 (Confirm Shaming) affects C5 (User fatigue) as emotional manipulation is quite draining for the users. Continuous exposure to emotionally inducing prompts leads to emotional depletion and decision fatigue that accelerates user fatigue. This is done as fatigued users are easier to manipulate. Generative AI triggers confirm shaming when consumers are most vulnerable, like long sessions and failed attempts, causing emotional strain that causes user fatigue.

C4 (Design Complexity) influences C3 (Confirm Shaming) as when design complexity is high, users cannot process the implications of the choices they are making, making confirm shaming more effective. Generative AI is used to dynamically create complex personalized interfaces, which masks the ability of users to understand that they are being manipulated. C4 (Design Complexity) also impacts C5 (User Fatigue) as when there are too many options for the user, they tend to make the easiest choice even when it is not the most productive for them.

C5 (User fatigue) affects C1 (Cognitive Bias) of the users as it restricts their attention span as well as their rational choice making capability which is needed to resist bias. Generative AI amplifies this problem as users defaults to bias-driven decisions when fatigue sets in among users. C5 (User fatigue) affects C3 (Confirm Shaming), as when users are mentally drained, they tend to become more emotionally vulnerable. Their resistance to guilt-laden prompts decreases and they become more submissive to the shamed option rather than resisting it. Thus, confirm shaming is more effective when users are fatigued.

C7 (Digital Literacy) influences C1 (Cognitive Bias) since lack of digital literacy reduces awareness among users. Lack of digital literacy amplifies cognitive bias as users are unable to track and predict the urgency cues and emotionally charged language created by generative AI. C7 (Digital Literacy) influences C2 (Emotional Triggers) as digital literacy is required among users in understanding emotional manipulation tactics (e.g.-Only 1 room left). Digital literate users understand emotionally charged prompts which makes the emotional prompts less effective. C7 (Digital Literacy) influences C3 (Confirm Shaming) and is considered the first firewall against confirm shaming. As Digital literacy increases, the impact of confirm shaming decreases. Users with low digital literacy fail to recognise that confirm shaming messages are algorithmically created by generative AI. C7 (Digital Literacy) influences C5 (User Fatigue) and has a meta-cognitive relationship. Increased digital literacy among users reduces their fatigue by enabling efficient navigation. C7 (Digital Literacy) influences C6 (User Awareness) as informed users are more likely to detect any manipulation in the interface. Users with low digital literacy often believe in emotionally charged choices created by generative AI to create intentional manipulation. C7 (Digital Literacy) influences C10 (Short-term user benefits) as consumers with low digital literacy are more likely to accept opt-in features without reading the terms and conditions or accept the permissions on websites to browse fast on the websites. Companies use generative AI to analyse the immediate benefits to hook different users like flash sales, free trials etc. Users with low digital literacy fail to understand such tactics used by companies and fall more in dark pattern design.

C8 (Designer Bias) has a reinforcing relationship with C1 (Cognitive bias) as designer bias amplifies the dark pattern and thus exploits the consumers' cognitive bias, making it even harder and complex for the consumers to detect. C8 (Designer Bias) has a direct reinforcing relationship with C2 (Emotional Triggers), as it shapes the interfaces in an emotionally intensifying, manipulative design that affects the rational decision-making power of consumers while interacting with AI-optimized dark patterns. C8

(Designer Bias) reinforces the impact of C3 (confirm shaming) as it makes the user habituated to the guilt-framing messages. Designer Bias promotes the hyper-personalization of confirm shaming tactics making it harder for consumers to decline the offers without emotional discomfort. C8 (Designer Bias) overloads consumers with micro-decisions, leading to C5 (User Fatigue). Repeated pop-ups and checkboxes are created to maximize user engagement but leads to cognitive bias, thus decreasing the ability of the user to critically evaluate with what is happening. AI then exploits the fatigued state of the user by presenting options such as "Accept all" and "Continue."

4.2. Level 2 Barriers (C1, C2, C6, C10)

C1 (Cognitive Bias) has a very strong reinforcing relationship with C2 (Emotional Triggers) and increases user vulnerability to emotional triggers like fear, guilt, making it easier for dark patterns to emotionally manipulate the users. AI understands through the type of cognitive bias required for different users and thus creates emotional messages accordingly to trigger their behaviour. Pop-ups like "Only one item left" make users click not because of need but because of emotional biased response like FOMO or loss aversion (fear of missed deal). C1 (Cognitive Bias) has a reinforcing relationship with C3 (Confirm-Shaming) as it increases the internal vulnerabilities that dark patterns exploit using confirm-shaming messages. C1 (Cognitive Bias) has a strong influence on C5 (User Fatigue) as it increases the decision-making process of the consumer, as they are presented with choice overload. Cognitive Bias like delay opting out or displaying multiple options before acting increases the cognitive effort of the consumer, which increases their mental exhaustion. C1 (Cognitive Bias) has a reinforcing relationship with C9 (Market Manipulation) and acts as enablers of market manipulation. Messages like "1,499 slashed from 4,999- Only for today" or countdown timers used by companies like Amazon makes consumer believe that companies are offering a huge discount. These messages although looks authentic but they are created just to manipulate the users and deviating them from normal market behaviour. C1 (Cognitive Bias) has a strong impact on C10 (Short–Term User Benefits) as these cognitive bias makes user to accept the immediate awards or favors like "Get 500 off today only-Just sign today" without understanding the privacy loss and thus these reward traps become normalised.

C2 (Emotional Triggers) has a reinforcing relationship on C3 (Confirm–Shaming) as it increases the effectiveness of confirm-shaming messages on customer behavior. A user who is already feeling anxious is more likely to fall for guilt-framed messages. C2 (Emotional Triggers) has a strong reinforcing impact on C10 (Short Term User Benefits) as emotionally triggered customers will look for immediate relief or satisfaction and thus, they will fall for short term benefits generated by AI, even if they are harmful in the long run. AI detects the emotional patterns of customers and then serves them with short term benefits when they are the most emotionally reactive.

C6 (User Awareness) has a mitigating relationship with C1 (Cognitive Bias) as high user awareness reduces the impact of cognitive bias on customers by allowing them to detect manipulative AI-driven tactics and thus they make a more rational decision. C6 (User Awareness) has a mitigating relationship with C2 (Emotional Triggers) as high user awareness reduces the impact of emotional triggers like guilt or fear of missing out (FOMO) on customers by allowing them to detect emotionally driven manipulative tactics in AI-created dark patterns. C6 (User Awareness) has a mitigating relationship with C3 (Confirm-Shaming) as high user awareness reduces the emotional and psychological impact of confirm shaming on customers by allowing them to detect manipulative AI-driven tactics and thus they make a more confident and conscious decision. C6 (User Awareness) has a mitigating relationship with C5 (User Fatigue) as high awareness helps consumers to detect unnecessary prompts early which reduces the cognitive load of consumers by shortening their decision path. C6 (User Awareness) has a mitigating relationship with C9 (Market Manipulation) as high user awareness acts as a defence against the market manipulation tactics like deceptive pricing, scarcity tactics and flawed demand signals created by AI-generated dark patterns. C6 (User Awareness) has a mitigating relationship with C10 (Short Term User Benefit) as user awareness reduces the impact of the trap of short-term benefits (like free product, free trial, instant discount) on customers by allowing them to recognise the hidden costs and future consequences of the manipulative AI-driven offers and thus they make a more informed decision.

C10 (Short Term User Benefits) has a reinforcing relationship with C1 (Cognitive Bias) as it intensifies the impact of cognitive bias on users. Short-term offers like "Get 10% cashback" make consumers act quickly and thus strengthen bias-driven behaviour. C10 (Short Term User Benefits) has a reinforcing relationship with C2 (Emotional Triggers) as it amplifies the impact of emotional triggers like fear and urgency on users-thus making them more susceptible to emotional manipulation triggers created by generative AI-created dark patterns. C10 (Short Term User Benefits) has a reinforcing relationship with C3 (Confirm Shaming) as it increases the impact of emotional pressure created by confirm shaming messages like "No thanks, I don't want to save", thus making the consumer feel guilty and amplifying the emotional sting of confirm shaming.

4.3. Level 1 Barrier (C9)

C9 (Market Manipulation) has a reinforcing relationship with C1 (Cognitive Bias) as it strengthens the impact of cognitive bias on consumers and makes it harder for them to detect. Market manipulation, like fake scarcity triggers scarcity bias and consumers act impulsively even if the scarcity is false. Generative AI also created personalized manipulation which exploits the biases individually. C9 (Market Manipulation) has a strong reinforcing relationship with C2 (Emotional Triggers) as tactics like "Sale ending in 5 minutes" increases user vulnerability to emotional triggers like fear, guilt, making it easier for dark patterns to emotionally manipulate the users and making them react irrationally. C9 (Market Manipulation) has a reinforcing relationship with C3 (Confirm Shaming) as it increases the impact of psychological pressure created by confirm shaming messages after creating a state of false demand or scarcity for the consumers. Fake markdown in prices like "Prices slashed by 90%" accompanied by confirm shaming messages like "No thanks, I don't want to save", makes the consumer feel irresponsible of rejecting a high value deal. C9 (Market Manipulation) has a reinforcing relationship with C5 (User Fatigue) as constant and aggressive market manipulation leads to cognitive and mental overload, causing user fatigue. This reduces the ability of consumers to detect and mitigate themselves from the impact of dark patterns. C9 (Market Manipulation) has a reinforcing relationship with C10 (Short term user benefits) as it inflates the perceived value of short-term user benefits making them look more exclusive and rewarding among the customers. Tactics like inflated discounts make consumers react impulsively without understanding the cost-benefit analysis of such schemes. Based on the consumer's history AI created personalized manipulation and makes the rewards more irresistible for each consumer.

5. CONCLUSION

The present study proposes an integrated phased technique TISM-MICMAC analysis to explore the influence relations among a set of barriers in detecting dark patterns. Total Interpretive Structural Modelling (TISM) was used to identify the contextual relationships among the barriers in detection of dark patterns. The barriers were then divided into three clusters based on MICMAC analysis. The results show that market manipulation arises as the most influential barrier, driving and reinforcing other barriers such as cognitive biases, emotional triggers, confirm shaming, user fatigue, and short-term reward traps. Generative AI amplifies these effects by continuously learning from user behaviour and optimizing manipulative interfaces in real time. This creates a self-reinforcing cycle where psychological vulnerabilities are systematically exploited, making detection and resistance increasingly difficult for users. At the intermediate level, cognitive bias, emotional triggers, user awareness, and short-term user benefits act as critical enablers that either magnify or mitigate the influence of AI-driven dark patterns. Overall, the study highlights an important contradiction. While generative AI improves personalization, efficiency, and engagement in digital marketing, it also increases ethical risks by enabling large-scale and hidden manipulation. The findings extend Resource Advantage Theory by showing that companies use advanced AI not only to gain a competitive edge but also to influence and control consumer behaviour.

This study highlights the need for regulators and platform designers to actively reduce market manipulation and user fatigue through ethical AI governance and transparency measures. Regulators need to work on algorithmic transparency and user autonomy by making it mandatory for the digital platforms to disclose their recommendations and pricing systems so that users can make informed decisions. To further mitigate the harms identified in the study, regulatory bodies should introduce binding standards for regulatory platforms to regularly audit the implementation of dark patterns on their platforms and assess their algorithmic impact. Design principles need to be developed that limit the use of urgency cues and scarcity signs. The above measures from regulatory authorities would help reduce market manipulation and foster trust, user autonomy, and respect for consumers in the digital environment.

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