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Dual Dopamine: AI Marketing's Hybrid Operant Conditioning via Positive-Negative Reinforcement Pathways

Dr. Rohini Nikam[1], Meet Yadav[2], Rutuja Shidodkar[3], Aishwarya Pednekar[4], Atharva bachhav[5], Vedant Gawande[6].

[1]Assistant Professor, SaiBalaji International Institute of Management Sciences, Pune
[2]Student, SaiBalaji International Institute of Management Sciences, Pune
[3]Student, SaiBalaji International Institute of Management Sciences, Pune
[4]Student, SaiBalaji International Institute of Management Sciences, Pune
[5]Student, SaiBalaji International Institute of Management Sciences, Pune
[6]Student, SaiBalaji International Institute of Management Sciences, Pune

Abstract

This study explores how AI-driven marketing systems in the digital economy influence consumer decision making through a dual process of positive and negative reinforcement. The concept of "dual dopamine" hybrid operant conditioning is examined, where rewards such as discounts and free trials coexist with pressures like ads, time limits, and FOMO triggers. Data were collected from digital consumers and analysed using descriptive and inferential statistics to identify behavioural patterns related to purchase motivation, pressure, and regret. The results highlight how AI systems leverage both reinforcement types to sustain engagement and spending. The study offers practical insights for companies and MSMEs to design commercially effective yet ethically balanced neuromarketing strategies in an increasingly dopamine-driven marketplace.

Keywords: *Neuromarketing; AI-driven marketing; Hybrid reinforcement; Digital subscriptions; Impulse buying.*

I. INTRODUCTION

Over the past decade, the rapid growth of digital commerce has fundamentally reshaped how consumers interact with brands, services, and technological platforms. Digital environments such as e-commerce websites, streaming platforms, social media networks, mobile applications, and AI-based tools now operate as an interconnected ecosystem in which consumer choices are increasingly influenced by algorithmically mediated experiences rather than solely by conscious and rational decision-making processes based on the research by Davenport et al. (2020) AI in marketing. Prior scholarly work such as Morin (2011) – in neuromarketing suggests that many of these digital interfaces are strategically designed to activate the brain's reward mechanisms, particularly dopamine-related pathways associated with anticipation, motivation, and pleasure, in order to enhance user engagement and stimulate impulsive consumption behavior.

In parallel, according to Davenport et al., (2020), advancements in artificial intelligence and data analytics have enabled firms to deploy highly personalized marketing strategies, including recommendation systems, dynamic pricing models, and real-time behavioral targeting. From the author's perspective, These technologies allow platforms to tailor content, offers, and product visibility at the individual level, thereby intensifying the psychological impact of digital marketing interventions on consumer decision-making. As a result, consumers are no longer passive recipients of advertisements but are continuously embedded within adaptive systems that learn from their interactions and modify persuasive strategies accordingly.

In contemporary digital settings, individuals are repeatedly exposed to a variety of stimuli such as push notifications, algorithmic recommendations, time-sensitive promotions, subscription reminders, and in-app purchases. This study conceptualizes these stimuli as strategically engineered reinforcement mechanisms. These stimuli do not operate merely by offering potential rewards but also by alleviating perceived negative states, including inconvenience, restriction of features, intrusive advertisements, or anxiety related to missing limited opportunities based on operant conditioning theory (Skinner, 1953). From the perspective of behavioral psychology, and particularly operant conditioning theory, such marketing mechanisms can be conceptualized as forms of positive reinforcement, where desirable outcomes such as discounts, premium features, or exclusive access are introduced—and negative reinforcement—where unpleasant conditions such as advertisements, functional limitations, or uncertainty are removed.

While prior studies have extensively examined the role of reward-based cues such as scarcity signals, flash sales, and personalized advertisements in driving impulsive buying behaviour (Rook, 1987; Verhagen & van Dolen, 2011; Aggarwal et al., 2011), much of this research has focused on isolated mechanisms within traditional product-based e-commerce settings. Comparatively less attention has been given to the broader digital consumption ecosystem, where purchasing decisions increasingly involve subscriptions to streaming services, premium mobile applications, cloud storage solutions, AI-powered tools, and digital memberships (Lamberton & Stephen, 2016; Wirtz et al., 2019).

In these emerging contexts, AI-driven platforms frequently integrate multiple persuasive mechanisms within a single interaction. For instance, users may encounter repeated advertising interruptions alongside prompts encouraging them to upgrade to premium versions to remove such disruptions, or receive notifications about trial expirations coupled with limited-time discounted renewal offers. In the context of this research, these hybrid strategies influence impulse buying. These hybrid strategies in parallel promise both the acquisition of additional benefits and the elimination of discomfort or constraints. Such dual reinforcement structures may exert a stronger influence on unplanned or impulsive spending behavior compared to reward-based or discomfort-reduction strategies implemented independently (Davenport et al., 2020; Rook, 1987).

Despite the growing prevalence of these hybrid AI-driven marketing tactics, empirical evidence regarding how consumers cognitively and emotionally process such combined stimuli remains limited (Davenport et al., 2020). This gap is particularly evident in the context of emerging markets, where digital adoption is increasing rapidly and AI-based personalization systems are increasingly integrated into everyday consumption experiences (Lamberton & Stephen, 2016). Therefore, the present study seeks to examine how positive and negative reinforcement mechanisms embedded within AI-driven digital marketing environments jointly influence consumer impulse purchasing behavior.

Neuromarketing

Neuromarketing can be conceptualized as a multidisciplinary research approach that integrates principles from neuroscience and psychology into marketing analysis in order to better understand how consumers process information and make decisions at a largely subconscious level. Unlike traditional marketing research methods that rely primarily on self-reported data such as surveys or interviews, neuromarketing focuses on measuring neural and emotional responses to explain consumer behavior more accurately (Morin, 2011).

The development of neuromarketing is closely linked to the broader expansion of neuroscience-based research during the 1990s, when scholars began applying brain-imaging technologies to economic and behavioral questions. Early academic contributions helped connect behavioral theories with neural models, enabling deeper insights into how individuals respond to external stimuli (Camerer et al., 2005). One of the most influential contributions was made by Zaltman, who used functional magnetic resonance imaging (fMRI) to demonstrate that consumer’s stated evaluations of brands and advertisements often differ from their underlying cognitive and emotional reactions (Zaltman, 2003).

The formal recognition of neuromarketing as a distinct field emerged in the early 2000s, following Smidts’ introduction of the term and Montague’s experimental research on brand perception, which illustrated how brand familiarity can shape neural activity and consumer preferences (Smidts, 2002; Montague, 2003). Since then, neuromarketing has gained increasing relevance in both academic and managerial contexts, with major corporations adopting these techniques to enhance marketing effectiveness. However, a substantial portion of industry-based neuromarketing research remains proprietary, limiting its accessibility for independent scholarly evaluation.

Conceptually, neuromarketing is grounded in the assumption that consumer decisions are not purely rational but are significantly influenced by emotional and neural processes that can be examined using neuroscientific methods (Morin, 2011; Camerer et al., 2005). From this perspective, neuromarketing seeks to bridge the gap between consumer behavior and brain science by explaining how cognitive and affective mechanisms shape responses to marketing stimuli.

To capture these processes, researchers employ techniques such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and eye-tracking, which allow for the observation of attention, emotional arousal, memory formation, and reward-related activation during exposure to marketing content (Ariely & Berns, 2010). Empirical findings indicate that purchasing behavior is closely associated with activity in brain regions linked to reward and emotion, suggesting that many consumer choices are driven by rapid and subconscious processes rather than deliberate reasoning (Knutson et al., 2007).

In digital consumption environments, this transformation has contributed to what can be described as a "dopamine-driven economy," in which platforms intentionally design reward-focused experiences to sustain user engagement and stimulate unplanned spending (Alter, 2017).

II. OBJECTIVE

1. To examine the impact of positive reinforcement mechanisms affects impulse buying and subscription decisions in digital environments.
2. To analyses the influence of negative-reinforcement mechanisms influences consumers' tendencies to upgrade, subscribe, or make unplanned digital purchases in order to remove annoyance, restrictions, or perceived loss of opportunity.
3. To investigate hybrid operant-conditioning patterns are combined in a single AI-driven message.
4. To assess whether such hybrid tactics are associated with stronger self-reported impulse buying and subscription uptake than either reinforcement type used alone.
5. To explore consumers' subjective experiences of these tactics to derive insights that can inform the development of AI-based neuromarketing strategies that balance commercial effectiveness with ethical and consumer-well-being considerations.

II. LITERATURE REVIEW

2.1 Operant Conditioning and Reinforcement Theory

The theoretical foundation of this study is based on operant conditioning, originally developed by B.F. Skinner in *The Behavior of Organisms* (1938), which explains behavior in terms of its consequences rather than internal mental states (Skinner, 1938; Skinner, 1953). Building on Edward Thorndike's Law of Effect, Skinner replaced subjective concepts such as satisfaction or discomfort with observable constructs of reinforcement and punishment (Thorndike, 1911; Thorndike, 1905).

Skinner identified two primary reinforcement mechanisms. Positive reinforcement refers to introducing a rewarding stimulus after a behavior, increasing the likelihood of its repetition, while negative reinforcement involves removing an unpleasant stimulus to strengthen behavioral recurrence (Skinner, 1953; Ferster & Skinner, 1957). Experimental studies on schedules of reinforcement showed that variable-ratio schedules, where rewards occur unpredictably, generate particularly persistent behavior that resists extinction (Ferster & Skinner, 1957; Catania, 1998).

In applied contexts, these principles extend beyond laboratories into domains such as education, organizational behavior, and consumer decision-making (Bandura, 1977; Herrnstein, 1990). In practical terms, purchasing behavior can be understood as a learned response shaped by repeated exposure to reward and relief mechanisms rather than purely rational evaluation. This perspective suggests that many consumption patterns reflect habit formation driven by environmental cues (Foxall, 1998; Foxall, 2002).

Within digital markets, incentives such as discounts, loyalty points, and promotional bonuses function as positive reinforcers, while the removal of advertisements or access restrictions operates as negative reinforcement (Nisbet, 2004; Foxall, 2002). Unlike classical operant research that isolated single variables, modern digital platforms simultaneously deploy multiple reinforcement mechanisms through AI-driven systems, creating complex behavioral environments that traditional operant models were not designed to fully explain (Foxall, 2010; Hoffmann & Novak, 2018).

2.2 Emergence of Neuromarketing and Consumer Neuroscience

Neuromarketing emerged during the late 1990s and early 2000s as researchers began applying neuroscientific methods to consumer behavior (Zaltman, 2000; Smidts, 2002; Lee, Broderick, & Chamberlain, 2007). The field developed in response to growing recognition that much of human decision-making occurs at subconscious levels that traditional surveys cannot fully capture (Kahneman, 2011; Damasio, 1994).

One of the earliest applied contributions was made by Gerald Zaltman, who conducted some of the first fMRI-based marketing studies in the late 1990s and introduced the Zaltman Metaphor Elicitation Technique (Zaltman, 1997; Zaltman & Coulter, 1995). His work demonstrated that consumers' verbal responses often differ from their underlying neural and associative reactions to brands and advertisements.

The term "neuromarketing" was introduced by Ale Smidts in 2002, and the field gained prominence following Read Montague's cola brand experiment, which showed that brand knowledge alters neural reward responses even when the physical product remains identical (Smidts, 2002; McClure et al., 2004; Montague, 2004). This study revealed that brand perception can override sensory experience, highlighting the power of symbolic meaning in consumption. Today, neuromarketing integrates tools such as fMRI, EEG, and eye-tracking to measure attention, emotional arousal, and reward activation (Lee et al., 2007; Hubert & Kenning, 2008). Empirical research consistently links purchasing decisions with activity in reward-related brain regions, supporting dual-process theories where fast emotional processing often dominates rational reasoning (McClure et al., 2004; Knutson et al., 2007; Kahneman, 2011).

Over time, neuromarketing has moved from academic laboratories into commercial practice. Firms now routinely use these techniques to optimize advertisements, product designs, and user interfaces (Morin, 2011; Ariely & Berns, 2010). However, ethical transparency remains uneven, particularly regarding consent and data usage (Ariely & Berns, 2010; Stanton, Sinnott-Armstrong, & Huettel, 2017).

2.3 Neuromarketing in Digital and AI-Driven Environments – with researcher citations

The rise of digital platforms and artificial intelligence has embedded neuromarketing principles directly into everyday consumer experiences. Scholars increasingly describe a "dopamine economy" in which platforms engineer reward-focused systems through personalized recommendations, flash sales, and gamified features designed to sustain engagement (Alter, 2017; Eyal, 2014; Turel & Bechara, 2016).

Firms now rely on real-time behavioral data to continuously test and optimize stimuli that trigger reward anticipation while reducing friction in purchasing processes (Wedel & Kannan, 2016; Davenport, Guha, Grewal, & Bressgott, 2020). At scale, these algorithmic systems can influence millions of users simultaneously, making behavioral optimization far more powerful than traditional marketing approaches.

Digital design research identifies several mechanisms underlying this influence. Scarcity cues such as countdown timers increase urgency, social proof signals such as ratings and live-purchase notifications shape perceived value, and default selections subtly guide user choices (Thaler & Sunstein, 2008; Cialdini, 2009; Dolan et al., 2012). What is notable is that these techniques often operate without users being fully aware of their behavioral impact.

Despite this, most neuromarketing research focuses on positive reinforcement, while relatively little attention is given to negative reinforcement processes such as relief from irritation or functional limitations (Smidts, 2012; Plassmann, Venkatraman, Huettel, & Yoon, 2015). This imbalance limits understanding of how digital systems truly shape behavior, particularly when reward and relief mechanisms are combined in sophisticated AI-driven architectures.

2.4 Identified Research Gaps

First, there is a strong emphasis on reward-based mechanisms, with limited empirical analysis of negative reinforcement in consumer contexts (Plassmann et al., 2015; Smidts, 2012). Second, most studies examine isolated stimuli rather than hybrid reinforcement structures that combine reward and relief in real digital environments (Karmarkar & Yoon, 2016; Venkatraman et al., 2015). Third, existing research prioritizes behavioral outcomes such as purchase intention while neglecting subjective experiences such as perceived pressure, regret, and feelings of manipulation, particularly in emerging markets (Ariely & Berns, 2010; Stanton et al., 2017).

2.5 How the Current Study Addresses These Gaps

From the author's perspective, this study addresses these limitations through three strategies. It jointly examines positive, negative, and hybrid reinforcement mechanisms using real-world digital scenarios, extending classic operant conditioning frameworks (Skinner, 1953; Ferster & Skinner, 1957) to AI-mediated consumer journeys. It focuses on authentic AI-driven platforms rather than laboratory simulations, aligning with recent calls for ecologically valid neuromarketing research in naturalistic contexts (Karmarkar & Yoon, 2016;

Research Design The study shows an analytical and descriptive and research design to examine how customer impulsively buy the product using AI driven Marketing strategies. The descriptive approach helps to understand consumer demographic characteristics exposure to AI marketing strategies (such as personalized ads, recommendation, notification). While analytical approach explains relationship between AI-generated stimuli, responses (dopamine-driven pleasure or avoidance) and consumer decision making behaviour. It also analyses how the combination of positive reinforcement and negative reinforcement creates a hybrid operant conditioning effect in AI marketing.

A) Data Collection

The research is based on primary data collected through a structured questionnaire. The questionnaire included questions on respondents' demographic details, exposure to AI-based marketing, and emotional and behavioural responses to positive and negative and hybrid reinforcement techniques used to attract the customers. Responses were measured using a Likert scale for quantitative analysis. Secondary data were collected from research journals, articles, and published reports to support the conceptual and theoretical framework of the study.

B) Sample and Sampling Method

The study is based on 202 respondents, mainly consisting of students and young working individuals. A sampling method was adopted due to time and accessibility constraints. The demographic analysis shows that 72.3% of respondents are in the 18–24 age group, indicating strong representation of young consumers. While this helps in understanding emerging consumer behaviour, it also reflects limited representation of older and high experienced individuals.

Data Analysis

The data collected through the questionnaire were analysed using quantitative analysis techniques. Descriptive statistical tools, such as frequency and percentage analysis, were used to understand respondents' demographic characteristics and overall response patterns. To examine relationships between AI-driven marketing stimuli, positive and negative reinforcement mechanisms, and consumer behaviour, inferential statistical methods, including correlation analysis and hypothesis testing, were applied. The statistical analysis was conducted using SPSS and MS Excel, ensuring accurate, systematic, and reliable interpretation of the results.

1. Messages such as “Complete your cart now and get free delivery before the timer ends” often make me add one more item or complete the purchase.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	44	21.8	21.8	21.8
	2	79	39.1	39.1	60.9
	3	51	25.2	25.2	86.1
	4	22	10.9	10.9	97.0
	5	6	3.0	3.0	100.0
	Total	202	100.0	100.0	

Interpretation

This data highlights the powerful combination between scarcity and immediate reward in driving consumer behaviour. 60% admit that timed "free delivery" offers push them to finalize a purchase or add more items to their cart, with 38.6% agreeing and 21.8% strongly agreeing. This exemplifies a hybrid reinforcement pathway: the "free delivery" acts as a positive reinforcer (reward), while the ticking timer serves as a negative reinforcer (the stress of losing a deal). While 25.7% remain neutral, only a small minority—roughly 14%—actively resist this pressure. The urgency is most effective when paired with a tangible benefit, so customers effectively react instantly to it such AI-timed triggers.

2. “Your trial ends today – continue now and get bonus months” pushes me to keep the subscription.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	34	16.8	16.8	16.8
	2	81	40.1	40.1	56.9
	3	58	28.7	28.7	85.6
	4	25	12.4	12.4	98.0
	5	4	2.0	2.0	100.0
	Total	202	100.0	100.0	

Interpretation

This data illustrates how the combination of a deadline and an added reward creates a powerful incentive to maintain a digital habit. Among your 202 respondents, over 56% feel motivated to continue their subscription when a trial expiration is paired with "bonus months," with 40.1% agreeing and 16.3% strongly agreeing. This analysis gives glimpse of a perfect hybrid of negative reinforcement (avoiding the loss of the service) and positive reinforcement (the reward of extra time). While 29.2% remain neutral, only about 15% resist this tactic. For an AI marketing model, this confirms that the most effective way to prevent "churn" is to soften the blow of a trial ending by immediately offering a new, unexpected benefit. It essentially re-shacks the user to the platform by turning a moment of potential exit into a moment of renewed value

3. When I see offers like “Only today: extra 20% off, offer ends in 2 hours”, I feel a much stronger push to buy than with normal discounts.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	35	17.3	17.3	17.3
	2	95	47.0	47.0	64.4
	3	51	25.2	25.2	89.6
	4	17	8.4	8.4	98.0
	5	4	2.0	2.0	100.0
	Total	202	100.0	100.0	

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Interpretation

The results indicate that very short-term deadlines significantly intensify purchase motivation. Nearly 64% of respondents reported feeling a stronger urge to buy when a limited 2-hour offer with an extra discount was presented, with 46.5% agreeing and 17.3% strongly agreeing. This shows that compressed time frames heighten emotional decision-making. Within the Dual Dopamine framework, the added discount acts as a reward, while the ticking deadline creates pressure to avoid loss. Although 25.2% remained neutral, most respondents were influenced by this urgency. For AI-driven marketing, this confirms that tight deadlines reduce overthinking and push consumers toward faster, instinct-based purchase decisions.

4. Many of my unplanned digital purchases happened because a paid plan removed problems and gave extra benefits.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	29	14.4	14.4	14.4
	2	91	45.0	45.0	59.4
	3	62	30.7	30.7	90.1
	4	17	8.4	8.4	98.5
	5	3	1.5	1.5	100.0
	Total	202	100.0	100.0	

Interpretation

This data uncovers the core mechanism of impulse spending within Dual Dopamine framework. A significant 59.4% acknowledge that their spontaneous digital purchases occur when a paid upgrade resolves an existing frustration while simultaneously offering new perks. Specifically, 45.5% agree and 13.9% strongly agree that this dual approach drives their decision-making. This serves as a definitive example of hybrid operant conditioning: the "problem removal and extra benefits. While 30.7% remain neutral, the low 9.9% disagreement rate suggests that most consumers are highly susceptible to this "double-hit" strategy. This validates that most effective way to trigger a conversion is to present a solution that satisfies the brain's desire for both escape and gain in a single transaction.

5. Hybrid offers that mix fear of missing out with rewards (discounts, bonus months, free features) create more urgency in me than either message alone.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	25	12.4	12.4	12.4
	2	94	46.5	46.5	58.9
	3	56	27.7	27.7	86.6
	4	24	11.9	11.9	98.5
	5	3	1.5	1.5	100.0
	Total	202	100.0	100.0	

Interpretation

This data highlights the superior effectiveness of hybrid marketing strategies that blend urgency with tangible rewards. 58% indicate that offers mixing the "fear of missing out" with perks like bonus months or discounts create more urgency. Specifically, 46.5% agree and 11.9% strongly agree that these multi-layered prompts are more persuasive. This provides direction that a combined approach triggers both reward-seeking behaviour and loss avoidance simultaneously. While 27.7% stay neutral, the low 14% disagreement rate shows that most users find these blended incentives difficult to ignore. Ultimately, the results reveal that providing a "gain" while highlighting a "potential loss" creates a psychological tension that effectively conditions users to take immediate action.

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Buying Behaviour & Self-Reflection

1. AI-based recommendations and notifications (on shopping apps, streaming apps, or AI tools) have increased my overall spending on digital products.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	32	15.8	15.8	15.8
	2	92	45.5	45.5	61.4
	3	58	28.7	28.7	90.1
	4	14	6.9	6.9	97.0
	5	6	3.0	3.0	100.0
	Total	202	100.0	100.0	

Interpretation

The survey results clarify that AI-driven personalization directly fuels consumer spending through targeted engagement. 61.3% acknowledge that AI-based recommendations and notifications have increased their overall digital expenditure, with 46% agreed and 15.3% strongly agreed. This reflects the success of positive reinforcement, where algorithmically "perfect" suggestions trigger a reward response in the user. While 28.7% remain neutral, only a minimal 10% feel these AI triggers are ineffective. These findings validate that AI acts as a powerful conditioning mechanism that encourages higher consumption by delivering the right "nudge" at the right moment.

2. I sometimes end up buying products that I don't need and regret digital purchases or subscriptions that I took because of limited-time or urgent offers.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	32	15.8	15.8	15.8
	2	85	42.1	42.1	57.9
	3	56	27.7	27.7	85.6
	4	19	9.4	9.4	95.0
	5	10	5.0	5.0	100.0
	Total	202	100.0	100.0	

Interpretation

This data illustrates a clear link between high-pressure digital marketing and post-purchase "buyer's regret". A significant 57.4% admit they sometimes regret subscriptions or products bought under the stress of limited-time offers, with 42.1% agreeing and 15.3% strongly agreeing. Revealing that while negative reinforcement is a highly effective sales driver, it often results in a negative emotional aftermath for the consumer. Only a small 14.4% of respondents feel they are immune to this regret, while 28.2% remain neutral.

Ultimately, these results emphasize that urgency-based tactics may boost immediate revenue but can potentially undermine long-term customer satisfaction and brand loyalty

3. I am aware that some apps or websites use psychology and brain-based techniques (neuromarketing) to influence my buying decisions.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	38	18.8	18.8	18.8
	2	105	52.0	52.0	70.8
	3	43	21.3	21.3	92.1
	4	13	6.4	6.4	98.5
	5	3	1.5	1.5	100.0
	Total	202	100.0	100.0	

Interpretation

This data highlights a high degree of consumer consciousness regarding modern persuasion tactics. A combined 70.3% recognize that digital platforms use neuromarketing and brain-based psychology to influence their spending, with 52% agreeing and 18.3% strongly agreeing. This demonstrates that these behavioural triggers are effective even when the user is fully aware of the manipulation. While 21.8% remain neutral, less than 8% are unaware of these techniques. These results confirms that the biological drive for reward or relief often overrides intellectual awareness, making AI-driven conditioning a dominant force in the digital economy.

4. Even though I know these tactics are used, I still get influenced by them in my digital purchases.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	32	15.8	15.8	15.8
	2	81	40.1	40.1	55.9
	3	56	27.7	27.7	83.7
	4	26	12.9	12.9	96.5
	5	7	3.5	3.5	100.0
	Total	202	100.0	100.0	

Interpretation

The survey results reveal psychological gap between a consumer's awareness of marketing tactics and their actual behaviour. Despite being conscious of these strategies, nearly 56% of the respondents admit they are still influenced by them when making digital purchases, with 40.6% agreeing and 15.3% strongly agreeing. While 27.7% remain neutral, only 15.8% believe they are truly resistant to these notifications. Ultimately, the data validates that behavioural conditioning remains highly effective because it operates on a subconscious level, proving that even "informed" users remain susceptible to well-timed AI prompts.

5. I feel that digital companies should use these AI and neuromarketing tactics responsibly and with clear transparency.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	44	21.8	21.8	21.8
	2	95	47.0	47.0	68.8
	3	48	23.8	23.8	92.6
	4	12	5.9	5.9	98.5
	5	3	1.5	1.5	100.0
	Total	202	100.0	100.0	

Interpretation

The survey data reveals a responsible call for corporate accountability regarding the use of psychological triggers. A remarkable 68.8% demand that digital companies apply AI and neuromarketing techniques responsibly and with clear transparency, including 47% who agree and 21.8% who strongly agree. With only 7.4% of respondents oppose the idea of honesty and responsibility in digital marketing. While 23.8% remain neutral, the majority sentiment favors that the future of AI-driven marketing depends on building trust rather than relying on manipulation.

Hypothesis Testing:

Hypothesis 1: **To examine the influence of AI-based recommendations on consumer buying behavior in digital platforms**.

$H0_1$ (Null Hypothesis):
There is no significant relationship between AI-based recommendations and consumer buying behavior.

$H1_1$ (Alternative Hypothesis):
There is a significant relationship between AI-based recommendations and consumer buying behavior.

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Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
"Recommended for you" suggestions on Amazon, Flipkart, or streaming apps often make me buy products or subscriptions I did not plan to buy. * AI-based recommendations and notifications (on shopping apps, streaming apps, or AI tools) have increased my overall spending on digital products.	202	100.0%	0	0.0%	202	100.0%

"Recommended for you" suggestions on Amazon, Flipkart, or streaming apps often make me buy products or subscriptions I did not plan to buy. * AI-based recommendations and notifications (on shopping apps, streaming apps, or AI tools) have increased my overall spending on digital products. Crosstabulation

Count

		AI-based recommendations and notifications (on shopping apps, streaming apps, or AI tools) have increased my overall spending on digital products.					
		1	2	3	4	5	Total
"Recommended for you" suggestions on Amazon, Flipkart, or streaming apps often make me buy products or subscriptions I did not plan to buy.	1	15	13	4	0	1	33
	2	13	59	20	3	0	95
	3	3	15	30	4	1	53
	4	1	5	4	5	1	16
	5	0	0	0	2	3	5
Total		32	92	58	14	6	202

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	141.332[a]	16	<.001
Likelihood Ratio	91.562	16	<.001
Linear-by-Linear Association	57.862	1	<.001
N of Valid Cases	202		

a. 14 cells (56.0%) have expected count less than 5. The minimum expected count is .15.

Interpretation: Hypothesis 1

There is a significant relationship between AI-based recommendations and consumer buying behavior.

To Taste this, A Chi-square test was conducted using IBM SPSS Statistics to examine the relationship between AI-based recommendations and consumer buying behavior. The Crosstabulation analysis included 202 valid responses.

The results of the Chi-square test indicate a Pearson Chi-Square value of 141.332 with 16 degrees of freedom, and a significance level (p-value) less than 0.001. Since the p-value is below the standard threshold of 0.05, the result is statistically significant. the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted.

Conclusion

The alternative hypothesis (H_1) is accepted while the null hypothesis (H_0) claims that there is no connection between AI-based recommendations and consumer purchasing behaviour is rejected. This suggests that consumers purchasing decisions are influenced by AI-driven recommendations. This relationships strength demonstrates how AI personalisation is increasingly influencing customer behaviour in online marketplaces.

The findings show a statistical correlation, indicating that both positive and negative AI-based reward mechanisms are important in influencing consumer impulse purchases, subscription choices, and interaction in digital environments.

Findings:

Overall

Overall, the findings show that AI-driven positive, negative, and hybrid reinforcement mechanisms exert a considerable influence impulse buying, subscription purchasing, and unplanned digital purchases among young, digitally active consumers.

Demographics

The study compromised of 202 respondents, with 72.3% in the 18–24 age group and 21.8% in the 25–34 age group demonstrating a robust representation of Generatio n Z and early Millennials. Students account for 61.9% and working professionals 27.7%. 41.1% of Respondents currently use paid digital subscriptions and 20.3% have discontinued past subscriptions, this reflects moderate, yet value-sensitive adoption of digital services.

Positive reinforcements

Promotional discounts such as (Get 3 months extra free) are influential with 66.8% of respondents agreeing that such offers encourages them to take digital subscriptions. Algorithmic Recommended for you suggestions drive unplanned buying, as 63.3% agree that they have purchased products or subscriptions they did not plan to buy due to such recommendations. Free trials motivate starting subscriptions with 59.4% agrees on that while cashback and reward points influence spending for 65.4% (22.8% strongly agree, 42.6% agree). Bundled offers are also powerful, with 67.8% agreeing that recharge with OTT bundles make them more likely to choose the bundle.

Negative reinforcements

Repeated advertisements interruptions act as negative reinforcement, with 64.8% reporting that repetitive ads push them to invest in Premium plans to stop the Advertisements. Usage-limit pop-ups influence decisions, as 59.0% agree these messages push them towards paid plans, while another 26.7% remain neutral but exposed.

Hybrid reinforcements

Hybrid offers combines relief plus reward are particularly impactful: 59.4% agree that messages like (Your trial ends today- continue now and get bonus months) push them to keep subscriptions. 58.9% agree or strongly agree that hybrid messages mixing FOMO with rewards create more urgency than either message alone, and 59.4% feel pressure when scarcity cues appear.

Buying behavior

AI-based recommendations and notifications increase overall digital spending, with 61.3% (15.8% strongly agree, 45.5% agree) stating that such offers have raised their spending on digital products.
Many respondents also acknowledge emotional consequences: 57.9% agree or strongly agree that they sometimes buy products they do not need and later regret purchases made under limited-time or urgent offers.

Recommendations:

For Marketers & Digital Platforms

- Prioritize hybrid tactics combination of positive rewards with negative relief (63.9% effectiveness for extra discount with deadline combinations.
- Application of variable-ratio reward schedules (unpredictable timing) to maintain long-term engagement
- Use trial expiry with bonus offers (56.4% effectiveness) for optimal subscription retention

For Ethical AI Design

- Increase transparency about algorithmic nudges - 70.3% consumers aware but still influenced
- Limit aggressive negative reinforcement (ad interruptions, FOMO pressure) - 57.4% report purchase regret
- 68.8% demand responsible AI marketing - prioritize trust over short-term conversions for Future Research
- Longitudinal tracking of impulse purchase regret and spending patterns

- Cross-cultural validation beyond Indian Gen Z/millennial digital consumers

  Key Takeaway: Hybrid reinforcement drives maximum engagement but requires ethical guardrails for the consumer trust.

Conclusion:

This research demonstrates that AI-driven neuromarketing has evolved neuromarketing principles from laboratory-based neural measurement (fMRI, EEG) into real-time, scalable behavioral engineering within digital platforms. By operationalizing operant conditioning—positive reinforcement via discounts and recommendations (66.8% agreement), negative reinforcement through ad interruptions and usage limits (64.8% influence), and hybrid tactics blending both (59.4% urgency)- AI systems create dopamine-driven pathways that significantly shape impulse buying and subscription behavior among young digital consumers (72.3% aged 18–24).

The Chi-square findings ($p < 0.001$) confirm that mechanisms' statistical effectiveness, supporting all five objectives: positive mechanisms drive adaption, in negative mechanism person upgrades it to escape annoyance, hybrids intensify unplanned spending, and consumers report both effectiveness and regret (57.9%).

AI-driven neuromarketing have shifted from understanding subconscious responses (Morin, 2011; Smidts, 2002) to actively designing them at population scale (Davenport et al., 2020) with this they have raised urgent ethical issues regarding to transparency, consent, and well-being safeguards in dopamine economies. Future research should explore long term effects and regulatory frameworks to ensure commercial power does not undermine consumer autonomy.

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