

ALGORITHMIC AI CONTROLLING: THE CONTROLLING ROLE OF ARTIFICIAL INTELLIGENCE IN DIGITAL CONSUMER BEHAVIOUR

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Abstract

This study examines the controlling effects of artificial intelligence-based algorithms on consumer behaviour from a marketing science perspective. Algorithmic controlling is defined as a set of digital mechanisms that filter, rank, and present content based on users' prior behaviour, search history, and preference data, thereby shaping decision-making contexts. The research employs a thematic and interpretative synthesis of recent European-focused literature. The analysis identifies six key mechanisms of algorithmic controlling: scarcity messages, recommendation systems, filter bubbles and echo chambers, dark patterns in user interface design, dynamic and personalised pricing, and social proof manipulation. The study contends that these algorithms are not neutral intermediaries but act as active control elements in the digital consumer environment, with significant implications for vulnerability, fairness, and trust. The discussion further situates these mechanisms within the evolving EU regulatory framework, with particular attention to the Digital Services Act and the AI Act. The contribution of this research is to offer an integrative framework that connects technological, behavioural, and regulatory dimensions for a more comprehensive understanding of algorithmic influence in digital markets.

Keywords: algorithmic controlling, AI ethics, consumer vulnerability, digital fairness, EU regulation

1. Introduction

The transformation of the digital economy has fundamentally redefined interactions between consumers and businesses. Artificial intelligence (AI)-based algorithms are no longer merely technical tools but active shapers of consumer experiences and decisions (Helberger et al., 2022). The concept of algorithmic controlling refers to the phenomenon in which AI systems systematically filter, select, and rank content, products, and information presented to users based on their prior behaviour, search history, demographic characteristics, and other data points (Kotras, 2020). This process may result in consumers encountering a reduced, narrowed content universe that does not necessarily represent the full market offering but rather an algorithmically curated segment.

The timeliness of this topic is established by several factors. European regulators are paying increased attention to the transparency and accountability of algorithmic systems, as evidenced by the adoption of the Digital Services Act (DSA) and the AI Act (Regulation EU 2022/2065; Regulation EU 2024/1689). There is growing demand in consumer protection to address asymmetries experienced in the digital environment (Helberger et al., 2021; Helberger et al., 2024). Marketing science is tasked with uncovering and interpreting the effects of new technologies on consumer behaviour (Akter et al., 2022).

The research objectives are threefold: (1) to comprehensively map the algorithmic mechanisms that perform a controlling function in the digital consumer environment, (2) to analyse the effects of these mechanisms on consumer behaviour and decision-making, and (3) to present the European Union's regulatory responses to these challenges. The study approaches the topic from the perspective of marketing science and consumer behaviour research, integrating relevant approaches from behavioural economics, information systems, and legal scholarship.

The significance of this research lies in providing a coherent framework for understanding algorithmic controlling by integrating fragmented literature. While previously individual mechanisms, such as scarcity messaging or dark patterns, were examined in isolation, this study places them within a unified controlling paradigm. This approach has not only academic relevance but also practical implications for corporate marketing, consumer protection, and regulation.

2. Literature review

2.1. The conceptual framework of algorithmic controlling

Algorithmic controlling refers to the ability of digital platforms and services to control, filter, and shape the information environment available to consumers using artificial intelligence tools (Gorwa et al., 2020). These systems differ fundamentally from traditional marketing communication because they not only transmit messages but also actively shape the context in which consumer decisions are made (Susser et al., 2019). Acemoglu et al. (2025) show that the combination of big data and machine learning enables the manipulation of consumer behaviour in finely tuned ways that were previously technically infeasible.

The manifestations of the controlling function are multilayered. At the information filtering level, algorithms determine which content reaches the user and which remains hidden (Van Drunen et al., 2019). At the ranking level, they influence the order in which consumers encounter alternatives, which decisively affects selection probabilities (Kordzadeh & Ghasemaghahi, 2022). At the contextualisation level, algorithms influence what information accompanies individual offers, such as scarcity messages or social proof (Barton et al., 2022). At the dynamic pricing level, algorithms can modify prices in real time based on individual consumer characteristics (Seele et al., 2021).

2.2. Consumer behaviour theories in the algorithmic environment

Understanding the effects of algorithmic control relies on several classical and modern theoretical frameworks. According to the Persuasion Knowledge Model, consumers actively interpret and respond to persuasion attempts when they recognise them (Friestad & Wright, 1994). However, research by Voorveld et al. (2023) indicate that European consumers' algorithmic persuasion knowledge is generally low. A significant proportion of users are unaware that the content they see is algorithmically filtered and personalised. This asymmetry is crucial to the effectiveness of controlling mechanisms.

The Elaboration Likelihood Model (ELM) is also relevant for understanding algorithmic influence (Shahab et al., 2021). According to this model, information processing can occur in two ways. Through the central route, which involves deeper, thoughtful processing, or through the peripheral route, which relies on superficial cues. Algorithmic control mechanisms, such as scarcity messages or social proof, typically activate the peripheral route, encouraging consumers to make quick, heuristic decisions (Park et al., 2024). Similarly, application of the Heuristic-Systematic Model reveals that information overload in digital environments increases the likelihood of heuristic processing (Zhang et al., 2014;

Lee and Hong, 2021). Nudge theory from behavioural economics (Thaler & Sunstein, 2008) is central to the theoretical understanding of algorithmic control. The concept of digital nudging (Weinmann et al., 2016; Schneider et al., 2018) refers to the deliberate design of user interfaces and decision architectures to influence consumer choices. A Swiss meta-analysis by Mertens et al. (2022) processed 455 studies, demonstrated that nudge interventions have significant effects on consumer behaviour (average effect size: $d = 0.43$), although the effect size varies considerably depending on the type and context of the intervention.

2.3. Consumer vulnerability in the digital environment

The concept of digital vulnerability is particularly relevant in the context of algorithmic control. Helberger et al. (2022) redefined consumer vulnerability for the digital economy, highlighting factors such as lack of digital literacy, algorithmic opacity, and manipulation of decision contexts. The OECD (2023) report also emphasises that traditional indicators of consumer vulnerability, such as age or income, are insufficient on their own to capture digital vulnerability. Rossi et al. (2024) propose a multidimensional framework encompassing technological, cognitive, situational, and social vulnerability factors. European Commission (2016, 2022) studies indicate that consumer vulnerability in digital markets is structural. Information asymmetry, decision overload, and algorithmic opacity together create new forms of vulnerability. Durovic and Poon (2023) suggest that EU consumer protection law must fundamentally reconsider the concept of vulnerability to address effectively the new risks created by digital decision architectures.

3. Methodology

The study aims to explore and interpret the role of algorithmic control in contemporary digital marketing and consumer interaction, as reflected in the relevant scientific literature. Accordingly, the research employs a thematic and interpretative literature synthesis rather than a systematic literature review. Academic sources were examined across Web of Science, Scopus, EUR-Lex, and major publication repositories of European research institutions. Searches focused on the conceptual and practical applications of algorithmic control in digital contexts, with particular emphasis on the following topics: scarcity and urgency mechanisms, recommendation systems and personalisation, filter bubbles and echo chambers, dark patterns in user interface design, dynamic and personalised pricing, and social proof manipulation.

Source selection was guided by theoretical relevance, scientific significance, and conceptual coherence. The review primarily relies on English- and German-language, peer-reviewed publications from recent years, complemented by earlier foundational works that provide conceptual grounding. The aim of the study is to identify current research directions and interpret emerging trends at the intersection of behavioural targeting, algorithmic control, and digital consumer protection.

While the analysis is rooted in broader European discourse, particular attention is given to the regulatory and theoretical frameworks shaping algorithmic practices within the EU context. This perspective enables both a conceptual understanding and practical interpretation of algorithmic control in digital environments.

4. Results

4.1. Scarcity and urgency mechanisms

Scarcity messages are among the most widespread and well-documented forms of algorithmic control. These messages indicate that a product or service is available in limited quantity (stock-based scarcity) or for a limited time only (time-based scarcity). Barton et al. (2022) synthesised 81 empirical studies and showed that scarcity messages have a significant positive effect on purchase intention (aggregated effect size: $d = 0.35$). An important finding was that demand-based scarcity (“other shoppers are viewing this”) had a higher effect size ($d = 0.43$) than stock-based scarcity ($d = 0.31$).

Ladeira et al. (2023) examined 45 studies, further nuanced the picture. The scarcity effect is stronger for utilitarian products and weaker for hedonic products. Cultural factors also moderate the strength of the effect. Stronger effects are observed in individualistic cultures than in collectivistic cultures. Shi et al.’s (2020) review, published in a European journal, systematises scarcity marketing research and highlights the role of psychological reactance. The perception of scarcity increases desire for the product because it threatens the consumer’s freedom of choice.

Regarding the algorithmic dimension, Pal et al.’s (2025) eye-tracking study found that online scarcity messages automatically attract visual attention, and this effect is independent of the consumer’s conscious intentions. This finding is consistent with the broader recognition that algorithmic control mechanisms often operate by bypassing conscious reflection. Tiemess et al. (2023) highlights the manipulative potential of timed countdowns. While this increases purchase probability, consumers often subsequently report regret and loss of trust when they recognise the artificial nature of the tactic.

4.2. Recommendation systems and personalization algorithms

Recommendation systems are central tools of algorithmic control that filter and rank content, products, and services displayed to consumers. Adomavicius et al. (2013) demonstrated that recommendation systems function as an anchoring effect. Values recommended by the algorithm influence consumers’ preference expressions. This effect persists even when consumers are aware of the recommendation, indicating the implicit nature of algorithmic influence.

Hazrati and Ricci (2024) further examined the effect of recommendation systems on consumer choices. Their results indicate that algorithms do not merely serve but actively shape consumer preferences. Preference for regularly recommended content strengthens over time, regardless of its objective quality. Fletcher et al. (2023) analyse the effect of recommendation systems on market competition. They demonstrated that these systems are prone to popularity bias, incumbent bias, and conformity reinforcement, which collectively reduce market competition and diversity of consumer choice.

The concept of mass personalisation was analysed in detail by Kotras (2020). Predictive marketing algorithms do not merely respond to consumer preferences but actively construct them. This finding is consistent with constructivist approaches to consumer behaviour, which hold that preferences are not predetermined but formed in the decision context (Bettman et al., 1998). Yun and Chun (2024) confirm that personalised recommendations significantly increase purchase intention, but this effect is moderated by the consumer’s perceived sense of control.

4.3. Filter bubbles and echo chambers

The concept of the filter bubble originates from Pariser’s (2011) work, which warned that personalisation algorithms trap users in information cocoons, limiting exposure to diverse viewpoints.

Ludwig et al. (2025) has provided experimental evidence for the existence of the filter bubble effect. Ideology-based news personalisation has a significant, though moderate, polarising effect ($d = 0.15\text{--}0.25$), with the effect being strongest among politically moderate individuals.

Meanwhile, critics of filter bubble theory have also produced important findings. Fu et al. (2024) reached a paradoxical conclusion. Intensive users are less likely to fall into filter bubbles because their more diverse content consumption patterns help them break out of the bubble. Erickson (2024) develops the concept of the “protective filter bubble”, noting that in certain cases filtering can serve a positive function by providing protection against harmful content. Eder and Sehl (2025) reveal that consumer awareness of algorithmic personalisation is low, and this lack of awareness increases vulnerability.

Du (2023) examines the concept of algorithmic literacy among users of news aggregator applications. Her results indicate that consumers with higher algorithmic literacy are more critical of personalised content and more actively seek alternative information sources. Lv et al. (2024), examining ways to “pierce” filter bubbles, conclude that encouraging novelty-seeking behaviour can be an effective strategy for mitigating the filter bubble effect.

4.4. Dark patterns in user interface design

The concept of dark patterns refers to user interface design solutions that deliberately deceive consumers or induce them to make decisions against their actual interests (Gray et al., 2018). Mathur et al. (2019) conducted an automated analysis of approximately 11,000 shopping websites, revealing that dark patterns are widespread in e-commerce. They identified 1,818 instances of dark patterns on 1,254 sites, representing about 11% of the websites analysed. The most common types included tactics related to hidden costs, obstruction, forced action, and confirm-shaming.

European research has paid particular attention to the relationship between dark patterns and data protection regulation. Nouwens et al. (2020) analysed post-GDPR cookie consent interfaces, demonstrating that the use of dark patterns on these interfaces is also widespread. Most pop-ups employ designs that steer users towards consenting to maximum data collection. Soe et al. (2020) reached similar results when examining online news portals. Recent large-scale audits of cookie banners in Europe indicate that only a small minority of interfaces fully comply with GDPR and ePrivacy requirements, while most implementations continue to use manipulative design patterns (see, for example, Bielova et al., 2024).

Luguri and Strahilevitz (2021) demonstrated that consumers exposed to aggressive dark patterns are nearly four times more likely to make unintended decisions. Bongard-Blanchy et al. (2021) Luxembourg research highlights a troubling paradox – most consumers do not recognise dark patterns, even when they expressly feel manipulated. Di Geronimo et al. (2020) examined dark patterns in mobile applications, finding that 95% of the 240 applications analysed contained at least one dark pattern. Kollmer and Eckhardt (2022), propose a conceptual framework for systematising dark patterns, highlighting connections between information asymmetry, exploitation of decision biases, and violation of consumer autonomy. Schäfer et al. (2024) are developing visual countermeasures against dark patterns that could help consumers recognise and avoid these manipulative techniques.

4.5. Dynamic and personalized pricing

Dynamic and personalised pricing is among the most controversial forms of algorithmic control. Seele et al. (2021) conducted a comprehensive ethical analysis of algorithmic pricing, distinguishing between dynamic pricing (which adjusts prices based on aggregate supply and demand) and personalised pricing

(which differentiates based on individual consumer characteristics). The latter is more ethically problematic, as it can exploit consumer vulnerability and violate the principle of fairness.

Hufnagel et al. (2022) used experimental methods to examine consumer reactions to personalised pricing. Their results indicate that consumers perceive personalised pricing as unfair, regardless of whether it benefits or disadvantages them. This finding aligns with Priester et al. (2020) who showed that personalised prices increase consumer distrust and trigger negative moral emotions such as indignation and anger.

Heidary and Pluut (2025) further nuance the picture. Perceptions of fairness in personalised pricing depend on the type of data used. Consumers judge pricing based on demographic data (such as age or location) as more unfair than differentiation based on transactional data (such as purchase history). Zuiderveen Borgesius and Poort (2017) examined the relationship between EU data protection law and online price discrimination, conclude that the GDPR provides some protection but does not comprehensively address the problem of personalised pricing. Pizzi et al. (2022) highlight that the use of biometric data (such as facial expression analysis) for pricing purposes triggers particularly strong consumer resistance.

4.6. Social proof manipulation

Social proof manipulation represents another aspect of algorithmic control. The market for fake reviews and opinions has grown significantly. According to He et al. (2022), fake online reviews make up a substantial portion of the review ecosystem and can significantly distort ratings and sales. Fake reviews take two forms: positive fake reviews to promote one's own products, and negative fake reviews to discredit competitors.

Walther et al. (2023) conducted a systematic literature review examining the consumer side of fake reviews. They found that most consumers are unaware of the extent of manipulation and place excessive trust in online reviews. Shat et al. (2024) integrate the antecedents and consequences of fake reviews, highlighting that platforms' algorithmic moderation efforts have achieved only limited success so far. Social proof manipulation is particularly effective because it exploits fundamental psychological mechanisms of social influence (Cialdini, 2006).

4.7. EU regulatory responses

The European Union has established a comprehensive regulatory framework in recent years to address algorithmic systems. The Digital Services Act (DSA, Regulation EU 2022/2065) pays particular attention to the transparency of recommendation systems. Very large online platforms (VLOPs) are required to disclose the main parameters of their recommendation systems and must enable users to choose non-profiled recommendations (Leerssen, 2023). Article 25 of the DSA explicitly prohibits dark patterns, although the exact scope and enforcement of this prohibition still raise questions (Santos et al., 2024).

The AI Act (Regulation EU 2024/1689) adopts a risk-based approach and explicitly prohibits certain algorithmic practices, such as subliminal manipulation or exploitation of vulnerability (European Commission, 2025). The GDPR continues to provide a relevant framework for limiting algorithmic profiling, although Sartor and Lagioia (2020) highlight the regulation's limitations in the context of artificial intelligence. Bayamlioglu and Leenes (2018) analyse the rule of law implications of data-driven decision making.

The Unfair Commercial Practices Directive (UCPD) is also relevant to algorithmic control. The European Commission's (2021) guidance explicitly addresses the specificities of the digital

environment, including dark patterns and manipulative personalisation. However, Namysłowska (2025) warns that EU consumer law requires structural reform to address digital challenges effectively. Graef (2023) criticises the fragmentation of EU regulation of dark patterns, proposing more coherent integration of different legal instruments.

5. Discussion

The research findings highlight the complex and multifaceted nature of algorithmic control in the digital consumer environment. Joint interpretation of the reviewed mechanisms – from scarcity messages and dark patterns to personalised pricing – enables the development of an integrative framework. Algorithmic control should not be understood merely as a set of marketing tools, but as a new influence paradigm that fundamentally transforms the context of consumer decision-making (Brenncke, 2024a, 2024b).

The theoretical implications of these findings are significant. Classical consumer behaviour theories, such as the Persuasion Knowledge Model and the ELM, remain relevant but require adaptation to the algorithmic environment. The Algorithmic Persuasion Framework proposed by Zarouali et al. (2022) offers a promising starting point, integrating technological, psychological, and contextual factors. A key insight is that algorithmic control often operates by bypassing conscious reflection, exploiting cognitive biases and heuristic processing.

The practical implications affect multiple stakeholders. For marketing professionals, the findings underscore the importance of ethical algorithm application. While short-term conversion increases may be achieved, these can result in loss of trust and consumer resistance in the long term, as confirmed by Trovato et al. (2023). From a corporate social responsibility perspective, transparent and ethical use of algorithmic control may offer a competitive advantage among conscious consumers.

For regulators, the findings confirm the legitimacy of the EU's proactive approach, while also highlighting limitations of the current framework. The DSA and AI Act are important steps, but complete prohibition of dark patterns and algorithmic manipulation is difficult to enforce in practice (Herman, 2024). Recommendations from civil organisations such as the Norwegian Consumer Council (2018) and BEUC (2022) may provide valuable contributions to identifying and addressing regulatory gaps.

Limitations of the research include language restrictions (English and German sources) and the possibility of publication bias (studies with significant results are more likely to be published). Given the rapidly changing technological and regulatory environment, the findings may require updating over time. Promising directions for future research include examining the development of consumer algorithmic literacy (Kozyreva et al., 2020), developing ethical algorithm design frameworks, and empirically evaluating the effectiveness of regulatory interventions.

6. Conclusions

This study provides a comprehensive overview of the phenomenon of algorithmic AI control in the context of digital consumer behaviour. The thematic and interpretative literature synthesis revealed that algorithms are not neutral intermediaries but active control elements that fundamentally shape consumer experiences and decisions. Scarcity messages, recommendation systems, filter bubbles, dark patterns, dynamic pricing, and social proof manipulation together form a system defined by the algorithmic control paradigm.

The findings lead to three main conclusions. Consumer vulnerability in the digital environment is structural and cannot be reduced to individual characteristics. The complexity of algorithms and decision architectures creates asymmetry, making it difficult even for informed consumers. EU regulatory responses, particularly the DSA and AI Act, represent significant progress, but further development and effective enforcement are required. Corporate responsibility is essential: ethical algorithm application is not merely a regulatory requirement but also a long-term business interest.

The contribution of this research to marketing science lies in offering an integrative framework for understanding algorithmic control, connecting technological, behavioural, and regulatory dimensions. In future, it will be crucial to increase consumer awareness, develop algorithmic literacy, and continuously adapt regulatory frameworks to technological developments. The phenomenon of algorithmic control is not a passing trend but a structural characteristic of the digital economy, which both research and practice must address in the long term.

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