Behavioral Manipulation In Big Data Implementation: Systematic Literature Review

Hendi Sama[1], Mangapul Siahaan[2], Nancy Vanessa*[3]
Program Studi Sistem Informasi, Fakultas Ilmu Komputer, Universitas Internasional Batam
E-mail : hendi@uib.ac.id[1], mangapul.siahaan@uib.ac.id[2], 2231021.nancy@uib.edu[3]*
**Corresponding author*
Received 17 November 2025; Revised 22 December 2025; Accepted 6 January 2026

Abstract - This study investigated the phenomenon of behavioral manipulation in big data implementation through a systematic literature review of thirty peer-reviewed articles published between 2020 and 2025. The objective of the review was to provide a comprehensive understanding of the mechanisms, impacts, and mitigation strategies related to the use of big data for influencing human behavior. The review was conducted following the PRISMA 2020 framework, ensuring transparency and reproducibility in the selection and evaluation process. Out of an initial 250 records identified across major academic databases, 30 studies were ultimately included based on predefined inclusion and exclusion criteria. The analysis revealed that behavioral manipulation was primarily executed through algorithmic recommendation systems, dynamic pricing models, deceptive interface design, and data-driven persuasion techniques. The reviewed studies indicated that such practices compromised individual autonomy, shaped consumer and political decisions, and contributed to psychological strain and social inequality. The findings also highlighted the paradox of algorithmic transparency, showing that disclosure without user comprehension could legitimize manipulation rather than reduce it. Furthermore, evidence suggested that emerging interventions, such as dynamic consent mechanisms and independent algorithmic audits, showed potential in restoring trust and protecting user rights, although their implementation remained limited. Approximately 83.3% of the reviewed studies concluded that behavioral manipulation through big data is a multidimensional challenge requiring an integrated response that combines technical safeguards, ethical design, adaptive regulation, and enhanced digital literacy.

Keywords - Behavioral manipulation, Big data implementation, Decision making

1. INTRODUCTION

The advancement of digital technology has positioned big data as a vital element across multiple sectors, including business, healthcare, technology, and public policy. Big data enables the efficient processing of vast amounts of information, offering significant benefits such as personalized user experiences, operational optimization, and predictive analytics. However, its use also presents ethical and social challenges, particularly when employed for behavioral manipulation. Big data–driven behavioral manipulation involves sophisticated algorithms designed to predict and influence individual decisions without their awareness, encompassing consumer activities, political orientation, and other forms of online interaction [1]. Scholars have increasingly emphasized that manipulation can occur not only through data-driven personalization but also through interface-level interventions, such as dark patterns, which exploit cognitive biases and systematically steer user decisions [2], [3]. For example, in a field experiment in educational technology, personalized recommendations were found to increase content consumption by approximately 60%, and overall app usage by 14%, compared to non-personalized systems [4]. These findings suggest that behavioral manipulation is embedded within both algorithmic and design-based infrastructures, making it a multifaceted phenomenon.

The urgency of this issue has grown alongside the integration of artificial intelligence into digital systems, which further strengthens the capacity of big data to analyze and influence human

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

behavior. The combination of machine learning models, predictive analytics, and real-time personalization allows organizations to generate highly adaptive manipulation strategies that users may not recognize as such. This creates significant risks, including privacy violations, erosion of individual autonomy, and reinforcement of existing social biases. In Bangladesh, for instance, 18.3% of e-commerce websites analyzed were found to contain one or more dark patterns, indicating that manipulative interface design is not just theoretical but already widespread in developing digital markets [5]. Likewise, a study involving recommendation AI for dietary habit improvement in Japan revealed that trust and usage of AI were significantly affected by how data management, user communication, and transparency were designed [6]. Similar concerns have been observed in online learning systems in Indonesia, where local studies note risks such as data breaches and unauthorized access undermining user trust [7]. Although numerous studies have examined the potential of big data for innovation, systematic academic discussions concerning the consequences of behavioral manipulation and strategies for ethical mitigation remain limited. Prior research has shown that manipulation not only influences short-term decision-making but also generates long-term psychological, social, and economic impacts. Additionally, the expansion of online-based management systems in education and organizational settings underscores the increasing reliance on digital infrastructures, which, while improving efficiency, also introduces risks of misuse and manipulation if not managed responsibly [8]. Theoretical work on dark patterns has emphasized that millions of users are daily exposed to such interface designs, yet user awareness remains low [3]. This study therefore seeks to provide a deeper understanding of the mechanisms, consequences, and mitigation strategies of behavioral manipulation through big data. The research was designed to address several key questions, including the ethical and practical implications for individuals and society. Furthermore, it aims to propose strategic recommendations to minimize negative impacts while ensuring responsible use of big data. In this way, the study is expected to serve as a robust academic foundation for the development of more sustainable and ethically grounded technology policies in the future.

2. LITERATURE REVIEW

Previous studies have demonstrated that big data techniques employ a combination of behavioral analysis, demographic information, and machine learning algorithms to influence users' decision-making processes. While such practices offer opportunities for innovation, they also raise pressing ethical concerns, including privacy violations and inequities in data usage. This phenomenon is frequently observed on social media platforms, where algorithms are designed to target users with specific content to maximize engagement, often altering individual preferences in the process. The Facebook–Cambridge Analytica scandal stands as an iconic example of how big data can be exploited for large-scale behavioral manipulation, triggering global debates on transparency and the ethics of data use. Such practices have generated critical questions regarding public trust in personal data management and the risks of privacy erosion [9]. This phenomenon is often found on social media platforms, where algorithms are used to target users with specific content to maximize engagement, even to the extent of altering user preferences. The Facebook–Cambridge Analytica scandal has become an iconic example of how big data can be used for behavioral manipulation on a passive scale, creating global concerns regarding transparency and the ethics of big data usage [10]. This practice has raised critical questions about public trust in the management of personal data and the risk of privacy erosion. In the context of the digital economy, behavioral manipulation is also frequently used in predictive marketing. Research has shown that companies can increase consumer conversion rates by presenting advertisements tailored to individual preferences based on behavioral analysis. Although this strategy enhances marketing efficiency, criticism may arise due to the lack of disclosure to users regarding how their data will be processed and used. In the public sector, the use of big data to guide user behavior through data-driven policies such as the social credit system in China has generated global discussion about the boundary between behavioral governance and the violation of individual

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

rights [11]. In addition, the development of machine learning and AI technologies has expanded the scope of behavioral manipulation through big data. These algorithms not only predict actions but can also actively influence decisions through recommendations designed to affect emotions, as seen on e-commerce and streaming platforms. Recent studies have shown that such algorithms often employ inherent biases in training data, which may worsen social inequalities, also referred to as discrimination [12].

Although many benefits can be derived from the implementation of big data, the ethical challenges it raises require serious attention. International organizations such as UNESCO and OECD have advocated the development of regulations that balance innovation with the protection of individual rights. This has become increasingly important as the adoption of big data continues to rise across global sectors. Therefore, it is essential to gain a deeper understanding of how big data can be used for behavioral manipulation and its implications for modern society. This study aims to explore the phenomenon of behavioral manipulation through the implementation of big data, which is becoming increasingly widespread across various sectors. The main focus of the study is to understand the methods used to influence individual behavior, such as predictive algorithms, machine learning, and content personalization designed based on user behavior patterns. In this context, the study will analyze the impact of behavioral manipulation on individual privacy, transparency, and social justice. This is particularly important given the criticisms of algorithmic bias and the potential misuse of data that may exacerbate inequality.

3. RESEARCH METHOD

This study employed a Systematic Literature Review (SLR) method to systematically identify, evaluate, and synthesize existing academic research on behavioral manipulation in big data implementation. The SLR approach was selected to ensure methodological rigor, transparency, and reproducibility in reviewing prior studies. The review process followed the PRISMA 2020 guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [13].

1. Search Strategy

The literature search was conducted across four academic databases: Scopus, PubMed, Google Scholar, and Frontiers. These databases were selected to ensure comprehensive coverage of interdisciplinary research spanning information systems, computer science, psychology, ethics, and social sciences.

a. Scopus was chosen for its broad coverage of high-quality peer-reviewed journals.
b. PubMed was included to capture studies addressing behavioral and psychological impacts.
c. Google Scholar was used to ensure wider coverage and minimize the risk of missing relevant studies.
d. Frontiers was selected due to its focus on interdisciplinary and emerging research topics.

The searches were conducted between 15–20 January 2025.

The search was applied to the title, abstract, and author keywords fields. The following Boolean search string was used with minor syntax adjustments depending on database requirements:

(“behavioral manipulation” OR “behavioural manipulation” OR “algorithmic manipulation” OR “dark patterns”)

AND (“big data” OR “data-driven systems” OR “algorithmic systems”)
AND (“decision making” OR “user behavior” OR “consumer behavior”)

2. Inclusion and Exclusion Criteria

To ensure consistency and quality, the following criteria were applied:

Inclusion Criteria

a. Peer-reviewed journal articles
b. Published between 2020 and 2025

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

c. Written in English
d. Explicitly addressing behavioral manipulation in the context of big data or algorithmic systems

Exclusion Criteria

a. Conference proceedings, books, theses, dissertations, and review-only articles
b. Non-English publications
c. Studies published outside the 2020–2025 period
d. Articles not directly related to behavioral manipulation in big data implementation

The inclusion and exclusion criteria are summarized in Table 1.

Table 1. Inclusion and Exclusion for the Implementation of Behavioral Manipulation in Big Data

	Inclusion Criteria	**Exclusion Criteria**
Source	Peer-reviewed journal articles indexed in Scopus, PubMed, Google Scholar, or Frontiers.	Conference proceedings, books, book chapters, theses, dissertations, reports, or non–peer-reviewed publications.
Language	Articles written in English**.**	Non-English publications.
Publication Year	Published between 2020-2025.	Published before 2020 or after 2025.
Title Screening	Titles explicitly related to behavioral manipulation, algorithmic manipulation, dark patterns, or data-driven influence in big data systems.	Titles unrelated to behavioral manipulation or not associated with big data or algorithmic systems.
Abstract Screening	Abstracts discussing big data implementation that influences user behavior, decision-making, or autonomy.	Abstracts focusing on big data without behavioral influence, or manipulation without data-driven systems.
Full-text Eligibility	Full text clearly addresses mechanisms, impacts, ethical issues, or mitigation strategies of behavioral manipulation in big data.	Full text does not substantively discuss behavioral manipulation in big data implementation.
Research Focus	Empirical studies or conceptual analyses addressing manipulation techniques, algorithmic bias, transparency, or regulation.	Purely technical studies without behavioral implications or purely descriptive studies.

3. Study Selection Process

The selection process consisted of two stages: initial screening and eligibility assessment. During the initial screening, titles and abstracts were reviewed to remove irrelevant studies. In the eligibility assessment stage, full-text articles were examined to ensure alignment with the research objectives.

Following the PRISMA 2020 flow, 250 records were initially identified. After removing 40 duplicate records, 210 articles were screened. A total of 150 articles were excluded based on title and abstract screening. Sixty full-text articles were assessed for eligibility, of which 30 were excluded due to language, publication period, or thematic irrelevance. Ultimately, 30 studies were included in the final synthesis.

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

4. Quality Assessment

The methodological quality of the selected studies was assessed using the Critical Appraisal Skills Programme (CASP) framework. Each article was evaluated based on clarity of objectives, methodological rigor, relevance of findings, and contribution to the research topic. Only studies meeting the minimum quality threshold were included in the final analysis.

5. Data Analysis

A **thematic narrative synthesis** approach was used to analyze the selected studies. Key data were extracted using a standardized form and grouped into thematic categories, including manipulation mechanisms, impacts on autonomy and decision-making, transparency and bias, and regulatory or ethical interventions. This approach enabled the identification of recurring patterns, divergences, and research gaps across the literature.

The following diagram illustrates the flow of the inclusion and exclusion process within the PRISMA framework (n: number of articles).

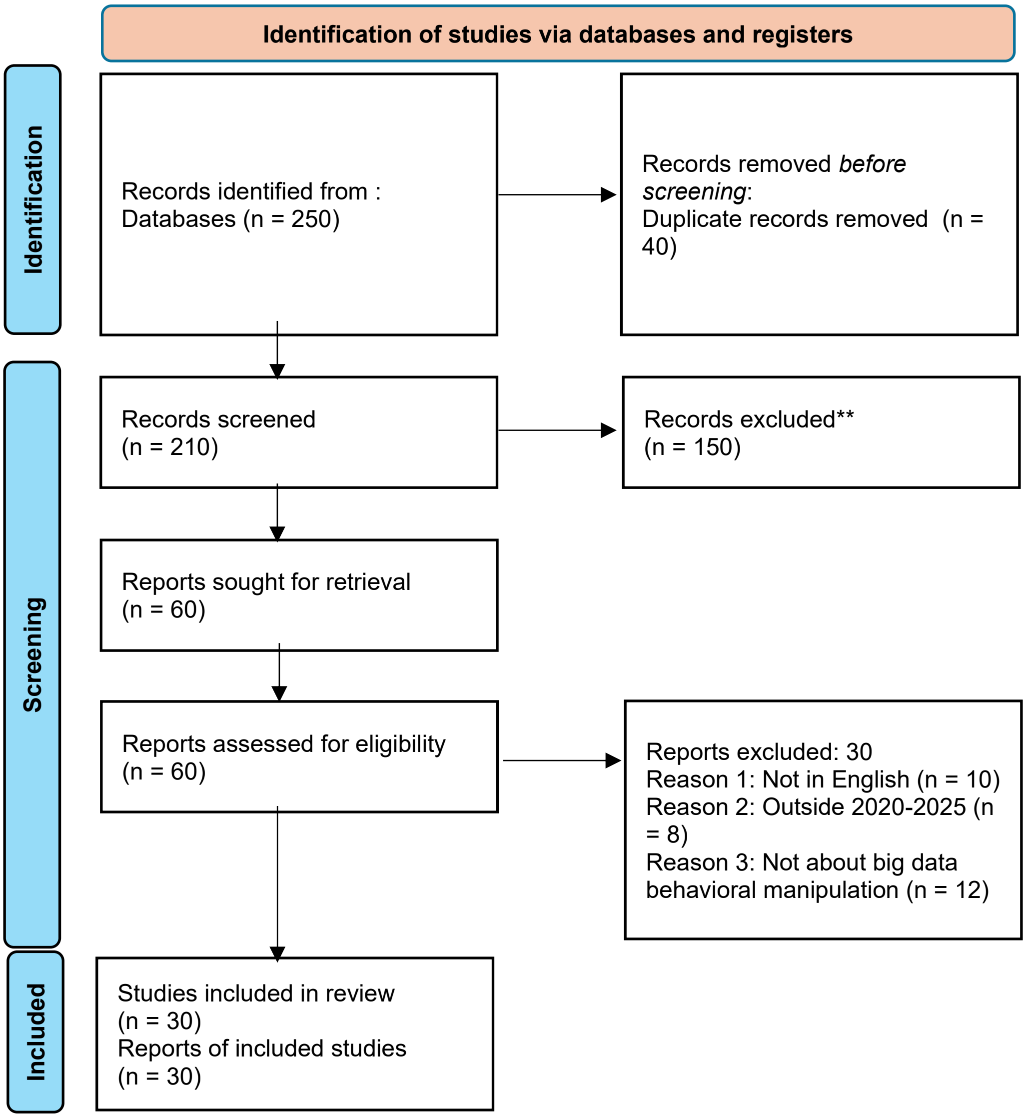

Figure 1. PRISMA Framework for the Implementation of Behavioral Manipulation in Big Data

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

The article selection process in this study followed the PRISMA 2020 flow. A total of 250 articles were initially identified from academic databases. After removing 40 duplicates, 210 articles remained for the screening stage. At this stage, 150 articles were eliminated after reviewing titles and abstracts because they were considered irrelevant, leaving 60 articles for the eligibility assessment. Of these, 30 articles were excluded, consisting of 10 that were not written in English, 8 published outside the 2020–2025 period, and 12 that did not specifically address behavioral manipulation in the implementation of big data. Consequently, 30 articles were included in the final stage for further analysis in this systematic literature review.

4. RESULTS AND DISCUSSION

A systematic review of 30 relevant articles on behavioral manipulation in the context of big data revealed that this phenomenon encompasses highly complex dimensions, including technical mechanisms, psychological and social impacts, ethical dilemmas and transparency, as well as regulatory frameworks and resistance strategies. From the literature analyzed, four major themes were identified: the mechanisms of manipulation, the impacts on user behavior and autonomy, issues of transparency and bias, and the role of regulation and ethical interventions.

A. Mechanisms of Manipulation in Big Data and Algorithms

The literature indicates that mechanisms of manipulation in big data operate through a combination of recommendation algorithms, price personalization, behavioral modification, and digital interface design incorporating dark patterns. Acemoglu and colleagues (2023, 2025) emphasized that companies with access to behavioral data can use surface attributes or glossy attributes to alter consumer perceptions even without changing the substantive qualities of a product [14], [15]. A classical study on price personalization by Li et al. (2022) further demonstrated that companies exploit granular data to differentiate prices among consumers based on their willingness to pay, creating a systematic form of economic manipulation [16]. Bandy (2021) reinforced this argument through an audit of algorithms showing how content visibility is distorted, leading users to be subtly steered toward certain decisions [17].

Technical manipulation also emerges in the context of security. Nguyen et al. (2024) discussed poisoning attacks against recommendation systems, whereby external actors inject false data to bias algorithms in favor of specific groups [18]. Jagielski et al. (2018) demonstrated that data poisoning can alter machine learning models in ways that are difficult to detect [19]. Meanwhile, Shmueli and Tafti (2023) explained how big data–driven predictions are often reinforced through behavioral modification techniques, thereby blurring the line between neutral prediction and manipulative intervention [20]. The literature on dark patterns adds another critical dimension. Punetha (2024), in a systematic review, found that interface designs such as confirmshaming, obstruction, and forced action are manipulative tactics deliberately employed to direct user behavior [21]. The official report *Patterns in the Dark* (DSB, 2024) empirically showed how governments must address dark patterns as part of manipulative digital infrastructure [22]. Collectively, the evidence demonstrates that manipulation in big data extends beyond prediction and recommendation into system design, pricing models, and security frameworks that can be exploited.

B. Impacts on Autonomy, Decision-Making, and User Experience

Data-driven manipulation has tangible consequences for individual autonomy and decision-making. Carroll et al. (2023) and Sabour et al. (2025) showed in experimental studies that humans are highly prone to following algorithmic suggestions, even when such suggestions are demonstrably suboptimal [23], [24]. This was further supported by Fan and Liu (2022), who found that algorithmic autonomy influences consumer decision-making in a

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

non-linear pattern, where moderate algorithmic control exerted the strongest impact on purchasing decisions [25].

The psychological and social impacts are also significant. Hu (2025) investigated social media and found that algorithmic recommendations enhance engagement while simultaneously producing frustration and mental fatigue [26]. Arora et al. (2024) warned about the long-term effects of social media algorithms on adolescents, including heightened stress, anxiety, and susceptibility to manipulative content[27]. Experimental work by Bogert et al. (2021) showed that as tasks become more difficult, individuals increasingly rely on algorithms over social influence, indicating a tendency to delegate decision-making to systems [28].

From a design perspective, Chang, Seaborn, and Adams (2024) explained the psychological mechanisms behind dark patterns, which operate by exploiting cognitive biases and human perceptual weaknesses [29]. Fagan (2024), through a review of persuasion psychology, added that tactics such as framing and seduction create an illusion of free choice when options are, in fact, constrained [30]. Ethnographic research by Overbye-Thompson (2025) showed that some users attempted to resist manipulation through workaround strategies, though such resistance was not always effective [31].

Other studies link manipulation to broader social vulnerabilities. Padarha (2023) described a dystopian data environment in which algorithmic manipulation perpetuates ongoing ethical violations and deepens structural inequities [32]. Stella, Ferrara, and De Domenico (2018) demonstrated how social bots amplify the spread of negative content, producing harmful psychological and social consequences [33]. Taken together, these findings underscore that algorithmic manipulation not only affects immediate behavior but also erodes psychological autonomy and long-term social trust.

C. Transparency, Bias, and Ethical Dilemmas

One of the central themes in literature is the paradox of algorithmic transparency. Klenk (2024) argued that transparency can itself be manipulative when it is merely formal and fails to grant users meaningful control [34]. Wang (2022) extended this argument by showing that transparency often functions as a normative instrument of power, reinforcing algorithmic dominance [35]. Ulrik Franke (2022), in his reflection, also questioned the extent to which society should care about transparency, as disclosure does not necessarily translate into meaningful understanding [36].

The issue of bias receives significant attention. Starke et al. (2022), in a systematic review of public perceptions of algorithms, found that people frequently perceive algorithms as unfair and nontransparent, especially when automated outcomes lack sufficient explanation [37]. Saura (2022) demonstrated that big data in the governance context poses serious challenges related to privacy and bias, undermining public trust [38]. Hacker (2023) further emphasized that algorithmic manipulation often manifests in commercial contexts as a form of unfair business practice [39].

The ethical discussion is reinforced by Hosseini et al. (2022), who found that the use of big data in social research introduces critical problems related to data reuse, methodological bias, and the absence of ethical regulation [40]. Padarha (2023) underscored that algorithmic manipulation and large-scale data use have created what amounts to near-permanent ethical violations [32]. Cellard (2022) proposed the concept of surfacing algorithms as a method to enhance accountability by making algorithms visible through documentation and representations that can be publicly scrutinized [41]. Thus, while transparency is often presented as a solution, the literature demonstrates that without interpretive capacity and genuine control, transparency may serve as a tool of legitimizing manipulation.

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

D. Regulation, Ethical Design Interventions, and Social Resistance

The final theme highlights the necessity of regulation and ethical design interventions to limit algorithmic manipulation. Yi and Li (2024), in a systematic review of dark pattern regulation, showed that legal interventions are beginning to take shape but remain partial and do not adequately address the technical dimensions of algorithms [2]. Fagan (2024) stressed that the psychology of digital persuasion requires regulatory measures that protect users from subconscious tactics [30]. Reports by the OECD (2024) and the Open Government Partnership (2023) on algorithmic transparency in the public sector further underscored the importance of policy instruments for ensuring openness and accountability [42], [43].

Lee et al. (2024) demonstrated the success of dynamic consent in healthcare data contexts, where users could tailor data permissions to specific situations [44]. This study highlighted the promise of participatory design approaches in reducing manipulation. Grimmelikhuijsen (2023) found that algorithmic transparency in the public sector enhanced perceptions of governmental legitimacy, even though users did not always comprehend technical details [45].

At the same time, user resistance to manipulation also emerges in the literature. Yuan (2025) observed that users fall along a spectrum, ranging from full compliance with algorithms to active rejection through personal strategies [46]. Ullah (2025) studied online reviews and found that dark patterns affect genders differently, indicating that certain groups are more vulnerable to manipulation [47]. Stella et al. (2018) reaffirmed that manipulation is not merely an individual interaction problem but also a systemic issue within information ecosystems amplified by bots and automation [33].

Overall, the evidence makes clear that solutions to behavioral manipulation through big data cannot rely on a single instrument. Public regulation, algorithm audits, ethical interface design, and digital literacy initiatives must operate in tandem. The *Patterns in the Dark* report (2024) illustrates how public policy has begun moving in this direction but also emphasizes the need for greater synergy among policymakers, researchers, and civil society [22].

In addition to the thematic synthesis presented above, recent studies provide more nuanced insights into whether personalization and recommendation systems generate benefits or harm in practice. Aridor *et al.* [48] conducted a large-scale field experiment using the MovieLens dataset and found that algorithmic recommendations significantly influenced user behavior, with approximately 40% of the content consumed being directly attributable to the recommendation mechanism. This indicates that personalization systems can meaningfully shape decision pathways by exposing users to previously unexplored options, thereby improving informational efficiency. However, empirical research also highlights substantial drawbacks. Mansoury *et al.* [49] demonstrated that feedback loops in recommender systems amplify popularity bias over time popular items receive disproportionate visibility while niche content becomes increasingly marginalized, reducing exposure diversity and user autonomy. Similarly, Kowald *et al.* [50] found that in the entertainment domain, popularity amplification led to a twofold increase in exposure inequality, with users receiving progressively narrower recommendation sets. These findings support the view that algorithmic personalization can unintentionally reinforce social and informational stratification when left unchecked.

Complementing this critical perspective, Ribeiro *et al.* [51] introduced the concept of the "amplification paradox," arguing that algorithmic influence does not always escalate linearly; rather, behavioral moderation from users and content saturation effects may limit the extent of manipulation. Their simulation studies revealed that algorithmic amplification plateaus after repeated exposures, implying that user agency and contextual engagement can buffer against total behavioral convergence. Taken together, these contrasting results underscore the dual nature of algorithmic personalization: while it enhances efficiency and user satisfaction under transparent

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

and well-calibrated conditions, it can also perpetuate bias, limit diversity, and erode fairness in opaque systems. Consequently, ongoing efforts to design accountable algorithms must integrate fairness metrics, transparency audits, and participatory oversight to mitigate manipulative risks while preserving user benefit.

5. CONCLUSION

A systematic review of thirty articles demonstrated that behavioral manipulation through big data is a multidimensional phenomenon involving technical mechanisms, psychological and social impacts, ethical dilemmas, and regulatory responses. On the one hand, recommendation algorithms, price personalization, dark patterns, and data poisoning attacks enable digital actors to subtly yet effectively shape user preferences and behaviors. Studies by Acemoglu, Li, Bandy, and Nguyen revealed how granular data and interface design can be directed to influence the decisions of both consumers and citizens. The impacts of such practices are evident in the reduction of individual autonomy, the increase of digital stress and fatigue, and the emergence of social biases that exacerbate structural inequalities, as described by Carroll, Hu, Arora, and Stella. Although transparency is often proposed as a solution, research by Klenk, Wang, Franke, and Starke highlighted that openness without the capacity for interpretation merely legitimizes manipulation. Mitigation efforts have emerged through regulation, participatory design, and social resistance for instance, through dynamic consent (Lee), OECD and OGP reports on transparency, and the findings of Yuan and Ullah on user resistance strategies, yet significant gaps remain in their broader implementation.

Based on these findings, a comprehensive strategy is required that integrates technical, regulatory, design, and social dimensions to limit behavioral manipulation in big data implementation. From the research perspective, future studies should focus more on developing countries and employ longitudinal approaches to capture long-term impacts more accurately. From the policy perspective, regulations must become more adaptive, not only demanding transparency but also granting users practical rights to control algorithms, reject recommendations, or opt out of personalization systems, accompanied by independent audit mechanisms. From the design perspective, user empowerment principles through participatory approaches such as dynamic consent should be expanded across sectors, while digital literacy must be strengthened so that individuals can recognize and resist manipulative patterns such as dark designs. With such a combination of strategies, algorithmic manipulation can be mitigated, and the use of big data can be more closely aligned with the principles of individual autonomy, social justice, and ethical sustainability.

REFERENCES

[1] D. Acemoglu, A. Makhdoumi, A. Malekian, and A. Ozdaglar, "When big data enables behavioral manipulation," *American Economic Review: Insights*, vol. 7, no. 1, pp. 19–38, 2025, doi: 10.1257/aeri.20230589.

[2] M. Li *et al.*, "A comprehensive study on dark patterns," *arXiv preprint*, arXiv:2412.09147, 2024.

[3] T. Kollmer and A. Eckhardt, "Dark patterns: Conceptualization and future research directions," *Business & Information Systems Engineering*, vol. 65, no. 2, pp. 201–208, 2023, doi: 10.1007/s12599-022-00783-7.

[4] G. N. Dec and K. Agrawal, "Personalized recommendations in EdTech: Evidence from field experiments," 2022.

[5] Y. Sazid and K. Sakib, "Prevalence and user perception of dark patterns: A case study on e-commerce websites of Bangladesh," *Proc. International Conference on Evaluation of Novel Approaches to Software Engineering (ENASE)*, pp. 238–249, 2024, doi: 10.5220/0012734900003687.

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

[6] S. Genovesi, K. Kaesling, and S. Robbins, *Recommender Systems: Legal and Ethical Issues*, Int. Library of Ethics, Law and Technology, vol. 40. Cham, Switzerland: Springer, 2023, doi: 10.1007/978-3-031-34804-4.

[7] S. Tjahyadi and E. Titoni, "Risk analysis in Indonesian educational online learning systems: A systematic literature review," *Journal of Informatics and Telecommunication Engineering*, vol. 8, no. 2, pp. 240–247, 2025, doi: 10.31289/jite.v8i2.13239.

[8] H. Sama, I. Deu, and S. Tjahyadi, "Development of an online-based management system to facilitate school events," *Conference on Management, Business, Innovation, Education and Social Sciences*, vol. 4, no. 1, pp. 26–39, 2024.

[9] R. A. García-Hernández *et al.*, "A systematic literature review of modalities, trends, and limitations in emotion recognition, affective computing, and sentiment analysis," *Applied Sciences*, vol. 14, no. 16, 2024, doi: 10.3390/app14167165.

[10] P. Greenfield, "The Cambridge Analytica files: The story so far," *The Guardian*, 2018.

[11] H. R. Kwon and E. A. Silva, "Mapping the landscape of behavioral theories: A systematic literature review," *Journal of Planning Literature*, vol. 35, no. 2, pp. 161–179, 2020, doi: 10.1177/0885412219881135.

[12] I. D. Raji *et al.*, "Saving face: Investigating the ethical concerns of facial recognition auditing," *Proc. AAAI/ACM Conference on AI, Ethics, and Society*, pp. 145–151, 2020, doi: 10.1145/3375627.3375820.

[13] M. J. Page *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, 2021, doi: 10.1136/bmj.n71.

[14] D. Acemoglu, A. Makhdoumi, A. Malekian, and A. E. Ozdaglar, "A Model of Behavioral Manipulation," *SSRN Electron. J.*, 2023, doi: 10.2139/ssrn.4638206.

[15] D. Acemoglu, A. Makhdoumi, A. Malekian, and A. Ozdaglar, "When Big Data Enables Behavioral Manipulation," *Am. Econ. Rev. Insights*, vol. 7, no. 1, pp. 19–38, 2025, doi: 10.1257/aeri.20230589.

[16] C. Li, Y. Chen, and Y. Shang, "A review of industrial big data for decision making in intelligent manufacturing," *Engineering Science and Technology, an International Journal*, vol. 29, 2022, doi: 10.1016/j.jestch.2021.06.001.

[17] J. Bandy, "Problematic machine behavior: A systematic literature review of algorithm audits," *Proceedings of the ACM on Human-Computer Interaction*, vol. 5, no. CSCW1, pp. 1–34, 2021, doi: 10.1145/3449148.

[18] T. T. Nguyen *et al.*, "Manipulating recommender systems: A survey of poisoning attacks and countermeasures," *ACM Computing Surveys*, vol. 57, no. 1, 2024, doi: 10.1145/3677328.

[19] M. Jagielski *et al.*, "Manipulating machine learning: Poisoning attacks and countermeasures for regression learning," *Proc. IEEE Symposium on Security and Privacy*, pp. 19–35, 2018, doi: 10.1109/SP.2018.00057.

[20] G. Shmueli and A. Tafti, "Rejoinder: How to 'improve' prediction using behavior modification," *International Journal of Forecasting*, vol. 39, no. 2, pp. 566–569, 2023, doi: 10.1016/j.ijforecast.2022.12.007.

[21] A. Punetha, "Dark Patterns in User Interfaces : A Systematic and Meta-Analysis," 2024.

[22] J. Baumeister *et al.*, *Patterns in the Dark: Deceptive Practices in Online Interactions*. Data Standards Chair Report, 2024.

[23] S. Sabour *et al.*, "Human decision-making is susceptible to AI-driven manipulation," *arXiv preprint*, arXiv:2502.07663, 2025.

[24] M. Carroll *et al.*, "Characterizing manipulation from AI systems," *Proc. ACM International Conference*, 2023, doi: 10.1145/3617694.3623226.

[25] Y. Fan and X. Liu, "The impact of algorithmic decision autonomy on consumer purchase decisions," *Frontiers in Psychology*, vol. 13, 2022, doi: 10.3389/fpsyg.2022.1009173.

[26] Z. Hu, "Impact of social media algorithms on user decision-making," *Applied Computing and Engineering*, vol. 174, no. 1, pp. 18–22, 2025, doi: 10.54254/2755-

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

2721/2025.po24665.
[27] S. Arora *et al.*, “Psychological impacts of AI-driven social media on teenagers,” *IEEE Conference on Digital Platforms and Societal Harms*, 2024, doi: 10.1109/DPSH60098.2024.10774922.
[28] E. Bogert, A. Schecter, and R. T. Watson, “Humans rely more on algorithms than social influence as a task becomes more difficult,” *Scientific Reports*, vol. 11, no. 1, 2021, doi: 10.1038/s41598-021-87480-9.
[29] W. J. Chang, K. Seaborn, and A. A. Adams, “Theorizing deception: A scoping review of dark patterns,” *Proc. CHI Conference on Human Factors in Computing Systems*, 2024, doi: 10.1145/3613905.3650997.
[30] P. Fagan, “Clicks and tricks: The dark art of online persuasion,” *Current Opinion in Psychology*, vol. 58, p. 101844, 2024, doi: 10.1016/j.copsyc.2024.101844.
[31] H. Overbye-Thompson and R. E. Rice, “Understanding how users work around algorithmic bias,” *AI & Society*, 2025, doi: 10.1007/s00146-025-02498-1.
[32] S. Padarha, “Data-driven dystopia: An uninterrupted breach of ethics,” 2023.
[33] M. Stella, E. Ferrara, and M. De Domenico, “Bots increase exposure to negative content,” *Proceedings of the National Academy of Sciences*, vol. 115, no. 49, pp. 12435–12440, 2018, doi: 10.1073/pnas.1803470115.
[34] U. Franke, “Algorithmic transparency, manipulation, and two concepts of liberty,” *Philosophy & Technology*, vol. 37, no. 1, 2024, doi: 10.1007/s13347-024-00713-3.
[35] H. Wang, “Transparency as manipulation?,” *Philosophy & Technology*, vol. 35, no. 3, 2022, doi: 10.1007/s13347-022-00564-w.
[36] U. Franke, “How Much Should You Care About Algorithmic Transparency as Manipulation?,” *Philos. Technol.*, vol. 35, no. 4, pp. 1–7, 2022, doi: 10.1007/s13347-022-00586-4.
[37] C. Starke *et al.*, “Fairness perceptions of algorithmic decision-making,” *Big Data & Society*, vol. 9, no. 2, 2022, doi: 10.1177/20539517221115189.
[38] J. R. Saura *et al.*, “Assessing behavioral data science privacy issues,” *Government Information Quarterly*, vol. 39, no. 4, 2022, doi: 10.1016/j.giq.2022.101679.
[39] P. Hacker, “Manipulation by algorithms,” *European Law Journal*, vol. 29, no. 1–2, pp. 142–175, 2023, doi: 10.1111/eulj.12389.
[40] M. Hosseini *et al.*, “Ethical issues in social science research employing big data,” *Science and Engineering Ethics*, vol. 28, no. 3, 2022, doi: 10.1007/s11948-022-00380-7.
[41] L. Cellard, “Surfacing algorithms,” *Qualitative Inquiry*, vol. 28, no. 7, pp. 798–813, 2022, doi: 10.1177/10778004221097055.
[42] M. Valderrama, M. P. Hermosilla, and R. Garrido, “State of the Evidence: Algorithmic Transparency,” *Open Gov. Partnersh.*, no. May, 2023.
[43] J. David Gutiérrez and A. Gillwald, “Algorithmic Transparency in the Public Sector A state-of-the-art report of algorithmic transparency instruments Acknowledgements,” no. November, 2024.
[44] A. R. Lee, D. Koo, I. K. Kim, E. Lee, S. Yoo, and H. Y. Lee, “Opportunities and challenges of a dynamic consent-based application: personalized options for personal health data sharing and utilization,” *BMC Med. Ethics*, vol. 25, no. 1, 2024, doi: 10.1186/s12910-024-01091-3.
[45] S. Grimmelikhuijsen, “Explaining Why the Computer Says No: Algorithmic Transparency Affects the Perceived Trustworthiness of Automated Decision-Making,” *Public Adm. Rev.*, vol. 83, no. 2, pp. 241–262, 2023, doi: 10.1111/puar.13483.
[46] Y. Yuan *et al.*, “Resistance or compliance to algorithmic awareness,” *Frontiers in Psychology*, vol. 16, 2025, doi: 10.3389/fpsyg.2025.1563592.
[47] “Dark Patterns , Online Reviews , and Gender : A Behavioural Analysis of Consumer Decision Making on TEMU in the E- Commerce Context,” pp. 1–61.
[48] G. Aridor *et al.*, “The economics of recommender systems,” *Proc. ACM Conference on*

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099

Economics and Computation, 2023, doi: 10.1145/3580507.3597677.
[49] M. Mansoury *et al.*, "Feedback loop and bias amplification," *Proc. ACM Conference on Information and Knowledge Management*, pp. 2145–2148, 2020, doi: 10.1145/3340531.3412152.
[50] D. Kowald, "Popularity bias amplification in recommender systems," 2025.
[51] M. Horta Ribeiro *et al.*, "The amplification paradox in recommender systems," *Proc. AAAI Conference on Web and Social Media*, vol. 17, pp. 1138–1142, 2023, doi: 10.1609/icwsm.v17i1.22223.

e-ISSN : 2356-2579 | p-ISSN : 1412-2693, DOI : 10.62411/tc.v25i1.15099