



Why Users Leave: A Dual-Pathway Reactance Model of Social Media Discontinuance and the Moderating Role of Algorithmic Awareness

趙, 唯可

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Doctoral Dissertation

Why Users Leave: A Dual-Pathway Reactance
Model of Social Media Discontinuance and the
Moderating Role of Algorithmic Awareness

なぜユーザーは離脱するのか：ソーシャルメディア離脱における二経路反感
モデルとアルゴリズム認知の調整効果

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神戸大学大学院経営学研究科

森村文一 研究室

経営学専攻

学籍番号 198B123B

氏名 趙 唯可

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1. Introduction

This chapter introduces the background, motivation, and overall framework of the dissertation by examining why and how users discontinue the use of social media platforms despite the growing sophistication of algorithmic recommendation systems (RS). It begins by outlining recent trends in social media usage and the rising concern over discontinuance, then explains the dual role of RS as both an engagement tool and a potential trigger of psychological strain. The chapter further identifies theoretical gaps in the literature on discontinuance, particularly the lack of attention to user autonomy and psychological reactance. Building on these insights, the chapter proposes a conceptual model and presents the central research questions and methodological overview of the dissertation.

Social media (SM) has become increasingly embedded in people's daily lives, enabling individuals to connect with others and the broader world while accessing, exploring, and sharing a wide range of information (Grover, Kar & Dwivedi, 2022). In the aftermath of the COVID-19 pandemic, social media platforms experienced substantial growth and emerged as indispensable tools for communication, entertainment, and information acquisition. With restrictions on physical mobility during lockdowns, users turned more frequently to platforms such as Facebook, Instagram, X (formerly Twitter), and TikTok, resulting in a sharp increase in usage frequency and user engagement. Recent statistics show that the penetration rate of SM in Japan has reached 78.1%, making it an integral part of everyday life (Statistic, 2024).

However, as the pandemic subsides and people resume their offline routines, social media usage has begun to decline for some users (Huang, Palvia & Mehta, 2024). A growing number of individuals are distancing themselves from social media platforms due to various concerns, such as exposure to redundant information (Chung, Chen & Meng, 2023) and heightened social pressure (Lim & Ahn, 2021). From the perspective of SM platform providers, this trend poses a significant challenge to long-term sustainability, as their business models heavily depend on sustained user engagement (Farooq et al., 2023). Major platforms like Facebook have already shown signs of decreased user activity (Turel, 2015), underlining the urgent need to retain users and mitigate discontinuance.

Building on these trends, recent observations show that user discontinuous usage is taking increasingly diverse forms. In addition to overall declines in activity, individuals are reducing usage frequency, temporarily deactivating accounts, or even permanently quitting specific services (Farooq et al., 2023). This intention is often associated with experiences of information and communication overload, excessive social interaction, privacy concerns, and emotional fatigue (Pang & Ruan, 2023a; Zhang et al., 2016; Fan et al., 2021; Dhir et al., 2018). Some users report feeling overwhelmed by redundant content or pressured by constant social connectivity, while others gradually distance themselves due to discomfort with algorithmic personalization and data use (Lim & Ahn, 2021; Vaghefi, Qahri-Saremi & Turel, 2020). Although these behavioral shifts are not always immediately visible, they point to a broader pattern of user withdrawal and highlight the growing complexity of maintaining engagement in digital environments. These behavioral shifts can manifest in various forms, ranging from abrupt quitting—such as account deletion or uninstalling apps—to more subtle and gradual withdrawal, including reduced activity, limited interaction, or silent avoidance of certain features (Kang, Zhang & Yoo, 2020; Lin et al., 2020; Luqman et al., 2020).

Given the increasing signs of user disengagement, it is crucial not to overlook the broader implications of social media discontinuance. Rather than being a temporary trend, this shift poses risks to the continued value that social media brings to individuals, businesses, and society at large. Social media remains indispensable due to its multifaceted value. For individuals, social media not only serves as a communication tool but also plays a vital role in enhancing psychological well-being by satisfying core socioemotional needs—such as emotional expression, social connection, and identity formation—and by offering self-esteem benefits and emotional support (Kross et al., 2021). For businesses, social media reshapes customer engagement through real-time, two-way communication, enabling firms to not only build trust and deliver timely services, but also generate commercial value by gathering customer insights, fostering brand loyalty, enabling co-creation of products and campaigns, and amplifying positive word-of-mouth through online communities and user-generated content (Aichner et al., 2021). Moreover, social media has become an integral part of the new retail environment, driving brand visibility, consumer engagement, and influencing website traffic and sales. By enabling peer-to-peer communication and facilitating word-of-mouth effects, it empowers retailers to shape consumer behavior at scale (Dolega, Rowe & Branagan, 2018). Taken together, these roles underline that social media is

not a dispensable tool but a critical infrastructure embedded in individuals' daily lives, commercial ecosystems, and societal communication networks.

Therefore, understanding why users disengage from social media—and uncovering the psychological mechanisms behind such behavior—is essential for improving user experience, enhancing service design, and promoting more sustainable digital strategies. These insights not only help platforms retain users, but also support businesses and organizations that rely on social media as a key channel for engagement and value creation.

To prevent user attrition and deepen platform involvement, social media companies have actively sought technological solutions to reinforce user engagement. Among the various strategies employed by SM platforms to foster user engagement and sustain their business models, algorithmic recommendation systems (RS) have emerged as a foundational component rather than merely a reactive solution. These systems play a central role in shaping user experiences by continuously delivering personalized content, thereby encouraging users to spend more time on the platform and increasing their likelihood of continued use (Zuo et al., 2019). For instance, the MIT Technology Review (2022) reports that more than 70% of watch time on YouTube is driven by RS-generated recommendations. Unlike traditional messaging applications such as WeChat or LINE, which are grounded in direct interpersonal networks, modern SM platforms are largely driven by algorithmically curated content streams. These systems do not simply push content—they actively influence how users perceive its diversity, relevance, and attractiveness (Rassameeroj & Wu, 2019), making them essential tools for maintaining user engagement. Recommendation systems have become central to social media platforms by leveraging users' behavioral histories and inferred preferences to deliver personalized content (Ghasemaghaei et al., 2019). Through this personalization process, RS aim to enhance user experience and ultimately increase engagement (Dolan et al., 2019).

However, the growing reliance on algorithmic recommendations has also introduced new challenges that complicate their long-term effectiveness. While such systems have proven effective in maintaining user interest and satisfaction, they are not without limitations. The continuous stream of tailored content can contribute to information overload (Cao & Sun, 2018; Chung, Chen & Meng, 2023), particularly when recommendations become repetitive or excessive. Moreover, algorithm-driven

environments have been linked to broader concerns such as the “filter bubble” (Klug & Strang, 2019) and “echo chamber” effects (Cinelli, 2021), which may restrict content diversity and reinforce existing biases. These unintended consequences have sparked growing concern among users, businesses, and researchers, raising important questions about the psychological and social costs of personalization. Therefore, understanding how to design RS that preserve the benefits of personalization while minimizing its negative effects has become a critical issue for platform providers seeking to retain users in the long term.

To understand the psychological underpinnings of social media discontinuance (SMD), this literature review addresses two key questions: (1) What do we know—and not know—about why users leave from social media platforms? and (2) How might recommendation systems, as a core design element, contribute to such discontinuance? Specifically, the first part reviews existing work on SM adoption and discontinuance, highlighting both established findings and overlooked psychological mechanisms. The second part shifts focus to RS, examining their technical goals, emerging psychological effects, and unresolved tensions in the user experience. Based on these two strands of research, three critical gaps are identified, which serve as the theoretical motivation for the present study.

The following section first examines how SMD has been approached in existing literature, with particular attention to both behavioral and psychological explanations. A substantial body of research has examined the adoption of SM platforms (Dwivedi et al., 2023). With the growing prominence of social media marketing (Grover et al., 2022), post-adoption research has expanded to explore how to sustain user engagement (Hu, Kettinger & Poston, 2015), how content influences user involvement (Dolan, 2019), and how social media shapes consumer behavior (Kian, 2017) and brand perception (Bilgin, 2018). More recently, scholars have started to focus on social media discontinuance (SMD)—defined as the voluntary reduction or cessation of social media use (Mahmud et al., 2023). Prior studies have identified factors such as information overload, social overload, fatigue, dissatisfaction, and stress as key antecedents to discontinuance (Lim & Ahn, 2021).

Yet, the issue of SMD remains underexplored, particularly with regard to the psychological mechanisms underlying discontinuance, the role of platform-specific design features such as recommendation systems, and the impact of users’ shifting

expectations toward personalization. While prior studies have acknowledged psychological strain as a factor in user disengagement, the underlying mechanisms remain theoretically fragmented and conceptually limited. Much of the existing work views discontinuance as a reactive outcome of cumulative stress or dissatisfaction, but fails to clarify how platform-specific features contribute to the formation of these psychological states. For instance, although emotional exhaustion, guilt, and cognitive fatigue have been linked to discontinuance intentions (Turel, 2015; Maier et al., 2015; Zhang et al., 2022), these explanations often overlook the evaluative and reflective processes through which users arrive at disengagement decisions. In particular, traditional continuance models—focusing on satisfaction or habitual use—do not adequately account for situations where users discontinue use despite enhanced functionality and improved interface design (Lin et al., 2020). This points to the presence of deeper psychological dynamics that are not yet fully captured in existing frameworks. Furthermore, little is known about how users interpret and respond to platform mechanisms that affect their sense of autonomy and control. Specifically, how perceived threats to freedom or psychological reactance emerge from ongoing interactions with algorithmic systems remains under-theorized (Farooq et al., 2023; Turel, 2015). Among these systems, personalized recommendation algorithms are particularly salient yet understudied in terms of their unintended psychological consequences. Although recommendation systems are central to shaping user experience, current models rarely consider their potential to trigger resistance, perceived manipulation, or cognitive narrowing (Ko et al., 2022; Bastani et al., 2022).

In addition, evolving user expectations concerning personalization—such as demands for transparency, diversity, and meaningful control—have received limited empirical attention. These expectations may significantly alter how users interpret personalized content and the platform’s underlying logic, thereby influencing disengagement decisions in ways that existing stress-based models cannot explain (Eslami et al., 2015; Klug & Strang, 2019). As such, despite growing interest in social media discontinuance, critical aspects of its psychological foundations—especially those linked to platform design and personalization—remain insufficiently understood.

While existing research has begun to shed light on the psychological drivers of SMD, it has largely focused on general stressors such as fatigue, overload, or dissatisfaction (Farooq et al., 2023). However, these psychological states are not formed in a vacuum—they often arise from the very structure and design of the platform itself.

Among these structural elements, RS play a particularly central role (Ko et al., 2022). As the primary interface between users and content, RS not only shape the quantity and type of information users encounter but also profoundly influence how users experience and respond to social media (Zuo et al., 2019). Therefore, a closer examination of RS as a potential antecedent to discontinuance behavior is both timely and necessary.

To clarify how platform features may shape psychological drivers of discontinuance, this section turns to RS, outlining what has been extensively studied and what remains insufficiently addressed. RS were first introduced in the 1990s and have since evolved with the advancement of IT technologies (Ko et al., 2022). Designed to filter and prioritize content, RS aim to increase user satisfaction, reduce search effort, and improve retention (Liang et al., 2006; Park, 2014; Zuo et al., 2019). In the information systems (IS) field, numerous studies have focused on improving algorithmic precision and optimizing system-level performance (Ko et al., 2022). However, in the consumer behavior domain, far less is known about how these systems influence user psychology—particularly how personalized content affects users’ perceptions and emotions. Recent studies suggest that personalization can sometimes exceed users’ cognitive processing capacities, resulting in mental fatigue and eventual disengagement (Farhoomand & Drury, 2002). In addition, algorithmic personalization is increasingly perceived as intrusive or manipulative, raising concerns about data exploitation and behavioral control (Aguirre et al., 2015; Pang & Ruan, 2023b). As Youn and Kim (2019) noted, when users are unable to understand or influence how recommendations are generated, their perceived freedom may be undermined. In this sense, RS serve not only as technical tools but also as psychological triggers that shape user attitudes and behaviors.

Therefore, beyond the volume of content presented, the quality and nature of personalized information deserve critical attention. Specifically, insufficient attention has been paid to the negative psychological experiences induced by personalization, including information overload, perceived threats to freedom, and psychological reactance. In highly saturated markets where user attention is limited, this gap restricts our understanding of how RS might unintentionally drive users away from platforms.

Based on the above discussion, three major gaps in the current literature can be identified:

First, there is a lack of comprehensive explanation regarding the psychological states underlying discontinuance. While many studies have emphasized stress-induced outcomes such as fatigue or exhaustion, these alone are insufficient (Fu et al., 2020). As Maslach, Schaufeli, and Leiter (2001) noted in the context of employee turnover, exhaustion is only one facet of a broader process. Similarly, Beaudry and Pinsonneault (2005) argued that technology discontinuance is not merely a reaction to stress, but may involve more complex psychological evaluations. Therefore, new perspectives are needed to better understand the cognitive and emotional mechanisms that lead to SMD.

Second, the relationship between RS and SMD remains largely unexamined. While RS research in IS has advanced significantly, consumer behavior research still lacks theoretical models that explore how personalization affects user experience at a psychological level. In particular, little is known about how personalization quality—not just quantity—may either enhance or disrupt user experience. RS often operate in a “greedy” and exploitative manner, reinforcing inferred preferences and potentially inducing psychological pressure or cognitive narrowing (Bastani et al., 2022). Despite this, few studies have examined how such system designs affect user disengagement or platform abandonment. Given that RS are the core of user-platform interaction, this gap is both theoretically and practically significant.

Third, as recommendation systems become increasingly algorithmically sophisticated, users’ expectations and psychological needs have also evolved. Concepts like the filter bubble (Pariser, 2011) illustrate how algorithmic curation can limit exposure to diverse viewpoints, reinforcing existing biases. Such personalization not only diminishes information diversity but can also elicit user dissatisfaction, distrust, and even active disengagement (Eslami et al., 2015; Klug & Strang, 2019). As users seek more transparency and control, understanding how these shifting expectations interact with RS design—and how this interaction affects the mechanisms behind SMD—remains an open question for future research.

To address the aforementioned gaps, this study proposes an integrated theoretical approach that centers on the psychological mechanisms through which RS influence SMD. Drawing on Farooq et al. (2023), who reviewed SMD research and classified its drivers into individual, relational, and platform-related categories, this study focuses on the platform-related direct drivers of discontinuance—specifically, the structural

and algorithmic features of RS. At this stage, potential inhibitors of discontinuance are deliberately excluded from the analysis to maintain a focused investigation.

Rather than evaluating the overall effectiveness of recommendation systems (RS), this study deliberately focuses on their unintended consequences and failure points. Following Markus and Robey's (1988) argument that studying technological failures can yield valuable insights into the mechanisms of user resistance, this dissertation deliberately focuses on the unintended and adverse consequences of RS. Although RS are widely implemented to enhance personalization, reduce search effort, and improve engagement, they are not universally experienced as beneficial. On the contrary, users may perceive such systems as manipulative, intrusive, or coercive—triggering psychological outcomes such as loss of control, motivational opposition, or even behavioral disengagement. Isolating these negative effects is not intended to deny the positive functions of RS, but rather to understand why users might resist or reject a technology that is otherwise designed to enhance their experience.

This approach aligns with the tradition of innovation resistance research (Ram & Sheth, 1989), which similarly focuses on the conditions under which users fail to adopt or actively reject beneficial innovations. The underlying rationale is that the very presence of expected benefits makes rejection particularly paradoxical and thus theoretically rich. As such, this study contributes to a more complete and balanced understanding of user–technology interaction by highlighting how and why certain platform design choices—such as algorithmic personalization—can unintentionally provoke psychological resistance and social media discontinuance. This research aligns with the theoretical stance that consumer resistance is not merely the opposite of adoption, but a distinct psychological and behavioral construct (Kleijnen, Lee & Wetzels, 2009). Their model illustrates that resistance manifests through rejection, postponement, or opposition, and stems from antecedents such as perceived risk, value misalignment, or negative perceptions—none of which are adequately explained by adoption-oriented models. Therefore, this study's focus on users' adverse responses to RS offers theoretical novelty and practical relevance.

To explain how such negative experiences emerge and evolve into discontinuance, this dissertation draws on Psychological Reactance Theory (PRT). While the Stressor-Strain-Outcome (SSO) framework has been widely used to explain technology-related fatigue and withdrawal (Koeske & Koeske, 1993), it conceptualizes users as passive

recipients of strain. In contrast, PRT offers a more active and motivational account, positing that individuals experience reactance when they perceive their autonomy to be threatened—particularly in contexts of manipulation, forced exposure, or reduced choice (Beaudry & Pinsonneault, 2005; Luqman et al., 2020). Reactance can manifest as oppositional behaviors, such as resistance, disengagement, or discontinuance. In personalization contexts, where recommendation systems reduce users’ sense of control, PRT provides a stronger explanatory framework than fatigue-based models (Pang & Ruan, 2023b). A detailed elaboration of PRT and its relevance to this research is provided in Chapters 2 and 3.

This dissertation adopts the definition of SMD proposed by Wang et al. (2021), which refers to “the cessation of using a specific social media platform, either temporarily or permanently, encompassing behaviors like reducing usage, quitting, or replacing the platform.” This inclusive conceptualization is chosen for three reasons.

First, the primary goal of this dissertation is to uncover the underlying psychological mechanism—specifically reactance—linking RS to discontinuance. Although some researchers have distinguished between abrupt quitting (“opt-out”) and gradual withdrawal (“oblivion”) (Kang, Zhang & Yoo, 2020), these categories have not been theoretically differentiated in terms of their psychological antecedents. As such, an integrated view of discontinuance behaviors—as seen in Lin et al. (2020) and Luqman et al. (2020)—is more appropriate for this study.

Second, the use of an inclusive definition enables a meaningful integration with reactance theory. Reactance is a motivational state that can lead to a broad range of behaviors aimed at restoring perceived autonomy, including reducing engagement, avoiding certain content, or withdrawing from a platform entirely (Rosenberg & Siegel, 2018; Lin et al., 2020). Capturing these varied responses under a unified construct of SMD enhances both theoretical coherence and explanatory power.

Third, from a practical standpoint, platform providers typically rely on observable user behaviors—such as decreased activity, shortened session duration, or unsubscriptions—as proxies for dissatisfaction (Heinonen & Strandvik, 2015). Therefore, this study focuses on discontinuance intention rather than actual quitting behavior, as it closely aligns with the metrics used in real-world platform management. Moreover, as Bandura (1998) suggests, behavioral intention is a well-established psychological precursor to action, reflecting users’ internal cognitive and emotional

states before any visible behavior takes place. By measuring intention, this study is able to capture the early-stage manifestations of disengagement, which are both theoretically meaningful and managerially actionable.

Importantly, this dissertation does not explicitly examine a particular subset of users—those who are psychologically disengaged but do not express any behavioral or intentional cues of withdrawal, commonly referred to as “silent leavers.” While these users may eventually discontinue use, their disengagement remains largely undetectable to both researchers and practitioners. Given the empirical and practical challenges associated with identifying such latent states, this study concentrates on users who exhibit measurable disengagement signals. This methodological choice ensures both theoretical robustness and practical relevance in understanding how users respond to algorithmic recommendation systems. In sum, this study investigates how platform-driven personalization may trigger psychological reactance and, in turn, lead to social media discontinuance. It focuses on discontinuance intention as a measurable and theoretically significant indicator of emerging user resistance, while positioning RS as the structural catalyst of this process.

In light of these gaps, this dissertation aims to explore the psychological mechanisms by which algorithmic personalization contributes to social media discontinuance. Specifically, the study is guided by the following research questions:

- RQ1: Does the use of RS affect users’ tendency to discontinue social media platforms? If so, through what mechanisms?
- RQ2: What role does personalization within RS play in shaping users’ discontinuance behaviors?
- RQ3: Does users’ understanding of the underlying algorithm influence their perceptions of RS and its psychological impact?

To address these questions, the dissertation employs a multi-method approach comprising three empirical studies:

Research 1 develops and validates a foundational model linking personalized recommendation, information overload, perceived threats to freedom, and psychological reactance. Drawing on the Stressor-Strain-Outcome (SSO) framework and Psychological Reactance Theory (PRT), this study empirically demonstrates that psychological reactance is a critical driver of discontinuous social media usage. It also

reveals that personalization—contrary to some theoretical expectations—can alleviate both cognitive and autonomy-related stressors in certain contexts.

Research 2 extends the initial model by introducing uniqueness neglect as a novel construct. This study highlights how users may resist personalized systems not only due to information overload, but also due to a perceived lack of individual recognition. It proposes a dual-pathway explanation: one rooted in cognitive strain (information overload) and the other in identity-based strain (uniqueness neglect). This study also begins to uncover the platform-specific nature of these effects, illustrating how different algorithmic architectures elicit different psychological responses.

Research 3 introduces algorithmic awareness as a boundary condition. It tests whether users' understanding of algorithmic processes moderates the relationship between personalization and perceived psychological stress. The findings suggest that algorithmic awareness amplifies the cognitive benefits of personalization (e.g., reduced overload), but has less impact on affective responses such as identity validation. This study underscores the importance of user cognition in shaping the effects of personalization.

Together, the three researches form a coherent empirical progression. Each study builds on the limitations and insights of the previous one. Each introduces new constructs or mechanisms to refine the explanation of why and how users disengage from personalized platforms. The cumulative result is a context-sensitive and psychologically grounded model of algorithmic discontinuance.

This dissertation makes several key theoretical contributions to the literature on algorithmic systems, user psychology, and social media discontinuance. It reconceptualizes psychological reactance as a central mechanism in explaining discontinuous usage, offering a motivational alternative to the fatigue-based explanations dominant in prior research. The proposed dual-pathway model identifies two distinct stress mechanisms—information overload and uniqueness neglect—that lead to reactance, thereby advancing a more nuanced understanding of how personalization systems can threaten user autonomy. Furthermore, the study introduces uniqueness neglect as a novel construct rooted in identity-based psychological strain and validates its role in shaping users' emotional responses to algorithmic curation. Finally, the dissertation establishes algorithmic awareness as a critical moderator that conditions the effects of personalization, contributing to emerging theories of human–

algorithm interaction by integrating user cognition into models of technological stress and resistance.

From a practical perspective, this research provides concrete guidance for social media platforms aiming to enhance user experience and retention. It highlights the psychological risks associated with excessive personalization and underscores the importance of preserving users' sense of control and individuality. The findings suggest that platforms should avoid overwhelming users with undifferentiated or irrelevant content and instead focus on enhancing transparency and offering meaningful personalization choices. By identifying algorithmic awareness as a key moderating factor, the study also points to the value of improving users' understanding of how recommendation systems work—through features like explainable AI, user-controlled filters, or educational prompts. Overall, the dissertation advocates for a user-centered design approach that balances efficiency with autonomy and personalization with identity recognition, helping platforms reduce churn and foster long-term engagement.

The structure of this dissertation is organized as follows. Chapter 2 provides a comprehensive theoretical review, outlining key concepts related to social media discontinuance and algorithmic recommendation systems. It identifies critical research gaps and lays the conceptual foundation for the empirical work. Chapter 3 presents the first empirical study, which applies the Stressor-Strain-Outcome (SSO) framework and Psychological Reactance Theory to examine how information overload and perceived threats to freedom contribute to discontinuous social media usage. Chapter 4 extends the model by introducing the concept of uniqueness neglect, exploring how algorithmic personalization may undermine users' sense of individuality and further amplify psychological reactance. Chapter 5 investigates the moderating role of algorithmic awareness, testing how users' understanding of recommendation mechanisms shapes their cognitive and affective responses to personalization. Finally, Chapter 6 summarizes the main findings, discusses theoretical and practical contributions, reflects on the limitations of the research, and outlines directions for future study. Figure 1 provides a visual summary of the overall structure and research flow of this dissertation.

Chapter 1: Introduction

	Social Media Discontinuance (SMD)	Recommendation Systems (RS)
Practical Background	Increasing user disengagement despite wide usage Forms of disengagement include reduced use, account deactivation Driven by information overload, social pressure, and digital fatigue Threatens platform sustainability and business performance	Widely used to boost user engagement and retention Core feature of major platforms (e.g., YouTube, TikTok) Provides personalized content based on user behavior Raises concerns over filter bubbles, information redundancy, and manipulation
Theoretical Background	Prior studies focus on general stressors (e.g., overload, fatigue) Lack of attention to user autonomy and decision-making processes Limited explanation for discontinuance despite improved platform features Need for greater emphasis on users' sense of freedom and autonomy in explaining discontinuance	Research emphasizes algorithm performance and user satisfaction Limited exploration of psychological impacts of personalization Insufficient psychological understanding of when personalization backfires and how it triggers perceived loss of control and resistance

Research Target:

- Those exposed to personalized recommendation systems and exhibiting observable discontinuance intentions, allowing the study to examine early-stage psychological responses such as reactance.

Research Question:

- RQ1: Does the use of RS affect users' tendency to discontinue social media platforms? If so, through what mechanisms?
- RQ2: What role does personalization within RS play in shaping users' discontinuance behaviors?
- RQ3: Does users' understanding of the underlying algorithm influence their perceptions of RS and its psychological impact?

Chapter 2: Theoretical review

Review of SMD and RS literature to identify key psychological gaps and support the development of the proposed research model.

Model Design and Analyze (Continued on next page)

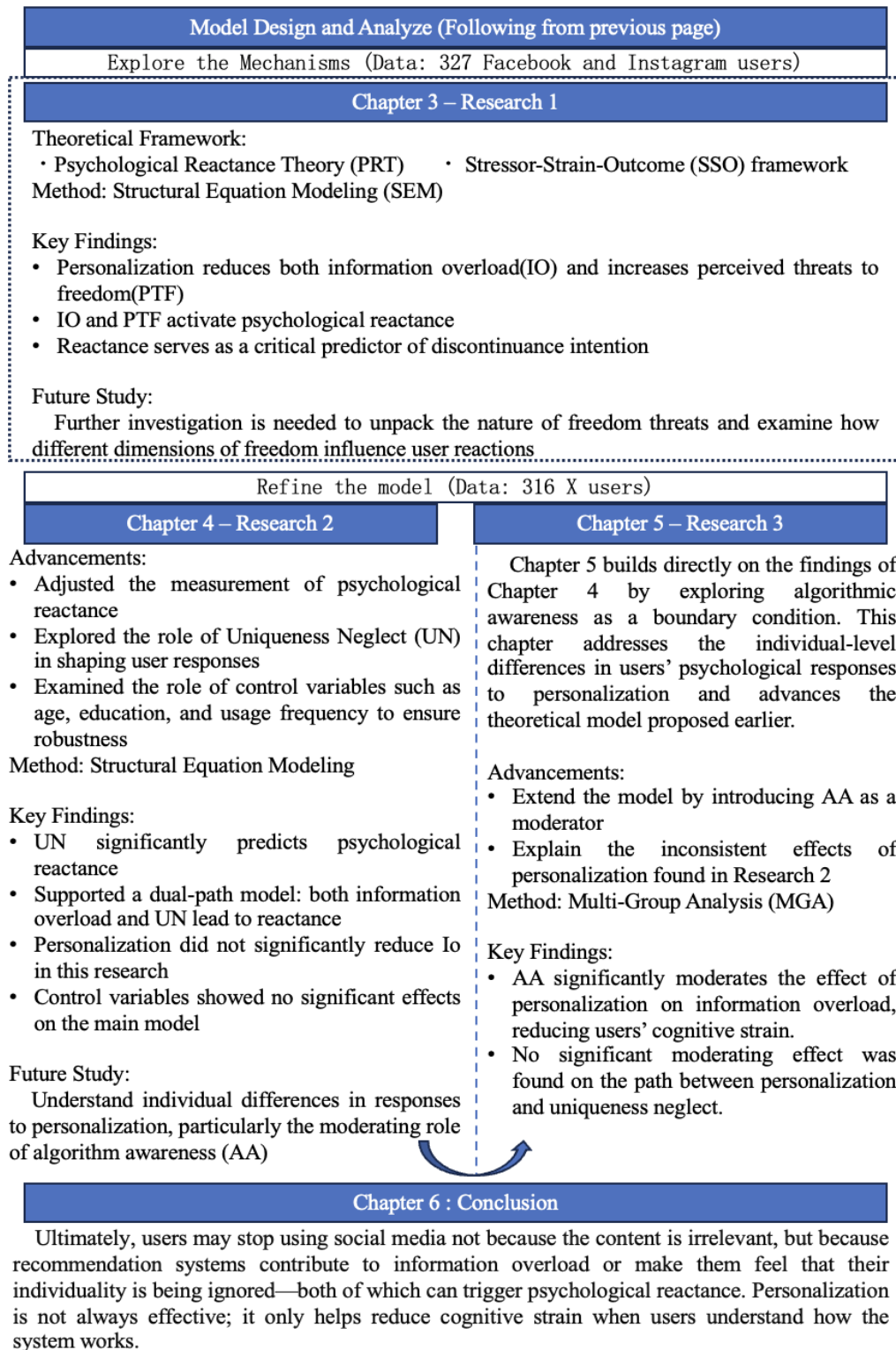


Fig.1 Dissertation Framework

2. Theoretical review

This chapter lays the theoretical groundwork for understanding why and how users discontinue social media use in algorithm-driven environments. The central aim is to synthesize interdisciplinary insights to explain a paradox increasingly observed in digital platforms: systems designed to enhance engagement—particularly personalized recommendation systems—may simultaneously provoke psychological resistance and disengagement. To address this phenomenon, this chapter is structured into three interrelated sections, each contributing to the formulation of the dissertation’s conceptual model.

Section 2.1 examines the concept of social media discontinuance (SMD) by reviewing its evolution from early adoption-focused research to recent studies emphasizing user fatigue, emotional strain, and behavioral withdrawal. It identifies discontinuance not as a singular act but as a cumulative process shaped by emotional, cognitive, and relational stressors. Importantly, this section highlights a critical oversight in existing literature: while prior studies emphasize fatigue or regret, they often neglect the role of psychological reactance—users’ active resistance when autonomy or individuality is perceived to be threatened.

Section 2.2 focuses on recommendation systems (RS) as a key structural force in today’s digital platforms. While these systems are designed to reduce information overload and enhance relevance, this section argues that their implementation—especially through greedy personalization algorithms—can create informational stressors such as narrowing, redundancy, and overload. These unintended outcomes not only undermine the benefits of personalization but also contribute to negative psychological responses, including perceived manipulation and identity misalignment. This section thus establishes RS as both enablers of engagement and potential triggers of user rejection.

Section 2.3 integrates insights from the previous two sections to propose a unified conceptual framework. It argues that RS-induced stressors and threats to autonomy are key mechanisms driving SMD, particularly when users feel their uniqueness is ignored or their content autonomy is constrained. This integrated perspective bridges the psychological mechanisms discussed in SMD literature with the technical dynamics of RS design, laying the foundation for this dissertation’s empirical focus on psychological reactance as a core pathway to discontinuance. It also introduces

algorithm awareness as a critical moderator that shapes how users perceive and respond to personalized content.

Together, these sections converge on the central claim that algorithmic personalization, while beneficial in reducing information burden, may inadvertently generate emotional strain and psychological reactance that lead to discontinuance behaviors. This theoretical review thus provides not only a comprehensive understanding of the phenomenon but also a novel lens for analyzing user-platform interaction in the age of algorithmic curation.

2.1 Social Media Discontinuance: Concepts, Mechanisms and Gaps

This section aims to clarify how and why users disengage from social media, by reviewing key concepts, theoretical frameworks, and overlooked mechanisms behind discontinuance.

Social media platforms have become deeply embedded in users' daily routines, and initial research predominantly focused on adoption, gratification, and continuous engagement. However, recent scholarship marks a paradigmatic shift toward understanding disengagement and discontinuance—a phenomenon increasingly visible in user behavior marked by account deactivation, reduced interaction, or content avoidance (Huang et al., 2024). Unlike adoption, which emphasizes initial motivation and perceived usefulness, discontinuance is rooted in accumulated negative experiences, including emotional strain and unmet expectations (Fu et al., 2020).

Discontinuance is now widely conceptualized as a multi-phase process rather than a single discrete act. Rather than abandoning a platform abruptly, users may first experience dissatisfaction that leads to temporary breaks or partial disengagement—such as muting, filtering, or limiting interactions—before ultimately ceasing usage altogether (Fan et al., 2021). This evolving, process-oriented view reflects an emerging consensus that discontinuance often stems from prolonged psychological strain, exacerbated by both algorithmic dynamics and social pressures, rather than being triggered by isolated events (Farooq et al., 2023).

Building on this view, scholars have begun to adopt a more holistic, triadic perspective that highlights the interaction among users, content creators, and the platform itself (Nieborg & Helmond, 2019). While users and creators remain central, the platform plays an active role in shaping user experiences through algorithmic

curation, interface design, and content governance. Among these mechanisms, recommendation systems are particularly influential, as they determine the visibility, diversity, and order of content. However, despite growing interest in platform governance, the specific role of recommendation systems in contributing to user dissatisfaction—such as through content saturation, fatigue, or perceived manipulation—remains underexplored (Farooq et al., 2023).

2.1.1 Theoretical Frameworks for Social media discontinuance

This subsection reviews prior theoretical approaches to SMD, outlining how the literature was selected and analyzed, and summarizing key psychological mechanisms and explanatory models that help explain why users leave from social media platforms.

Social media discontinuance has been examined through multiple theoretical lenses, each offering unique insights into user behavior. Table 1 summarizes studies on the discontinuous usage of SM published in top journals after 2014, as older studies might not accurately reflect the current SM landscape. These studies were primarily sourced from the Web of Science (WoS) database, using specific search keywords: "social media" or "social network" or "SNS" or "social platform" combined with "discontinue" or "discontinual" or "discontinuous." The selection criteria focused on papers published in highly reputable and influential journals within the fields of information technology, management, and consumer behavior research, such as *Computers in Human Behavior*, *Information & Management*, *Internet Research*, *International Journal of Information Management*, *Journal of Retailing and Consumer Services*, and *Information Systems Journal* and so on. Additionally, the studies were required to investigate the discontinuous usage of SM among general consumers (excluding clinical psychology treatments, etc.), and the papers needed to be accessible for download. As summarized in Table 1, the reviewed studies adopt a variety of theoretical lenses to explore the psychological mechanisms underlying SMD, primarily focusing on users' cognitive appraisals, emotional strain, and contextual influences.

The Push-Pull-Mooring (PPM) framework is one such model, conceptualizing discontinuance as a migration behavior driven by dissatisfaction (push), attraction to alternatives (pull), and contextual constraints (mooring) (Chang et al., 2014). Complementary to this migration logic, cognitive and emotional models emphasize internal psychological states—such as guilt, regret, and dissatisfaction—as key antecedents of disengagement (Turel, 2015; Zhang et al., 2016; Fu et al., 2021).

Stress-based theories further deepen the understanding of SMD by highlighting how environmental stimuli act as stressors. The Stimulus-Organism-Response (SOR) framework posits that features such as technostress, content saturation, and over-personalization provoke affective and cognitive strain (Luqman et al., 2017; Cao & Sun, 2018), while the Stressor-Strain-Outcome (SSO) model shows how platform-induced stress—through mechanisms like privacy intrusion or surveillance—results in emotional exhaustion and withdrawal (Huang et al., 2024; Farooq et al., 2023). These frameworks converge in portraying SMD as a process rooted in accumulated strain, not singular discontent.

Social Cognitive Theory (SCT) complements these perspectives by introducing the mediating role of self-efficacy and control beliefs. When users perceive diminished autonomy or misalignment between system functions and personal goals, they may develop resistance or dissatisfaction, influencing their disengagement decisions (Cao et al., 2020). These models collectively suggest that SMD is not merely a behavioral shift but a psychological negotiation between system design and user agency. Collectively, these frameworks highlight that SMD reflects a complex psychological process shaped by users' internal evaluations and the external pressures embedded in platform design and algorithmic structures.

2.1.2 Psychological and Behavioral Drivers of Discontinuance

While the previous section outlined the broad theoretical models of SMD, this subsection shifts focus to a more detailed examination of the psychological and structural factors that lead users to resist, reduce, or ultimately discontinue their use of social media platforms.

Building on these theoretical foundations, empirical research identifies individual, relational, and platform-level drivers of SMD. At the individual level, emotional exhaustion—stemming from excessive stimulation, repetitive content, or hedonic overuse—has been repeatedly cited as a primary antecedent of discontinuance (Maier et al., 2015; Farooq et al., 2023). Users often experience psychological reactance when they perceive their autonomy is compromised, especially by personalized algorithms that offer limited choice or over-curated content.

Cognitive drivers such as privacy concerns, perceived utility loss, and opportunity cost also play crucial roles. Recommender systems that present redundant or stereotypical content may trigger perceptions of manipulation or identity misalignment,

reducing users' sense of control (Hong & Oh, 2020). These cognitive dissonances reinforce emotional strain, contributing to the desire to disengage.

On the relational level, social overload—where users feel pressured to maintain numerous interactions or perform visibility—generates dissatisfaction and regret (Maier et al., 2015; Wang et al., 2021). Recommendation systems may amplify this burden by prioritizing socially performative or comparative content, thus reinforcing fatigue and withdrawal intentions (Cho et al., 2020).

At the platform level, content saturation and algorithmic intrusion emerge as key drivers. When recommender systems prioritize engagement metrics over content diversity, users may encounter redundant, hyper-targeted information that fosters mistrust and boredom (Xie & Tsai, 2021). The feeling of being “locked in” to a behavioral profile intensifies perceptions of uniqueness neglect, prompting users to withdraw to regain autonomy.

While inhibitors of SMD—such as habit, sunk cost, and peer influence—do exist (Turel, 2015; Luqman et al., 2018), their effect tends to diminish when emotional strain reaches critical levels. Thus, emotional and cognitive discomfort remain the most decisive predictors of discontinuance.

2.1.3 Research Gaps and Conceptual Contributions

Although research on social media discontinuance (SMD) has expanded in recent years, the field remains theoretically fragmented and lacks a unified understanding of its core psychological drivers. Existing studies often emphasize user fatigue, emotional strain, or accumulated dissatisfaction as the primary reasons for discontinuance (Turel, 2015; Maier et al., 2015), yet they tend to treat these responses as reactive outcomes, offering limited insight into the platform-specific mechanisms that give rise to such psychological states. As Farooq et al. (2023) note, current models frequently neglect the structural and algorithmic features of social platforms that mediate user experience. Similarly, Eslami et al. (2015) and Klug & Strang (2019) argue that user responses to personalization—particularly in relation to autonomy, transparency, and control—remain under-theorized and insufficiently integrated into discontinuance research. These observations suggest that while user-side experiences are increasingly documented, there is a lack of conceptual attention to the platform-induced psychological dynamics that precede discontinuance, thereby leaving important explanatory gaps in the literature.

Several critical gaps persist in the SMD literature. First, although stress and fatigue are widely recognized as precursors of discontinuance, little work has focused on how algorithmic personalization actively produces these emotional states. Most models overlook the psychological salience of recommendation systems and their capacity to shape user cognition and emotion, particularly via greedy recommendation algorithms that emphasize exploitation over exploration. Unlike exploration-based strategies that seek to learn diverse user preferences, greedy algorithms rely solely on past behavior to repeatedly recommend content with the highest estimated utility. This short-term optimization leads to narrow and repetitive exposure, often neglecting novelty or individual nuance. Over time, such over-personalization can saturate users with similar content, heighten cognitive burden, and reduce the perceived autonomy of choice, thereby intensifying informational pressure and emotional exhaustion (Bastani et al., 2022).

Second, while existing research has extensively emphasized emotional discomforts such as fatigue, burnout, or regret as key drivers of social media disengagement (Farooq et al., 2023), the role of psychological reactance has received surprisingly limited attention. Many models implicitly assume that user discontinuance stems from accumulated strain, yet they tend to conflate passive emotional states with active resistance. This lack of conceptual clarity obscures the motivational dynamics that differentiate simple dissatisfaction from reactance—a defensive response to perceived threats to freedom or autonomy (Tucker, 2014; Lee & Lee, 2009). As a result, we still know relatively little about how users’ awareness of manipulation, loss of control, or forced personalization may trigger oppositional attitudes and behavioral rejection (Chen et al., 2019a).

Third, user-level differences, such as algorithm awareness, digital literacy, and uniqueness orientation, are rarely incorporated into discontinuance models. These variables may significantly moderate how personalization is experienced and interpreted, influencing whether users feel supported or constrained by algorithmic systems (Puntoni et al., 2021). For instance, users with high algorithm awareness may attribute content homogeneity to system design, while others may internalize it as a personal failure or loss of identity.

Fourth, few studies offer mechanistic models that trace the full pathway from algorithmic personalization through cognitive strain (e.g., information overload,

redundancy) and emotional responses (e.g., reactance, alienation) to behavioral outcomes like disengagement or discontinuance (Huang et al., 2024). The absence of such models limits explanatory power and impedes the design of targeted interventions aimed at mitigating negative user outcomes (Chen et al., 2019).

This dissertation addresses these limitations by constructing an integrated framework that links algorithmic personalization, information overload, uniqueness neglect, and psychological reactance to discontinuance behavior. It introduces algorithm awareness as a key moderator, allowing for a nuanced analysis of how users interpret and respond to personalized systems depending on their cognitive readiness and media.

In summary, social media discontinuance is a multifaceted phenomenon, shaped by emotional, cognitive, relational, and algorithmic factors. Existing theories such as the SSO and SOR frameworks have laid a strong foundation, but they often treat recommender systems as peripheral rather than central to user experience. By integrating insights from stress theory, cognitive psychology, and personalization research, this dissertation repositions RS as psychologically active agents that both enable and undermine engagement. This reframing not only explains current gaps in understanding discontinuance but also offers new conceptual tools for examining user–platform interaction in the age of algorithmic curation. The next section further explores the role of recommender systems in digital environments and presents the guiding research questions for this dissertation.

Table 1. Researches on Discontinuous usage of SM

Author	Theory/Framework	Keywords	Findings and Contributions
Wang et al., 2021	Two-factor theoretical model	Regret, Inertia	Regret arises from dissatisfaction with social media behavior, while inertia prevents behavior change due to habitual use.
Luqman, Masood & Ali, 2018	Self-Determination Theory (SDT), Theory of Planned Behavior (TPB)	Motivation, Scoial norm, Attitude, Control	Both autonomous and controlled motivations significantly influence SM discontinuance intention. Autonomous motivation enhances intrinsic motivation, while controlled motivation exerts external pressure.

Author	Theory/Framework	Keywords	Findings and Contributions
Pang & Ruan, 2023a	Cognition-Affect-Conation (CAC) Model	Information overload, Communication overload, Social network exhaustion, Privacy invasion	Information and communication overload significantly influence social network exhaustion, which in turn affects privacy invasion and discontinuous usage intention.
Cao, Khan, Ali & Khan, 2020	Social Cognitive Theory (SCT)	Cyberbullying, Social overload, Distress, SNS exhaustion	Cyberbullying and social overload significantly impact distress and SNS exhaustion, leading to increased discontinuous usage intentions.
Vaghefi, Qahri-Saremi & Turel, 2020	Cognitive-Affective Model	SNS addiction, Guilt, Cognitive dissonance, Perceived Self-Efficacy	Cognitive dissonance (as primary cognitive response) and guilt (as primary affective response) mediate the relation between SNS addiction and decision to discontinue SNS use
Wu, Kao & Chiu, 2019	Expectation-disconfirmation theory, TAM	TAM, Perceived dissatisfaction, Comprehensibility, Information overload	Discontinuous intention is influenced by perceived usefulness, perceived ease of use, and perceived enjoyment of mobile instant messaging services.
Pang & Ruan, 2023b	Stressor-Stress-Outcome framework	Information overload, Communication overload, Exhaustion	Information irrelevance, overloads lead to exhaustion, predicting discontinuance intentions. Provides insights for managing social media adoption behavior.
Zhang et al., 2016	Stressor-Stress-Outcome framework	Socializing fatigue, Dissatisfaction, System feature overload, Information overload, Social overload	Socializing fatigue leads to discontinuous usage behavior. Perceived enjoyment and social interaction are significant predictors.

Author	Theory/Framework	Keywords	Findings and Contributions
Fan, Jiang, Deng, Dong & Lin, 2021	Social Cognitive Theory (SCT)	Role conflict, Privacy concerns, Social media fatigue, Self-esteem	Role conflict positively affects privacy concerns and social media fatigue. Self-esteem moderates the effect of role conflict on privacy concerns but not on social media fatigue.
Luqman, Cao, Ali, Masood & Yu, 2017	Stimulus-Organism-Response (SOR)	Social, cognitive, and hedonic uses, Technostress, Exhaustion	Psychological and behavioral consequences compel users to discontinue or reduce Facebook use due to exhaustion and technostress.
Qaisar, Nawaz Kiani & Jalil, 2024	Cognition-Affect-Conation (CAC) Model	System feature overload, Information overload, Social overload, Depression, Anxiety	Perceived information overload, perceived social overload, and perceived system feature overload directly affect depression and anxiety among social networking site users, which directly leads to discontinuous intentions.
Lo, 2019	Social Support Theory	Social overload, exhaustion, satisfaction, social support, loneliness, emotional instability	Social support reduces exhaustion and improves satisfaction but doesn't benefit everyone equally, especially lonely and emotionally unstable users.
Cao & Sun, 2018	Stimulus-Organism-Response (SOR)	Information overload, Communication overload, Exhaustion, Regret	Information and communication overload lead to discontinuous intention through psychological strain and organism responses.
Sun & Lee, 2022	Stress-Strain-Outcome Framework (SSO)	Instant messaging fatigue, Communication overload, Social overload, Technostress	Communication and social overload predict instant messaging fatigue and technostress, which in turn lead to discontinuous intentions.
Kim, Ma & Son, 2024	Comparative Model	Information overload, Social overload, Time cost, Fatigue	Different social media platforms induce varying levels of stress and fatigue, affecting user discontinuance differently.

Author	Theory/Framework	Keywords	Findings and Contributions
Zhang, He & Peng, 2022	Stress-Strain-Outcome Framework (SSO)	Social media fatigue, Information overload, FoMO, Time cost, Privacy	Perceived pressure significantly impacts social media fatigue behavior. Higher perceived pressure increases the likelihood of social media fatigue among WeChat users.
Guo, Lu, Kuang & Wang, 2020	Stress-Strain-Outcome Framework (SSO)	Information irrelevance, Information overload, Social overload, Fatigue	Information irrelevance and overload lead to information avoidance behavior. Time pressure exacerbates this avoidance, highlighting the need to manage information quality and user time constraints.
Lin, Lin, Luo & Liu, 2021	Stress-Coping Theory	Information overload, Social overload, Communication overload, Fatigue	Information, communication, and social overload initiate adaptive coping mechanisms in users, whereas only communication overload triggers maladaptive coping.
Luqman, Masood, Weng, Ali & Rasheed, 2020	Stress-Strain-Outcome Framework (SSO)	Excessive SNS use, Technological friction, Strain, Discontinuance, Guilt	Excessive SNS use and technological friction lead to strain, which influences discontinuance. Guilt moderates this relationship.
Dhir, Yossatorn, Kaur & Chen, 2018	Stress-Strain-Outcome Framework (SSO)	Social media fatigue, Compulsive use, FoMO, Anxiety, Depression	Compulsive use and fear of missing out significantly increase social media fatigue and related psychological health issues, such as anxiety and depression.
Mahmud, Wen, Fern, Ling & Ramayah, 2023	Stress-Strain-Outcome Framework, Stress-Coping Theory	Information overload, Social overload, Communication overload, Fatigue, Exhaustion	Social overload has the strongest effect on coping strategy. Exhaustion and fatigue strongly affect discontinuance intention.
Lim & Ahn, 2021	Psychological Reactance Theory	Social overload, Interaction, Dissatisfaction, Threat to freedom	Social overload influences discontinuance intention through fatigue and regret. Cultural context affects the reactance mechanism in SNS fatigue.

Author	Theory/Framework	Keywords	Findings and Contributions
Lin, Lin, Turel & Xu, 2020	SOR, Flow Theory	Social overload, Information overload, Communication overload, Fatigue	Flow experience reduces perceptions of fatigue and discontinuance intentions and weakens the effects of fatigue on discontinuance intentions.
Chen, Li & Duan, 2024	Cognitive Dissonance Theory (CDT)	Self-efficacy, Discontinuous usage, Information overload, User addiction	Information overload and user addiction increase cognitive dissonance, which leads to discontinuous usage. Self-efficacy moderates these effects.
Park, 2014	Social Exchange Theory	Personalization, user continuance, Information overload, Cognitive dissonance	Personalization enhances user satisfaction and continuance intention but excessive personalization can lead to information overload and fatigue.
Maier, Laumer, Weinert & Weitzel, 2015	Technostress	Technostress, Switching stress, Exhaustion	Technostress and switching stress significantly influence discontinuous usage of Facebook.
Gan, Li & Liu, 2024	Social Cognitive Theory (SCT)	Excessive use, Regret, Self-efficacy, Exhaustion, Habit, Switching-stress	Social media discontinuance behavior in China is significantly influenced by self-efficacy. SNS-stress creators and SM-exhaustion lead to discontinuous usage intentions, while switching-stress creators and switching-exhaustion reduce these intentions.
Fu, Li & Liu, 2021	Push-Pull-Mooring (PPM) Framework	Fatigue, Dissatisfaction, Norms, Habit, Alternative Attractiveness	Push factors (fatigue and dissatisfaction), pull factors (alternative attractiveness), and mooring factors (personal norms and habit) significantly influence Facebook discontinuance.

2.2 Recommendation Systems: Capabilities, Dilemmas, and User Impacts

While prior research on social media discontinuance has shed light on users' psychological responses—such as emotional exhaustion, privacy concerns, and social overload—these studies have predominantly adopted a user-centric perspective. Yet, discontinuance does not occur in isolation from platform design. The systems that shape users' everyday experiences, particularly RS, may actively contribute to the very conditions that drive users to reduce or discontinue their use. Despite their central role in mediating content exposure, perceived autonomy, and cognitive load, RS remain underexamined as psychological agents in most discontinuance frameworks. Therefore, to better understand how discontinuance is shaped by platform-level mechanisms, this section turns to the structure, function, and unintended consequences of RS.

Recommendation systems have become integral components of modern digital platforms, functioning as information filtering mechanisms that reduce users' cognitive burden by predicting preferences and presenting ranked lists of relevant content (Adomavicius & Tuzhilin, 2005). Initially developed through collaborative filtering techniques in the 1990s, RS have since expanded to include content-based and hybrid models, continuously evolving in sophistication and application scope (Adomavicius & Tuzhilin, 2005). These systems leverage both explicit data (e.g., ratings) and implicit behaviors (e.g., clickstreams) to personalize content streams across various domains, from e-commerce and streaming services to social and short-video platforms.

Importantly, RS are often introduced with the aim of alleviating information overload—a prevalent concern in digital environments inundated with content. By narrowing the pool of potentially relevant content, RS enhance decision efficiency and user satisfaction. However, as personalized systems become increasingly ubiquitous and intrusive, the very mechanisms intended to enhance user experience may generate new challenges that compromise engagement and autonomy (Nguyen et al., 2014).

2.2.1 Emerging Concerns about Recommendation Systems

While much of the early literature praised recommendation systems for their ability to boost relevance, reduce search costs, and increase user participation (Liang et al., 2006), recent scholarship has begun to highlight their psychological and behavioral drawbacks. In particular, algorithm-driven personalization may inadvertently lead to user discomfort, resistance, and eventual discontinuance, especially when users

perceive the system as opaque, coercive, or misaligned with their self-image (Chen et al., 2019).

Users' negative responses to RS can be divided into two main types: psychological responses (e.g., reactance, perceived manipulation) and behavioral responses (e.g., reduced usage, discontinuance) (Beaudry & Pinsonneault, 2005). Among these, psychological reactance—defined as the motivational state that arises when individuals perceive their freedom to be threatened—is especially relevant. Studies show that when users sense an infringement on their autonomy due to over-personalized content, they may exhibit oppositional behavior or intentional disengagement (Lee & Lee, 2009). Such resistance is particularly salient in recommendation contexts where control over content exposure shifts from the user to the algorithm. Compared to subscription-based content channels, recommendation-based environments are marked by lower source credibility and reduced user control, both of which weaken user engagement and increase reactance (Puntoni et al., 2021).

2.2.2 Another side of Recommendation Systems

While much attention has been paid to users' psychological and behavioral responses, less focus has been placed on the structural sources of such responses—particularly the informational stressors embedded in recommendation system design. In this regard, recent studies have pointed out that recommendation systems, despite aiming to alleviate information overload, may paradoxically introduce new forms of cognitive stress. This is especially true when systems adopt greedy algorithms—that is, those that optimize for short-term engagement by repeatedly presenting content deemed most immediately relevant, while minimizing exploration of diverse or novel content (Bastani et al., 2022). Though effective in increasing click-through rates, this optimization often leads to content redundancy, perceptual monotony, and reduced informational diversity, which can trigger emotional fatigue and dissatisfaction.

To systematically understand these hidden burdens, prior research has highlighted three major types of informational stressors in RS-driven environments—grounded in studies on information overload, user experience, and algorithmic curation (e.g., Eppler & Mengis, 2004; Eslami et al., 2018): content overload, redundancy saturation, and relevance pressure. More specifically, recent studies further delineate these into the following forms:

1. **Information Narrowing:** As RS expose users to content closely aligned with prior behaviors, users are progressively shielded from diverse or dissenting information. This phenomenon, often referred to as the “filter bubble,” restricts exploration and reduces perceived informational breadth (Nguyen et al., 2014).

2. **Information Redundancy:** When algorithms repeatedly recommend highly similar content, users experience decreased novelty and increased cognitive fatigue, which may erode interest and trust in the system (Liang & Fu, 2017).

3. **Information Overload:** Even personalized feeds may become overwhelming when content is pushed continuously without explicit user request. In short-video platforms, for instance, users are inundated with a stream of high-frequency recommendations, leading to mental fatigue and stress (Chung, Chen & Meng, 2023).

These stressors disrupt the intended value of personalization by creating emotional strain and reducing perceived control, thereby increasing the likelihood of stop using SM.

2.2.3 The Central Role of Personalization in Recommender Systems

Building on the previous discussion of informational stressors in RS environments, this section turns to the core mechanism underlying many of these stressors—personalization. As the most defining and impactful feature of RS, personalization plays a central role in shaping both the volume and the nature of content users receive. Understanding its functioning is therefore critical for explaining how certain algorithmic strategies contribute to user fatigue, dissatisfaction, or even discontinuance (Ghasemaghaei et al., 2019).

Personalization refers to the algorithmic tailoring of content to match individual user preferences, behaviors, and inferred needs. By leveraging large volumes of behavioral data—including past interactions, clickstreams, watch time, and social connections—RS aim to construct predictive models that identify and deliver content with high relevance to each user. This process is not merely a backend operation, it directly shapes the user-facing experience by determining what content is visible, prioritized, or omitted. In doing so, personalization functions as a gatekeeper of digital attention and becomes the primary lens through which users engage with the platform. Because of its central role, personalization has become a critical dimension through which users evaluate the quality, utility, and credibility of recommendation systems. Prior research has shown that perceived personalization—the user’s subjective assessment of how

well content matches their interests—strongly influences satisfaction, trust, and engagement (Chen et al., 2019). Users tend to view platforms more favorably when they believe recommendations are accurate, timely, and responsive to their evolving preferences.

However, personalization is also a multifaceted construct. While it aims to reduce information overload and increase relevance, its implementation often prioritizes behavioral predictability over diversity or exploration. This may result in overly narrow content streams that continuously reinforce established user profiles. Such algorithmic tendencies have raised growing concerns about the trade-offs between short-term personalization optimization and long-term user satisfaction. Recent studies have pointed out that optimizing for metrics such as click-through rate may overlook deeper engagement or informational diversity, thereby limiting the perceived usefulness or sustained interest of users (Yi et al., 2014).

In sum, personalization is not only the operational core of RS but also the focal point of how users interpret algorithmic curation. Understanding its structure and evaluative dimensions is essential for assessing how RS affect user experience, and for explaining downstream psychological or behavioral responses—topics further explored in subsequent sections.

2.2.4 Platform Dynamics and Moderating Mechanisms

While earlier sections have discussed the psychological impacts of recommendation systems in general, it is important to recognize that these effects are not universal. The influence of RS varies depending on contextual factors and individual user characteristics, which may either amplify or mitigate users' negative reactions. This subsection therefore explores how differences in platform design and user-level awareness shape the psychological outcomes of personalized recommendation. The impact of recommendation systems is not uniform across contexts. For instance, differences in channel design (e.g., recommendation vs. subscription) can affect user perceptions of control, trust, and reactance. Compared to content sourced through subscription—which implies user choice and content familiarity—AI-curated recommendation feeds are typically perceived as less credible and more manipulative (Chiou and Tucker, 2017).

Moreover, the level of algorithm awareness—users' understanding of how recommendations are generated—may moderate their psychological response.

Research suggests that users with higher algorithm literacy are more capable of interpreting content curation as system-driven rather than manipulative, thereby reducing feelings of coercion and reactance (Lee, 2018). Conversely, users with lower algorithm awareness may misattribute personalization as intrusive, further intensifying negative emotional reactions.

Thus, examining the interaction between algorithmic features and user characteristics is essential for unpacking the conditions under which RS foster engagement versus those that provoke rejection.

2.2.5 Research Gaps and Future Directions

Despite growing interest in the user experience of recommendation systems, current research remains limited in its ability to explain how specific algorithmic strategies—particularly those designed for optimization—produce unintended psychological outcomes. While prior studies have acknowledged issues such as information overload and user fatigue, few have theorized how these effects emerge from design-driven informational stressors. Specifically, scholars are encouraged to examine how “greedy” recommendation strategies—those that prioritize immediate engagement metrics—contribute to the narrowing of content exposure, redundancy of information, and heightened cognitive overload (Bastani et al., 2022). These informational stressors may not only undermine the user experience but also function as mediating mechanisms linking algorithmic design features to negative outcomes such as psychological reactance and platform discontinuance.

In addition, future research should pay greater attention to user-level moderators that shape these dynamics. Characteristics such as algorithm awareness, digital literacy, and individual differences in cognitive styles may significantly influence how users perceive and respond to personalized content environments. Integrating theoretical perspectives like psychological reactance theory and self-determination theory would allow for a deeper understanding of how users’ needs for autonomy, competence, and relatedness are either supported or threatened by algorithmic systems.

Moreover, methodological advancements are needed to move beyond correlational insights. Experimental designs or longitudinal studies can offer stronger causal evidence about the effects of different recommendation system configurations on user attitudes and behaviors over time. By pursuing these directions, future research can move toward a more comprehensive framework that balances the operational

efficiency of recommendation systems with the protection of user freedom, content diversity, and cognitive well-being.

2.3 Toward an Integrated Understanding: Linking Social Media Discontinuance and Recommendation Systems

The previous sections have independently reviewed the psychological mechanisms of social media discontinuance and the design characteristics of recommendation systems. However, these two strands of research have rarely been brought into direct dialogue. Given that RS are the primary channels through which users experience content, a more integrated perspective is needed to understand how platform design features contribute to discontinuance behavior. While research on SMD has primarily emerged from the social sciences and increasingly centers on post-adoption behaviors driven by fatigue and exhaustion, studies on RS have predominantly been situated within the information systems (IS) domain. The RS literature has traditionally emphasized the technical optimization of algorithmic performance—focusing on precision and efficiency in content delivery (Ko et al., 2022). However, recent developments in IS research have begun to recognize that user satisfaction is not solely determined by accuracy, but also by the psychological experience of choice. For instance, Iyengar and Lepper (2000) demonstrated that although individuals prefer having more options, an overabundance of choices can paradoxically reduce satisfaction. Similarly, Kim, Choi and Li (2021) argued that benign algorithmic design should incorporate a degree of randomness and diversity to improve user satisfaction, rather than solely pursuing accuracy.

Despite these emerging insights, current research has yet to sufficiently explore the psychological mechanisms underlying such user experiences. A critical gap remains: how personalized recommendation systems may unintentionally trigger psychological and informational stressors that drive discontinuance. As users engage with algorithmically curated content, they may experience narrowing of information, content redundancy, and overload—outcomes often resulting from greedy personalization strategies (Ma et al., 2022). These are not merely cognitive inconveniences; they can threaten users' sense of autonomy, voice, and uniqueness, thereby inducing psychological reactance (Chen et al., 2019). Over time, such responses can escalate into platform rejection or discontinuation of use (Farooq et al., 2023).

Surprisingly, few studies have explicitly explored this paradox: while recommendation systems are designed to enhance user engagement, they may simultaneously create conditions that undermine it. This oversight is particularly notable given that RS serves as the primary interface between users and platforms in contemporary social media environments. Moreover, key psychological constructs such as reactance, perceived threats to autonomy, and informational stress—now central in SMD studies—remain under-theorized in RS research, especially in terms of explaining user disengagement and behavioral exit.

Building on this gap, Research 1 aims to theoretically examine how the informational and psychological characteristics of personalized recommendation systems influence social media discontinuance, thereby establishing a conceptual linkage between RS-driven user experiences and discontinuance behaviors.

3. Research 1: Understanding Reactance in Social Media Discontinuance

This chapter presents the first empirical investigation of this dissertation, aiming to explore the psychological mechanisms underlying social media discontinuance (SMD) by integrating the Stressor-Strain-Outcome (SSO) framework and Psychological Reactance Theory (PRT). While previous research has predominantly relied on stress-based models to explain discontinuance—emphasizing emotional fatigue and cognitive overload—these approaches often fall short in capturing more active forms of resistance triggered by perceived autonomy loss. Given the increasing pervasiveness of personalization, understanding how users psychologically respond to content curation mechanisms is essential for uncovering the deeper causes of platform rejection.

To address this issue, this research proposes a theory-driven model in which perceived threats to freedom and information overload serve as the key strain variables linking platform-induced stressors—such as personalization—to users’ psychological reactance and their intention to discontinue social media use. The integration of SSO and PRT allows for a more nuanced view: while the SSO framework provides a processual explanation of how external stressors translate into internal strain and behavioral outcomes, PRT adds a motivational dimension by focusing on users’ active resistance against perceived restrictions to freedom. And to empirically validate this integrated model, the study adopts a quantitative survey approach, collecting responses from 324 Japanese users of Facebook and Instagram. Structural equation modeling (SEM) is used to test the hypothesized relationships between all variables.

The chapter is structured as follows. Section 3.1 provides a detailed review of the SSO framework and its application in prior information systems and social media research. Section 3.2 introduces Psychological Reactance Theory, highlighting its relevance in understanding motivational forms of withdrawal. Section 3.3 develops the hypotheses based on SSO framework by linking key constructs including information overload, perceived personalization, threat to freedom, psychological reactance, and discontinuous usage intention. Section 3.4 outlines the research methodology, including data collection, measurement instruments, and the structural equation modeling (SEM) procedure used for testing the model. The empirical findings are presented and discussed in Section 3.5, followed by theoretical and practical implications. Finally, Section 3.6 addresses the study’s limitations and proposes directions for future research, with Section 3.7 concluding the chapter.

By situating psychological reactance as a central explanatory mechanism, this study contributes to a deeper understanding of how users process algorithmic environments and why they may actively choose to withdraw from platforms—even when functional performance is enhanced. The findings of this chapter form the foundation for subsequent analyses of content-level and perception-level mechanisms in the chapters that follow.

To build this integrated model, it is first necessary to revisit how previous studies have conceptualized discontinuance and identify where existing explanations fall short.

Despite extensive research on SMD, important theoretical and empirical gaps persist—particularly in relation to the psychological mechanisms through which users disengage from algorithm-driven platforms. As reviewed above, prior studies have predominantly focused on emotional fatigue or exhaustion as key drivers of discontinuance (Fu et al., 2020), often framed within stress-based models such as the Stimulus-Organism-Response (SOR) or Stressor-Strain-Outcome (SSO) frameworks. However, this emphasis on fatigue may be insufficient to capture the full complexity of user motivation. As noted by Maslach, Schaufeli, and Leiter (2001), exhaustion constitutes only one dimension of withdrawal behavior, and focusing solely on it may obscure more active, motivational forms of resistance such as psychological reactance (Beaudry & Pinsonneault, 2005).

In addition, while the stressors leading to discontinuance have been widely studied—such as information overload (Pang & Ruan, 2023b), social overload (Fu et al., 2022), and fear of missing out (Bright & Logan, 2018)—less attention has been given to the perceived restriction of autonomy in the context of SM usage. Social media platforms, especially when powered by personalized recommendation systems, can create environments where users feel their freedom to explore, express, and choose is constrained. Research has shown that such perceptions of control loss can elicit adverse reactions (Luqman et al., 2020), particularly when users interpret algorithmic recommendations as intrusive or manipulative (Lim & Ahn, 2021). These experiences may lead users not only to feel stressed, but also to engage in deliberate resistance—discontinuing use as a means of restoring autonomy.

A third limitation lies in the dual nature of recommendation systems. While prior studies have acknowledged that personalized recommendations increase user satisfaction and retention by enhancing relevance (Park, 2014), recent work also

highlights rising dissatisfaction due to issues such as privacy invasion and content redundancy (Huang et al., 2024). Despite their prevalence, few studies have examined how and when recommendation systems transition from engagement-enhancing tools to sources of psychological burden and disengagement.

In response to these gaps, this study adopts an integrative theoretical framework combining the Stressor-Strain-Outcome (SSO) model with Psychological Reactance Theory (PRT). The SSO framework enables a systematic examination of how external stressors (e.g., information overload) lead to internal psychological strain (e.g., perceived threats to freedom), and eventually to behavioral outcomes (e.g., discontinuance) (Koeske & Koeske, 1993). While the SSO framework helps trace this causal chain, PRT complements it by offering a deeper understanding of the motivational dynamics behind disengagement. According to PRT, when individuals perceive a threat to their autonomy, they experience reactance, a motivational state that prompts resistance or behavioral rejection of the source of threat (Beaudry & Pinsonneault, 2005). In the context of social media, this means that personalization—if perceived as excessive or controlling—can lead to negative emotional reactions and withdrawal, not merely fatigue.

By integrating these two frameworks, this research aims to answer the following research questions:

1. Is psychological reactance a significant factor contributing to social media discontinuance?
2. What platform-level and content-level factors contribute to perceived strain in SM usage, particularly threats to freedom?
3. How does algorithmic personalization facilitate or hinder continued social media usage?

Japan provides an ideal context for examining these questions. With a high penetration rate of SM platforms such as Facebook and Instagram—both of which rely heavily on personalization—Japanese users are routinely exposed to content selected by opaque algorithms. While usage rates remain high, recent evidence shows a gradual plateau, particularly among younger cohorts who report increased dissatisfaction and skepticism toward personalized services. By focusing on this demographic, the study

investigates the psychological mechanisms behind discontinuance in a mature, algorithm-intensive market environment.

This research uses a quantitative survey methodology. A total of 327 valid responses were collected from Japanese Facebook and Instagram users. The hypotheses were tested using structural equation modeling (SEM) to uncover latent psychological structures and behavioral outcomes. Through this empirical approach, the study seeks to offer a more comprehensive understanding of how algorithmic personalization contributes to user disengagement—not merely through cognitive overload or emotional exhaustion, but via perceived threats to freedom and ensuing psychological reactance.

3.1 Review on Stressor-Strain-Outcome framework

The Stressor-Strain-Outcome (SSO) framework, as defined by Koeske and Koeske (1993), provides a comprehensive structure to understand how stressors from information systems or information technology induce strain and ultimately influence user behavior. This framework comprises three primary components: stressors, strain, and outcomes. Stressors refer to environmental stimuli that are perceived and interpreted by individuals as troublesome and potentially disruptive. Strain denotes the adverse psychological and emotional impact of these stressors on individuals. Outcomes represent the behavioral or psychological responses or consequences resulting from the strain (Ma et al., 2022). The SSO framework has been extensively applied in the context of information technology to explain users' negative reactions from the perspective of stressors. It is particularly useful for examining the adverse effects of information systems on users' psychological states and behaviors (Cao et al., 2018; Ma et al., 2022). For example, Dhir et al. (2018) utilized the SSO framework to explore how excessive SMuse, privacy concerns, and self-disclosure (stressors) can lead to psychological strain, subsequently impairing students' academic performance (outcome). Recent studies have also employed the SSO framework to investigate social media avoidance and discontinuance behaviors, identifying overload and information irrelevance as significant stressors that affect individuals' psychological and emotional states, such as exhaustion and fatigue, ultimately leading to negative outcomes like discontinuance intention (Fu et al., 2020; Guo et al., 2020; Zhang et al., 2020).

In this research, we aim to understand the factors leading to SM discontinuous usage, particularly focusing on whether the psychological stress caused by platform-pushed

information is one of the reasons for discontinuance. The SSO framework provides a robust explanation of the underlying psychological mechanisms from content stimulus to stress-induced outcomes. Given the increasing relevance of personalized content recommendations in shaping user experiences on social media platforms, the application of the SSO framework is both timely and essential. It is expected to contribute to the existing literature on the dark side of information system use and provide a nuanced understanding of the psychological processes driving social media discontinuance. This understanding is critical for developing strategies to mitigate the adverse effects of personalized recommendations and enhance user satisfaction and retention on social media platforms.

3.2 Psychological Reactance Theory

Psychological Reactance Theory (PRT), proposed by Brehm (1966), is rooted in the tradition of cognitive dissonance theories. PRT posits that behavioral freedom is a fundamental and beneficial aspect of human life. When such freedom is threatened, individuals experience a motivational drive to restore it (Brehm, 1966). This resistance to change is a longstanding psychological phenomenon that has garnered interest across various fields of applied psychology, from health to organizational psychology (Gardner & Leshner, 2016; Proulx, Inzlicht & Harmon-Jones, 2012; Rosenberg & Siegel, 2018).

Reactance research has divided into two primary directions: trait reactance and state reactance. Trait reactance refers to an individual's general tendency to resist influence and advice from others, displaying non-compliance as a personality trait (Pavey & Sparks, 2009). Individuals with higher trait reactance are more sensitive to external threats, often reacting with anger or complaints, while those with lower trait reactance are less likely to respond to such threats (Rosenberg & Siegel, 2018). This area of research mainly focuses on clinical fields. Conversely, state reactance is defined as a motivation to restore behavioral freedom when it is threatened (Shen, 2015). The intensity of state reactance depends on the importance of the threatened freedom in meeting essential needs. Dillard and Shen (2005) conceptualize psychological reactance as a motivational state that mediates the relationship between its antecedents and consequences. They argue that understanding the factors that elicit reactance is crucial for predicting its occurrence and mitigating its effects. To fully grasp PRT, it is essential to clarify the concept of "freedom" within the theory. Wicklund (1974)

describe freedom as a "concrete behavioral reality" that extends beyond instrumental actions to include emotions, attitudes, and other affective states. The theory rests on two primary assumptions: people perceive themselves to have a set of behaviors they are free to perform, and when these behaviors are threatened or eliminated, a motivational drive to restore freedom is elicited (Brehm, 1966).

In the context of SM, Psychological Reactance Theory is typically applied to understand user responses to perceived threats to their autonomy and freedom of choice. For instance, SM platforms often utilize recommendation systems to personalize content recommendations. While these systems aim to enhance user experience by providing relevant content, they can also be perceived as intrusive and controlling, thereby threatening users' sense of autonomy (Do et al., 2020). Research has shown that when users perceive excessive personalization of content, they may experience psychological reactance, leading to adverse reactions such as disengagement or discontinuation of use (Rains, 2013). This phenomenon is particularly relevant in the digital age, where users are increasingly aware of and sensitive to how their data is used to shape their online experiences. PRT provides a valuable framework for analyzing the discontinuous usage of SM. The theory posits that when users feel their freedom to interact with the platform is constrained by overly personalized content or invasive data practices, they may experience reactance, leading to discontinuous usage as a way to restore their autonomy (Chen et al., 2019).

In this research, psychological reactance is conceptualized as a situationally induced motivational state (i.e., state reactance) that underpins users' decisions to discontinue using social media platforms. While trait reactance reflects stable personality characteristics and long-term predispositions to resist external influence, it is less suitable for capturing the dynamic, platform-specific user responses observed in digital environments. In contrast, state reactance is triggered by immediate contextual threats to perceived autonomy, making it more appropriate for examining user experiences shaped by real-time algorithmic interactions and data-driven personalization strategies. Accordingly, this research adopts PRT as a guiding framework to investigate how users respond when their freedom of choice is threatened by perceived over-personalization or intrusive data practices. The theory's emphasis on the motivational drive to restore threatened freedoms offers valuable insight into the psychological mechanisms that lead to disengagement behaviors. By applying PRT through the lens of state reactance, this research aims to deepen understanding of the antecedents of user discontinuance

and inform the development of design strategies that mitigate such effects—ultimately enhancing the sustainability of user engagement on social media platforms.

3.3 Hypotheses Development

This section presents the theoretical development of the hypotheses guiding the current research. Drawing upon PRT and the SSO framework, we identify key stressors triggered by recommendation systems on social media (SM) platforms and propose a sequence of psychological and behavioral responses. Specifically, we focus on two prominent stressors—information overload and perceived threats to freedom—that are frequently associated with personalized content delivery. The subsequent strain responses, particularly psychological reactance, are then examined as antecedents to discontinuance intention, which serves as the final outcome of the model. To enhance clarity and coherence, this section is organized into five sub-parts that follow the logic of the SSO framework. Specifically, the hypotheses are developed in a stepwise manner that begins with identifying stressors, proceeds to strain responses, and concludes with the behavioral outcome. In particular, information overload and perceived threats to freedom are conceptualized as stressors, psychological reactance as the strain, and discontinuance intention as the outcome. Through this logical progression, the proposed model aims to clarify how algorithmic personalization on SM may trigger negative psychological responses and contribute to users' withdrawal behaviors. The development of each hypothesis is grounded in relevant theoretical frameworks and supported by prior empirical findings.

Threat to Freedom and Information Overload as the Stressor

In the context of SM, various stressors induced by content recommendations can significantly impact users' psychological states and behaviors. Numerous studies have explored stress-inducing factors within the SM context, such as information overload, communication overload, and social overload (Cao & Sun, 2018). This research focuses on information overload and perceived threats to freedom as stressors, which have been identified as particularly relevant. The rationale for focusing on these two stressors is twofold. First, compared to other stressors such as social or feature-related pressures, the association between recommendation systems and these stressors is more direct and pronounced. Users, as recipients of information, are less likely to experience social pressure or spend time learning new features due to recommendations. Instead, the primary impact of recommendations is through the information provided and the

perceived autonomy in choosing that information. Second, prior research has consistently highlighted and demonstrated that recommendation algorithms often lead to information overload and perceived threats to freedom. For instance, excessive information from recommendations can overwhelm users, making it difficult for them to process and manage the content (Chung et al., 2023). Additionally, the perception that content is dictated by algorithms can erode users' sense of control over their SM experience, making them feel that their freedom is being compromised (Ma et al., 2022).

In PRT, a threat to freedom refers to the psychological response that arises when individuals perceive their ability to make choices or decisions autonomously is restricted or taken away (Brehm, 1966). When individuals perceive such a threat, they typically experience a compulsion to resist and restore their lost freedom. This response can lead to resistance behaviors, such as defying rules or instructions, and significant psychological stress.

Research indicates a strong correlation between threats to freedom and stress. When individuals feel their behavioral freedom is constrained, they often experience high levels of psychological stress. This stress stems from feelings of helplessness and a loss of control (Brehm, 1966). When individuals encounter threats or stress, their bodies exhibit similar hormonal responses, such as increased levels of cortisol and adrenaline, alongside the activation of the autonomic nervous system (Weber, Angerer & Apolinário-Hagen, 2022). For example, in an experiment, researchers found that participants who were informed that their choices were limited reported significantly higher stress levels than those who did not perceive such a threat (Miron & Brehm, 2006). These findings suggest that threats to freedom can provoke substantial psychological and physiological stress responses, making them a critical factor in understanding stress reactions within PRT.

In addition to perceived threats to freedom, another key stressor relevant to the social media context is information overload. Information overload in SM refers to a situation where users are confronted with an overwhelming amount of information that exceeds their capacity to process and manage (Pang & Ruan, 2023b). This phenomenon is particularly pertinent to our study, as it directly results from the push notifications and recommended content provided by these platforms. When users are exposed to excessive information, their ability to handle and process it is impaired, leading to feelings of burden and stress, which in turn cause negative emotional arousal

(Farhoomand & Drury, 2002). Empirical studies have demonstrated a positive relationship between perceived information overload and users' discontinuance behavior on social media platforms like Facebook and Weibo (Chung et al., 2023). The primary goal for users on SM platforms is to engage with relevant content and maintain social connections. However, the influx of information from recommendations can interfere with this goal, overwhelming users with excessive and often irrelevant content. Unlike information from social circles, which carries social pressures to engage, recommended content primarily contributes to information overload without such social obligations (Lin et al., 2020).

Information overload leads to psychological stress and negative emotions (Eppler & Mengis, 2004). As individuals have limited information processing abilities, an abundance of information can result in feelings of burden and overwhelm, ultimately causing exhaustion (Ma et al., 2022). Numerous studies have highlighted the significant impact of information overload on psychological fatigue and emotional exhaustion (Fu et al., 2020; Guo et al., 2020).

Personalization Strategies and the Perception of Personalization

To understand how recommendation systems influence users' psychological and behavioral responses, it is essential to examine the role of personalization—a core mechanism driving content delivery on social media platforms. While many platforms rely on sophisticated algorithms to tailor content based on user behavior and preferences, it is not the technical complexity of these systems, but rather how users perceive the personalized content, that ultimately shapes their reactions. This distinction between actual and perceived personalization is particularly relevant in the context of psychological stress and reactance, as users' subjective evaluations often mediate their emotional and behavioral responses. Accordingly, this section elaborates on how personalization operates in current SM platforms, and why perceived personalization is adopted as a key construct in this study.

Personalization strategies have become central to user experience design on digital platforms, particularly in the context of social media. These strategies aim to tailor content to individual users based on their preferences, behaviors, and social connections. From a system perspective, actual personalization refers to the technical implementation of such customization—using algorithms to analyze data and push relevant content. The goal is to enhance engagement, satisfaction, and ultimately

platform retention. Contemporary platforms have adopted divergent yet equally complex approaches to personalization. X (formerly Twitter) leverages a network-based recommendation algorithm that synthesizes signals such as follows, likes, shares, replies, and watch history to generate content feeds. Notably, it offers users control over how content is delivered—allowing toggling between algorithmic (“For You”) and chronological (“Following”) timelines—and integrates content eligibility filters to maintain informational integrity (X Corp., 2024). In contrast, Instagram employs a deep personalization architecture composed of over 1000 machine learning models operating across Feed, Reels, Stories, and Notifications. These models are distributed across a multi-stage ranking funnel, adapting in near real-time to user behavior with specialized metrics to monitor model stability and engagement quality (Levis et al., 2024).

Despite their technical sophistication, these strategies do not guarantee that users perceive the resulting content as personalized. Research increasingly shows that users’ psychological and behavioral responses are shaped more by perceived personalization—the subjective feeling that content is tailored to them—than by the actual presence of algorithmic customization (Li, 2016). This distinction arises because individuals differ in how they interpret and evaluate external stimuli. As emphasized in Optimal Stimulation Level (OSL) theory, users seek stimulation levels that match their personal thresholds, and will evaluate content based on perceived novelty and relevance rather than the system’s underlying complexity (Zheng et al., 2023; Gu et al., 2016). Moreover, what a system intends to deliver does not always align with what users experience as meaningful or engaging. Platforms like X attempt to bridge this gap by signaling personalization efforts through user interfaces, while platforms like Instagram rely more on backend optimization, which may leave personalization opaque to users.

This psychological divergence between actual and perceived personalization has led scholars to call for a stronger emphasis on users’ subjective perceptions when evaluating the impact of personalization. Prior research supports this approach. For instance, Aguirre et al. (2015) identified that personalization can produce unintended negative reactions depending on how it is perceived, coining the term “personalization paradox.” Brinson et al. (2018) further demonstrated that personalization may trigger psychological reactance if users feel their freedom is threatened, again depending on perception. Chen et al. (2022) also emphasized that effective personalization must

balance technological capabilities with how consumers perceive privacy and relevance trade-offs. Reflecting this consensus, these studies—along with the current research—conceptualize and operationalize personalization as a perceptual construct, rather than relying solely on system-level characteristics.

Therefore, this study adopts perceived personalization as a central construct to explain user psychological and behavioral responses. By doing so, it aligns with both platform realities and theoretical developments, recognizing that it is not the sophistication of the algorithm, but rather how users experience and interpret its output, that determines the ultimate success of personalization strategies.

The Duality of Personalization

When using SM, users often browse not only their friends' information but also seek content that interests them for entertainment purposes (Luqman et al., 2020). However, whether on Facebook or Instagram, tens of thousands of pieces of content are generated and shared online every minute. Finding content of interest within this vast sea of information poses a significant cognitive challenge for users. When users need to sift through an overwhelming amount of information to find what they need, they experience information overload, leading to various negative effects (Farhoomand & Drury, 2002). However, personalized content recommendations can mitigate this issue by suggesting highly relevant content based on users' behaviors and preferences. On one hand, these highly relevant recommendations increase the likelihood that users' interests will overlap with the recommended content, thus reducing the need for users to search through excessive information. On the other hand, due to the self-referential effect, users can respond to and evaluate information more quickly and effectively (Tam & Ho, 2006).

Based on the above reasoning, it can be posited that the vast amount of information on SM may overwhelm users. However, if the recommended content is personalized based on user behavior, it can help users find content of interest more quickly and effortlessly, thus reducing information overload. Therefore, we hypothesize:

H1: Personalized recommendations can reduce users' perceived information overload. The higher the degree of personalization, the lower the perceived information overload.

As discussed in the previous section, the effects of personalization are not always positive. There are several reasons why the positive effects of personalization might

fail to manifest. On one hand, by providing users with familiar content, personalization can help users process information quickly. However, the sense of relevance brought by self-referent content may lead users to perceive a "diversion of attention," viewing the recommendations as purpose-driven (Dijkstra, 2008). This perception can make users feel that their freedom in decision-making is being interfered with (Dong et al., 2024). In the context of SM, users may similarly believe that the platform is recommending content to make them spend more time on the platform, feeling that they are using the service as the platform intends, which threatens their expectation of freely using SM. On the other hand, besides the perceived limitation due to the platform's intent, users who see overly relevant content may become aware that they have fallen into the "filter bubble" trap. The higher the degree of personalization, the more pronounced this perception becomes (Klug & Strang, 2019). As mentioned in the previous section, personalized content can lead to user distrust, as users feel manipulated and concerned about the lack of transparency in how information is filtered (Eslami et al., 2015). Additionally, excessive homogeneous content can make users feel that their freedom to explore information is restricted (Klug & Strang, 2019). Therefore, we posit that personalization might cause SM users to feel that their freedom to use the platform is threatened due to the high homogeneity of the content and the perception of the platform's intent. Hence, we propose Hypothesis 2:

H2: Personalized recommendations can increase users' perceived threat to freedom. The higher the degree of personalization, the higher the perceived threat.

Information Overload and Threat to Freedom

According to Self-Determination Theory (SDT), the pursuit of autonomy is one of the basic human needs, and people using SM also desire to have control over their usage (Luqman, Masood & Ali, 2018). On one hand, the vast amount of information provided by SM offers users numerous channels to obtain information. However, on the other hand, when individuals lack the capacity to process excessive information, they may feel a sense of being overwhelmed and out of control (Zhang et al., 2016). Threat to freedom refers to the psychological response that arises when individuals perceive their ability to make choices or decisions autonomously is restricted or taken away (Brehm, 1966). When individuals feel incapable of processing information, they also experience a threat to freedom. Faced with an overwhelming amount of information on SM, users may feel powerless to manage it, leading to a sense of losing

control over their SM usage and thereby threatening their freedom of usage. Therefore, we posit Hypothesis 3:

H3: Perceived information overload is positively associated with perceived threats to freedom on SM.

Reactance as a kind of Strain

Strain refers to the disruptive impacts on an individual's concentration, physiology, and emotions, resulting in negative reactions tied to situational stimuli. According to Koeske and Koeske (1993), strain manifests in various forms, including burnout and other psychological consequences of stressful situations. Burnout, particularly emotional exhaustion, is often identified as a mediator of the impact of perceived stressful events on attitudinal and behavioral outcomes. This implies that only individuals experiencing burnout under conditions of perceived stress are expected to exhibit negative outcomes (Koeske & Koeske, 1993). Previous research on strain in the context of SM use has predominantly focused on variables such as emotional exhaustion and technostress. Emotional exhaustion describes feelings of being emotionally overextended, capturing the psychological consequences of stressful situations (Wright & Cropanzano, 1998). For instance, Luqman et al. (2017) suggested that excessive use of SM induces exhaustion and technostress, highlighting how these strains negatively impact user behavior (Luqman et al., 2020). Similarly, Mahmud et al. (2023) noted that stressors like information overload, communication overload, and social overload can lead to exhaustion, an unconscious psychological response to stressful situations characterized by fatigue (Maier et al., 2015).

While previous studies have extensively examined the link between stressors and exhaustion, it is crucial to recognize that exhaustion is often an aversive and unconscious psychological response (Mahmud et al., 2023). In contrast, reactance is a conscious and active psychological response to perceived threats to freedom, making it more suitable for understanding users' intentional discontinuance behaviors. PRT posits that individuals experience reactance when they perceive a threat to their freedom, leading to a motivational state aimed at restoring the threatened freedom (Brehm, 1966). This theory provides a robust framework for understanding how users respond to perceived threats from recommendation systems on SM platforms. Specifically, the perceived threat to freedom induced by excessive and intrusive

content recommendations can trigger reactance, leading users to resist and potentially discontinue their use of the platform.

Based on PRT, the relationship between reactance and perceived threats to freedom is well-established. The greater the threat users feel, the stronger their desire to restore their freedom (Brehm, 1966). When users perceive that their freedom to use SM is constrained, they are likely to experience reactance. Therefore, we hypothesize the following:

H4: Perceived threats to freedom are positively associated with psychological reactance on SM.

Information overload induces negative emotions and can lead to a state of psychological reactance. Information overload can push users to the brink of their cognitive capacity, leaving them feeling overwhelmed (Cao & Sun, 2018). Numerous studies have demonstrated that information overload increases users' feelings of exhaustion or fatigue (Luqman, Masood & Ali, 2018). Additionally, research indicates that overload can also lead to other emotions such as anxiety and regret (Cao & Sun, 2018). Regardless of the specific emotions involved, from a self-regulation perspective, individuals control their desires and behaviors through judgmental and self-monitoring processes (LaRose, Lin & Eastin, 2003). Users actively seek ways to avoid undesired states, including overload and feeling out of control (Cao & Sun, 2018). Psychological reactance is a state triggered by negative emotions and the desire to eliminate the resulting discomfort through action (Brehm, 1966). When users on SM encounter an overwhelming amount of information that they cannot process, this feeling of overload induces negative emotions. To mitigate or avoid these negative feelings, users may take actions that lead to a state of reactance. Therefore, we posit:

H5: Perceived information overload is positively associated with psychological reactance on SM.

Discontinuous Usage as an Outcome

In this research, discontinuance intention is selected as the outcome variable for both theoretical and practical reasons. This decision builds on the inclusive definition of SMD proposed by Wang et al. (2021), which encompasses a variety of behaviors such as reduced usage, temporary withdrawal, and platform replacement. While some studies have attempted to distinguish between abrupt quitting (“opt-out”) and gradual fading (“oblivion”) (Kang, Zhang & Yoo, 2020), these distinctions are not well-defined

in terms of their psychological antecedents. Therefore, consistent with Lin et al. (2020) and Luqman et al. (2020), this study adopts a holistic perspective to understand discontinuance more broadly. More importantly, using intention rather than actual behavior aligns with the core aim of this research: to uncover the psychological mechanisms—particularly reactance—that trigger the motivation to discontinue. Reactance is a motivational state that can manifest in various resistance behaviors, ranging from reduced usage to complete withdrawal (Rosenberg & Siegel, 2018; Chen et al., 2019). Capturing these tendencies at the level of intention allows for theoretical coherence with PRT.

From a methodological standpoint, behavioral intention serves as a reliable and measurable proxy for future action. According to Bandura (1998), intention reflects a user's internal cognitive-emotional state prior to behavioral execution, making it a meaningful indicator of discontinuance tendencies. In the platform management context, intentions often precede measurable outcomes such as shorter session times or account deletion, and thus offer valuable predictive insights (Heinonen & Strandvik, 2015). Focusing on intention also allows researchers and practitioners to identify early warning signs of user dissatisfaction and resistance before actual quitting occurs. It is also important to clarify that this study does not address the “silent leavers”—users who are psychologically disengaged yet exhibit no visible signs of behavioral or intentional withdrawal. Due to empirical challenges in identifying such latent states, the study concentrates on users who express measurable discontinuance intentions. This focus enhances both theoretical rigor and practical applicability in examining how algorithmic personalization may threaten autonomy and motivate users to discontinue.

According to the SSO framework, the “outcome” component refers to users' behavioral or psychological responses following strain. Strain—manifesting as fatigue, frustration, or other adverse emotional states—leads to various user responses, including reduced engagement or discontinuance (Dhir et al., 2018; Mahmud et al., 2023). On SM, these behaviors include quitting, pausing usage, or switching to other platforms (Lin et al., 2020). Behavioral intentions are strongly shaped by the psychological experience of social media use, whether positive or negative (Zhang et al., 2016), and prior research supports the use of intention as a predictor of behavior across digital contexts (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). Specifically, discontinuance intention represents a user's behavioral response to negative psychological experiences with social media (Luqman et al., 2020).

While both psychological reactance and discontinuance intention fall under the broader category of psychological constructs, they represent distinct phases of user response. Reactance is an immediate, emotionally charged motivational state that arises when a person perceives a threat to their freedom (Sittenthaler, Traut-Mattausch & Jonas, 2015; Shen, 2015; Dillard & Shen, 2005). In contrast, discontinuance intention is a deliberate, cognitively mediated behavioral plan formed after individuals process and reflect on their experiences. As Ajzen (1991) explains, behavioral intention is a volitional construct that indicates a conscious plan to perform a specific action. Gollwitzer (1999) further emphasizes that intentions emerge when emotional responses or non-committal desires are translated into concrete goals through self-reflection. Therefore, while reactance represents an early-stage affective response, discontinuance intention reflects a later-stage reasoned decision. Distinguishing between the two allows for a more accurate understanding of how users move from internal resistance to planning discontinuance behavior.

This theoretical distinction is reinforced by empirical studies applying PRT in digital contexts. Many of these studies model reactance as a mediating mechanism linking external threats—such as intrusive personalization or information control—with user behaviors such as ad avoidance, app deletion, or platform discontinuance (e.g., Rains, 2013; Frantz, 2021; Zhang et al., 2022). In social media settings, users who experience reactance in response to perceived algorithmic overreach often limit their engagement or leave the platform (Chen et al., 2019). For example, Youn and Kim (2019) found that Facebook users experiencing reactance toward feed advertisements were more likely to avoid such content. Similarly, Ma et al. (2022) showed that users acted swiftly to escape negative emotional states by distancing themselves from platforms.

This body of research justifies modeling reactance as a psychological antecedent and discontinuance intention as the resulting behavioral outcome. Our study follows this logic to clarify how users translate perceived threats into specific discontinuance intentions. Therefore, we propose the following hypothesis:

H6: Psychological reactance is positively associated with discontinuance intention on SM.

The proposed research model is illustrated in the following diagram (Fig. 2):

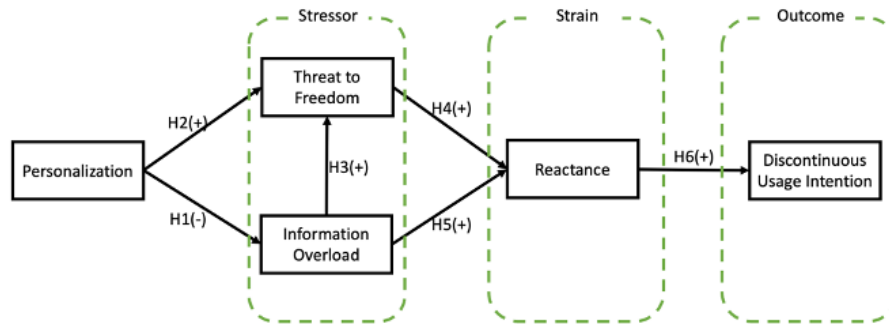


Fig.2 The research model

3.4 Research Methodology

3.4.1 Data Collection

To test our hypotheses, a quantitative survey method was employed, targeting users of Facebook and Instagram in Japan. These platforms were selected due to their extensive user base and the prominent role of personalized content recommendations, which are presumed to elevate user awareness of system influences, thereby facilitating the measurement of psychological reactance and its consequences.

Data were collected on March 29, 2024, through the Yahoo! Crowdsourcing platform, a widely recognized crowdsourcing service in Japan. This platform allows registered Japanese internet users to complete online tasks, such as surveys, in exchange for PayPay points (a popular digital payment reward), making it a useful tool for rapid and diverse data collection. The service's mechanism is designed to solve business tasks through the collective input of a large user base. In this study, participants were offered point-based incentives, and the high response speed was attributed to the platform's extensive user pool and the monetary reward mechanism.

Prior to launching the survey, the questionnaire was carefully designed and uploaded as a task on the platform. A filter question was embedded to ensure that only users of Facebook or Instagram could proceed with the survey. Participants were informed about the study's background and were explicitly asked about their prior experience with these platforms. After completing this screening process, data collection was automatically terminated once 350 valid responses were obtained.

The decision to collect 350 responses was based on methodological considerations. To ensure the statistical adequacy of covariance-based structural equation modeling

(CB-SEM), a minimum sample size of 300 valid responses was targeted. According to Kline (2023), CB-SEM generally requires larger sample sizes than alternative estimation methods, particularly when involving multiple latent variables and complex paths. Likewise, Hair et al. (2017) recommend a sample size between 200 and 400 for models estimated using the maximum likelihood method, with 300 or more considered ideal for models of moderate complexity. By collecting 350 responses, we accounted for the possibility of low-quality data (e.g., patterned answers, inconsistent responses, or abnormally fast completion times) to ensure a robust final dataset.

Following data collection, a two-step screening process was conducted. First, responses were checked to confirm whether participants were indeed Facebook or Instagram users. Second, several attention-check items were embedded throughout the questionnaire. For example, respondents were asked to solve a simple arithmetic question (“ $200 + 300 = ?$ ”) or follow a specific instruction (e.g., “Please select ‘Strongly Disagree’ for this question”). Responses that failed these checks or demonstrated clear internal inconsistencies were removed. As a result, 23 responses were excluded, leaving a final sample of 327 valid responses, yielding a usable response rate of 93.4%. The final sample consisted of 61.8% male participants (202 respondents), with an average age of 37.3 years. Detailed demographic information is presented in Table 2.

To minimize potential biases caused by nonresponse and common method variance (CMV), two post-hoc statistical tests were conducted to ensure the robustness of the data.

First, an Early–Late Response Comparison was performed to assess potential nonresponse bias. This method, originally proposed by Armstrong and Overton (1977), assumes that late respondents are more similar to non-respondents than early ones. If no significant differences are observed between early and late respondents, it can be inferred that nonresponse bias is unlikely. Widely adopted in online survey research (Rogelberg & Stanton, 2007), this approach was implemented by dividing responses into early and late groups based on submission time. Independent sample t-tests were conducted for five key constructs: information overload, personalization, freedom threat, reactance, and discontinuance. The results revealed no statistically significant differences between the two groups (e.g., information overload: $t = -0.632$, $p = 0.528$;

reactance: $t = 0.754$, $p = 0.452$), suggesting that nonresponse bias was not a major concern.

Second, to assess the risk of common method variance (CMV), the Harman's Single Factor Test was conducted following the recommendation of Podsakoff et al. (2003). All survey items—both independent and dependent variables—were entered into an exploratory factor analysis (EFA) using principal component analysis (PCA) without rotation in SPSS 23. The test evaluates whether a single general factor emerges or dominates the variance structure. In this study, the first unrotated factor accounted for 40.44% of the total variance, which is below the commonly accepted threshold of 50% (Podsakoff et al., 2003). This indicates that CMV is unlikely to pose a serious threat to the validity of the results.

This carefully controlled sampling process and platform selection ensured that participants had adequate exposure to algorithmic recommendation systems, enabling reliable measurement of the key psychological constructs under investigation.

Table 2. Demographic Information

Variable	Category	Frequency	Percentage
Gender	Male	202	61.8%
	Female	125	38.2%
Age	18-30	53	16.3%
	31-40	151	46.5%
	41-50	119	36.6%
	above 50	2	0.6%
Education Level	High School	81	24.8%
	University	183	56.0%
	Graduate School	15	4.6%
	Junior College	26	8.0%
	Middle School	9	2.8%
	Other	13	4.0%
Frequency of SM Daily Usage	Less than once/week	4	1.2%
	1–5 times/week	18	5.4%
	Once/day	32	9.6%
	2–4 times/day	87	26.2%
	5+ times/day	186	57.5%

3.4.2 Survey Design and Measurements

The proposed research model was operationalized by capturing data on respondents' demographic characteristics, social media discontinuance intentions, and other constructs. Variables were assessed using a 7-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). All measurement items were adapted from existing literature to fit the research context.

The construct of 'Perceived Recommendation Personalization (Per)' was assessed using a measurement adapted from Chen, Sun & Liu (2022), comprising three items designed to evaluate the degree of personalization perceived by users in the platform's content delivery. The 'Threat to Freedom (Free)' was evaluated using a four-item scale developed by Youn & Kim (2019), designed to assess the perceived restrictions imposed by social media platforms on user autonomy. 'Reactance (Re)' was quantified using a modified version of the scale proposed by Shen and Dillard (2005), consisting of five items that measure the resistant behavior elicited by perceived threats to user freedom. 'Information Overload (Io)' was measured through a four-item scale derived from Fu et al. (2020), which captures the extent to which users feel overwhelmed by the volume of information presented on social media. Lastly, 'Discontinuous Usage Intention (DUI)' was gauged using a four-item scale based on the work of Zhang et al. (2016), assessing the likelihood of users discontinuing the use of social media platforms. The Appendix at the end of the paper provides a comprehensive list of all measurements and their sources.

For hypothesis testing, Structural Equation Modeling (SEM) was utilized. SEM is a multivariate technique that integrates multiple regression and confirmatory factor analysis, suitable for testing empirical data against a priori theoretical assumptions (Chin & Todd, 1995). Covariance-Based Structural Equation Modeling (CBSEM) was chosen for its proficiency in managing complex theoretical models involving multiple constructs like reactance and behavior intention. CBSEM is adept at delineating the relationships among these variables, crucial for deciphering consumer responses to recommendations. Moreover, it excels in analyzing latent variables that are pivotal in consumer psychology, such as reactance and information overload, which, though not directly observable, can be measured through indirect indicators. CBSEM also supports path analysis and hypothesis testing, facilitating a precise examination of causal relationships between constructs such as consumer attitudes, perceptions, and behavioral intentions, essential for validating the research hypotheses (Reinartz, 2009).

Previous research has not adequately explored the mediating role of Reactance or the mediation effects of Threat to Freedom on Information Overload and Reactance. To bridge this gap, a bootstrap approach was employed to analyze these mediation effects, a method well-regarded for its robustness in mediation analysis, allowing for a nuanced understanding of the indirect effects among these variables.

3.4.3 Structural Model

To ensure the reliability and validity of the scales used in this study, SPSS 23 and AMOS 23 were employed for model assessment. Scale reliability was assessed using Cronbach's alpha (Nunnally, 1978), adhering to the benchmark of 0.7 for acceptability. The composite reliability (CR) for each construct exceeded the threshold of 0.8 (Fornell & Larcker, 1981), indicating strong internal consistency. CR reflects the extent to which a set of items consistently represents the latent construct, and values above 0.7 are considered satisfactory, while values above 0.8 are preferred for more rigorous assessment.

In the measurement model, one loading (Io4) was slightly below the threshold of 0.5. Given that the other three loadings for Information Overload were above 0.7, demonstrating good measurement of Io, the item with a loading below 0.5 was dropped as it did not adequately measure the construct. Factor loadings represent the strength of the relationship between an observed variable and its underlying latent construct. A commonly accepted threshold is 0.5 (Hair et al., 2017), as it indicates that the indicator explains at least 25% of the variance of the latent construct (since $0.5^2 = 0.25$). Retaining items below this level may introduce measurement error and reduce construct validity. Furthermore, the average variances extracted (AVE) for each construct were above the 50% benchmark (Fornell & Larcker, 1981), demonstrating adequate convergent validity. AVE measures the average amount of variance that a latent construct captures from its indicators relative to the amount due to measurement error. A value above 0.5 indicates that more variance is captured than lost, ensuring that the construct is well represented by its indicators.

These results, detailed in Table 3, meet all established criteria for reliability and convergent validity. The discriminant validity of the model was ascertained by comparing the square roots of the AVE values with the squared inter-construct correlations (Fornell & Larcker, 1981), as illustrated in Table 4. All the square roots of the AVEs satisfactorily exceeded the correlations with other constructs, indicating

good discriminant validity. This criterion ensures that a construct shares more variance with its own indicators than with other constructs, which is essential to confirm that the constructs are distinct from each other.

Path analysis with AMOS 23.0 was used to test the structural model. The model was evaluated using the ML method and a correlation matrix. In this study, we utilized AMOS 23.0 for path analysis to examine our proposed structural model, opting for the Maximum Likelihood (ML) method for estimating model parameters. Moreover, a correlation matrix was used as the input, aligning with standard SEM practices to assess the relationships between variables.

Table 3. Reliability and convergent validity analysis (Io4 was eliminated).

	Item	Standardized factor loading	CR	AVE	Cronbach's α
Personalization (Per)	Per1	0.839	0.951	0.730	0.737
	Per2	0.909			
	Per3	0.812			
Threat to Freedom (Free)	Free1	0.675	0.971	0.589	0.761
	Free2	0.611			
	Free3	0.896			
	Free4	0.851			
Information overload (Io)	Io1	0.752	0.931	0.659	0.705
	Io2	0.898			
	Io3	0.778			
Reactance (Re)	Re1	0.621	0.886	0.612	0.852
	Re2	0.774			
	Re3	0.810			
	Re4	0.856			
	Re5	0.828			
Discontinuous usage intention (DUI)	Dui1	0.868	0.813	0.511	0.781
	Dui2	0.633			
	Dui3	0.615			
	Dui4	0.757			

Table 4. Correlation matrix

	Mean	Per	Free	Io	Re	DUI
1. Personalization	4.731	0.854				
2. Threat to Freedom	3.701	-0.291	0.767			
3. Information Overload	3.903	-0.146	0.617	0.812		
4. Reactance	3.526	-0.462	0.753	0.574	0.782	
5. Discontinuous Usage Intention	3.650	-0.405	0.507	0.466	0.706	0.715

Note: Diagonal numbers are the square root of AVE

AMOS, renowned for its efficacy in structural equation modeling (SEM), offers an intuitive graphical interface, making it a preferred choice for complex model specifications. The selection of the ML method was based on its well-documented accuracy and efficiency in large sample sizes, a characteristic essential for SEM with its multiple variables and intricate relationships (Byrne, 2016). Despite its assumption of multivariate normality, ML is relatively robust to mild deviations from this assumption, a feature particularly pertinent given our data's approximate adherence to normal distribution. Additionally, the ML method is advantageous in SEM due to its facilitation of various goodness-of-fit measures, enabling a thorough model evaluation. This comprehensive approach to model assessment is crucial in SEM, where the fit between the model and observed data is paramount (Byrne, 2016). The integration of AMOS 23.0 with the ML method provided a robust framework for this analysis, ensuring reliable and valid conclusions. Moreover, we used a correlation matrix as the input, a standard practice in SEM for assessing direct relationships between variables. In this study, AMOS 23.0 was utilized for path analysis to examine our proposed structural model, with the Maximum Likelihood (ML) method selected for estimating the model parameters (Reinartz, Michael & Jörg, 2009).

In structural equation modeling (SEM), evaluating model fit is essential to determine how well the hypothesized model structure replicates the observed data. Given the multidimensional nature of model performance, researchers are widely encouraged to adopt a multi-index approach rather than rely on a single fit statistic (Schermelleh-Engel, Moosbrugger & Müller, 2003; West, Taylor & Wu, 2012). Accordingly, this study reports five commonly used fit indices: chi-square divided by degrees of freedom (χ^2/df), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA).

First, χ^2/df is a normalized index derived from the chi-square statistic, reflecting the discrepancy between the observed and model-implied covariance matrices. A value below 3.0 is generally regarded as indicating acceptable fit (Hayduk, 1987), and the value obtained in this study was 2.785.

Second, the GFI and AGFI are absolute fit indices. GFI indicates the proportion of variance in the observed covariance matrix that is accounted for by the model, while AGFI adjusts GFI based on model complexity and degrees of freedom. Although these indices are known to be sensitive to sample size (MacCallum & Hong, 1997), they are still widely reported in marketing and consumer research due to their interpretability and tradition (Baumgartner & Homburg, 1996). Values above 0.80 are considered acceptable in applied settings. This study reported GFI = 0.883 and AGFI = 0.848, both exceeding the threshold.

Third, the CFI compares the specified model with a baseline model in which all variables are uncorrelated. A value above 0.90 is considered to represent good fit (Bagozzi, 1988), and a more conservative benchmark of 0.95 is sometimes suggested for excellent fit (Hu & Bentler, 1999). The current model achieved a CFI of 0.928, indicating substantial improvement over the null model.

Finally, the RMSEA is a parsimony-adjusted index that estimates the model's error of approximation in the population. Values below 0.08 suggest reasonable fit, and values below 0.05 indicate close fit (Schermelleh-Engel et al., 2003). The RMSEA observed in this study was 0.074, falling within the acceptable range, particularly considering the complexity of the model and the moderate sample size (Kenny, Kaniskan & McCoach, 2015).

While the thresholds adopted in this study are considered relatively lenient compared to the most stringent criteria (e.g., $\text{CFI} \geq .95$, $\text{RMSEA} \leq .06$; Hu & Bentler, 1999), this decision is theoretically and methodologically justified. Marsh, Hau, and Wen (2004) warn against the rigid application of strict cutoffs, arguing that they may lead to the rejection of substantively meaningful models, especially when the model structure is complex or the sample size is moderate. Moreover, indices such as RMSEA and GFI are known to be sensitive to model degrees of freedom and sample size, which may make the strict cutoffs overly conservative in practice (Kenny et al., 2015; MacCallum & Hong, 1997).

Therefore, in line with current best practices in applied SEM, the fit indices adopted in this study are consistent with the “reasonable fit” standards commonly used in marketing and consumer research (Schermelleh-Engel et al., 2003; Kline, 2023). Given that all reported indices exceed the recommended thresholds for acceptable fit, and that each captures a different dimension of model adequacy, the model can be judged as statistically valid and theoretically meaningful. The model fit indices for the structural model are presented in Table 5.

Table 5. Model fit

Indicator	Criteria	Source	Result
Chi-square/d.f.	<3.0	Hayduk (1987)	2.785
GFI	>0.8	Baumgartner & Homburg (1996)	.883
AGFI	>0.8	Baumgartner & Homburg (1996)	.848
CFI	>0.9	Bagozzi (1988)	.928
RMSEA	<0.08	Bagozzi (1988)	.074

3.4.4 Mediation analysis

In our model, two primary pathways were identified. The first pathway involves Information Overload influencing Discontinuous Usage Intention by causing Reactance. The second pathway suggests that Information Overload intensifies the perception of Threat to Freedom, which in turn indirectly strengthens Reactance, thereby affecting Discontinuous Usage Intention. Our analysis focused on determining whether Threat to Freedom acts as a mediating variable between Information Overload and Reactance, and whether Information Overload indirectly rather than directly influences these outcomes.

The mediation effects were examined using the bootstrap method, which provides more accurate estimates of indirect effects in mediation analysis (Cheung & Lau, 2008). By resampling the data multiple times, it generates an empirical distribution of the mediation effect, allowing for precise estimation of its size and significance. For this study, we set the resampling number to 2000 and the confidence interval to 95%, employing the maximum likelihood method for implementation. As demonstrated in Table 6, the results indicate significant findings regarding the influence of Information Overload. Both the direct impact on Reactance and the indirect impact through Threat to Freedom were significant, confirming the mediating role of Threat to Freedom. Regarding the overall pathways, this study also validated the indirect effects of Information Overload on Discontinuous Usage Intention. Specifically, Information

Overload influences Discontinuous Usage Intention indirectly through the Threat to Freedom and Reactance. The findings reveal that Information Overload not only directly triggers reactance but also elevates the perception of a threat to the freedom of using social media, which in turn heightens reactance, ultimately strengthening the intention for discontinuous usage.

Table 6. Results of the mediation analysis

Path		Estimate	Lower	Upper	P
Io → (Re)→ DUI	IO indirect	0.524	0.392	0.696	0.001
	IO direct	0.709	0.513	0.907	0.001
	Total	0.078	-0.084	0.22	0.324
Io → (Free)→ Re	IO indirect	0.269	0.171	0.393	0.001
	IO direct	0.114	0.028	0.207	0.013
	Total	0.382	0.274	0.505	0.001

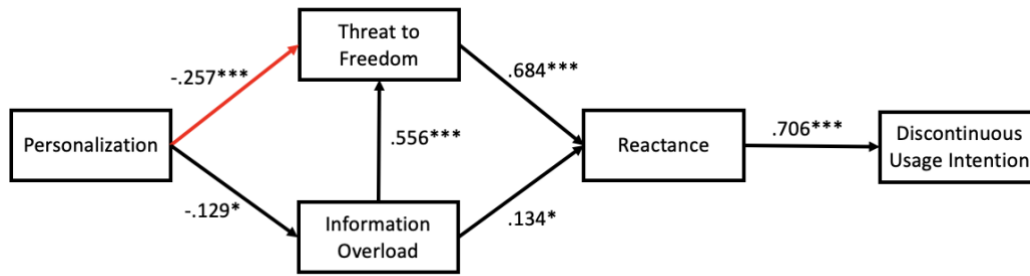
Note: Io = Information Overload, Re = Reactance, Free = Threat to Freedom
DUI = Discontinuous Usage Intention

In conclusion, except for the result of H2 which contradicts the prediction, all of the hypotheses proposed in this study have been empirically tested and verified. The detailed outcomes of these tests are presented in Table 7 and Figure 3. This comprehensive validation reinforces the theoretical framework established in this research and provides robust empirical support for the hypothesized relationships between Personalization, Information Overload, Psychological Reactance, and Discontinuous Usage Intention.

Table 7. Summary of hypotheses test.

	Hypothesis	Estimate	C.R.	P	Results
H1	Personalization → Information Overload	-0.129	-2.065	*	Support
H2	Personalization → Threat to Freedom	-0.257	-4.868	***	Contradict
H3	Information Overload → Threat to Freedom	0.556	9.032	***	Support
H4	Threat to Freedom → Reactance	0.684	10.195	***	Support
H5	Information Overload → Reactance	0.134	2.257	*	Support
H6	Reactance → Discontinuous Usage Intention	0.706	11.993	***	Support

Note: *p < .05. **p < .01. ***p < .001.



Note: * $p < .05$. ** $p < .01$. *** $p < .001$.

Fig. 3 Structural equation modeling results

3.5 Discussion

3.5.1 Findings

This research, grounded in Psychological Reactance Theory (PRT) and the Stressor-Strain-Outcome (SSO) framework, developed and tested a conceptual model to understand why users discontinue using SM services from the perspective of perceived stress. A survey of 327 Facebook/Instagram users in Japan provided data supporting all the hypotheses, indicating that reactance is a significant psychological factor leading to discontinuous usage intention. Information overload and perceived threats to freedom caused by recommended content on the platform both promote reactance, increasing the likelihood of users leaving the platform. Conversely, personalized recommendations effectively alleviate both information overload and perceived threats to freedom.

Firstly, the study confirmed the close correlation between reactance and discontinuous usage intention, aligning with previous research that perceived threats are a more crucial factor influencing disengagement behavior (Ma et al., 2022). When in a state of reactance, consumers are likely to take action to counterbalance this mindset, which in the context of using SM, may manifest as temporary or permanent discontinuance of the platform's services. This provides a new and strong motivational explanation for resistance behaviors towards SM.

Secondly, by adopting the SSO framework, we highlighted the negative effects of psychological stress in the use of SM. The study verified that users might feel stressed from both information overload and threats to freedom while using SM. This is consistent with findings from previous research, which demonstrated that users daily encounter vast amounts of information, not only from friends but also from platform

recommendations (Fu et al., 2020). Excessive information can overwhelm users, impeding their original purpose for using SM. Furthermore, algorithmically curated push notifications might make users feel that their means of obtaining information are restricted. Both of these stressors can drive users into a state of reactance.

Lastly, the study examined the effects of personalized recommended content. Contrary to the prediction that personalization could be a double-edged sword, the results showed that personalization could reduce both information overload and threats to freedom. Consistent with previous research, personalized recommendations can reduce the effort users need to filter information, thereby reducing cognitive burden (Chung et al., 2023).

However, the personalization paradox suggests that such content may infringe on users' privacy or user experience (Aguirre et al., 2015). Especially with the increasing awareness of filter bubble effects, this could threaten users' autonomy and undermine their right to freely access information and use SM. Contrary to our initial hypothesis, higher levels of personalized recommendations can decrease perceived threats to freedom. In our hypotheses, we identified two potential reasons why personalized recommendations might enhance the threat to freedom: awareness of being trapped in a "filter bubble" and resistance to the platform's persuasive intent to keep users engaged. However, our analysis revealed that for Japanese Facebook/Instagram users, higher personalized recommendations actually reduced perceived threats to freedom. We believe there are several reasons for this finding.

First, cultural differences may influence how users in different countries perceive the intrusion of their freedom to use SM. The threat to freedom generally emphasizes the perception of being restricted, focusing on self-perception (Graupmann, 2018). Numerous studies have indicated that this sense of self can vary across countries (Ng et al., 2021; Hofstede et al., 2010). For example, compared to Western countries that emphasize individualistic cultures, countries with collectivistic cultures (e.g., China, Japan) may place greater importance on collective feelings. Kim et al. (2017) found that Koreans, compared to Americans, showed higher tolerance for words that stimulate the threat to freedom. Similarly, in collectivistic Japan, users may have a higher tolerance for such intrusions or may not perceive them as such. According to identity process theory (Stets & Burke, 2000), people in groups seek to find a sense of belonging. On SM, by viewing content that aligns with their interests or viewpoints,

users can more easily find their community and feel a sense of belonging, thus reducing perceived threats.

Second, the context of usage significantly affects the perceived threat. The same application or statement can evoke different levels of threat depending on how it is presented. For example, Aguirre et al. (2015) found that if sufficient transparency is provided or users are informed about their choices, the perceived threat to freedom can be greatly mitigated. Both Facebook and Instagram offer users options to reduce the frequency of similar content, potentially alleviating the perceived threat to freedom. Additionally, many users may not even perceive the filter bubble or the restriction on the diversity of information they receive. Future research could explore the cultural differences across different countries or further investigate how the usage context and perception of the filter bubble might affect the perceived threat to freedom.

3.5.2 Theoretical Implications

This paper makes several key academic contributions: First, this paper empirically verifies and extends the proposed SSO framework. The SSO framework is frequently used to understand how stress in the IS field affects consumer behavior. Within this framework, factors such as exhaustion or fatigue are often studied and discussed as forms of strain. However, few studies have extended this framework to explore other stress-related psychological states. To better explain consumer resistance behavior, it is crucial to identify variables or theories that can effectively link psychological states to behavior. This research explores reactance as such a psychological state. The motivation to regain freedom and eliminate feelings of discord under the state of reactance can provide robust support for understanding consumer resistance behaviors. Our model effectively demonstrates this relationship, contributing a novel perspective to the SSO framework by incorporating reactance as a critical strain component.

Second, this research investigates and confirms the relationship between information overload and reactance. The research finds that the pressure from information on SM impacts users in two significant ways. Firstly, the information provided can interfere with users' original purposes for using SM (such as connecting with friends or viewing friends' updates) or fail to meet users' expectations, leading to a sense of constrained freedom in using SM. Secondly, this imbalance between users' information processing capabilities and the volume of information results in a sense of powerlessness. This powerlessness directly triggers reactance, and simultaneously, this feeling of

inadequacy infringes upon users' autonomy, exacerbating the threat to freedom. To our knowledge, this is the first research to establish a direct relationship between information overload and reactance, thus enriching the literature on information overload by linking it to psychological reactance.

Third, this research discusses the personalization paradox by examining the positive aspects of personalization. Our findings indicate that personalization helps alleviate consumer stress and reduces threats to freedom. This differs from the paradox suggesting that increased personalization may lead to feelings of intrusion. Considering potential cultural differences and situational contexts that may influence these results, future research could further explore under what conditions this paradox arises. Understanding the conditions under which personalization either alleviates or exacerbates user stress can provide deeper insights into optimizing personalized content for various user groups and contexts (Chung et al., 2023; Aguirre et al., 2015).

In conclusion, this research advances our theoretical understanding of the interplay between personalization, information overload, and psychological reactance in the context of social media discontinuance. By extending the SSO framework and exploring new dimensions of strain and user behavior, this research provides valuable insights for academics and practitioners aiming to improve user experience and retention on SM platforms.

3.5.3 Practical Implications

This research offers several practical insights for SM platforms to enhance user retention and satisfaction. SM platforms should strive to avoid inducing psychological reactance in users. Psychological reactance can be triggered by both information overload and perceived threats to freedom. To mitigate these risks, platforms must take proactive measures.

To prevent information overload, SM platforms should implement strategies to filter and control the amount of information delivered to users. By carefully curating the content that is pushed to users and limiting the volume of such content, platforms can reduce the cognitive burden on users. This approach ensures that users are not overwhelmed by excessive information, which can otherwise lead to stress and eventual disengagement.

To minimize perceived threats to freedom, platforms should avoid overloading users with information that interferes with their intended use of the SM. This can be achieved

by providing users with sufficient choices and control over the content they receive. For example, platforms can offer users the option to customize the amount and type of push notifications they receive, thereby enhancing their sense of autonomy and control. Allowing users to manage their preferences can significantly reduce the perceived threat to their freedom and increase their satisfaction with the platform.

Personalized recommendations emerge as an effective strategy in this context. Personalized content can effectively reduce both information overload and threats to freedom. By tailoring content to individual users' preferences and behaviors, SM platforms can deliver more relevant and meaningful information. This targeted approach not only reduces the volume of unnecessary information but also aligns with users' interests, making the content more engaging and less intrusive. Enhancing the specificity and accuracy of recommendations can help prevent users from feeling overwhelmed or restricted, thereby fostering a more positive user experience and reducing the likelihood of discontinuance.

Furthermore, it is essential for SM platforms to consider cultural and situational factors that might influence user perceptions of personalization and control. Future research could delve deeper into understanding how these factors play a role in the effectiveness of personalization strategies, ensuring that platforms can adapt to diverse user needs and contexts.

In conclusion, by addressing information overload and perceived threats to freedom through strategic content management and personalized recommendations, SM platforms can enhance user satisfaction and retention. These practical implications provide a roadmap for platforms to create a more user-centric experience, reducing the risk of user disengagement and fostering long-term loyalty.

3.6 Limitations and Future Research

While Research 1 offers valuable insights into how algorithmic stressors contribute to social media discontinuance through psychological reactance, several limitations remain that warrant further investigation.

First, the research's conceptualization of freedom was relatively general. Although empirical findings confirmed that perceived threats to freedom play a critical role in triggering reactance and discontinuance, the specific sources of these perceived constraints remain underexplored. In algorithmically curated environments, users may

not only feel restricted in terms of choice, but also experience deeper threats such as diminished individuality or self-expression. Without unpacking the mechanisms through which perceived freedom is threatened, the current model provides only a partial explanation. This gap underscores the need for future research to refine the definition of freedom and investigate its psychological and structural antecedents.

Second, while the research addressed personalization as a stressor, it did not fully capture the dual nature of personalized recommendation systems. Previous research has noted that personalization can enhance user satisfaction, platform attachment, and relevance (Park, 2014), while also triggering concerns over privacy and control (Huang et al., 2024). The present research focused primarily on the negative implications of personalization and did not test the personalization paradox in full. Exploring under what conditions personalization supports versus undermines user autonomy remains a pressing direction for future work—particularly in cultural contexts such as Japan, where users may have distinct thresholds for algorithmic interference.

Third, there are limitations related to potential bias in sample composition and platform context. The data were collected via Yahoo! Crowdsourcing in Japan, which may introduce sampling bias due to the platform’s user base. Specifically, the sample displayed a gender imbalance (61.8% male) and an older average age, which could skew the findings toward the preferences and behaviors of more mature male users. Such demographic characteristics may not adequately reflect the broader population of social media users, especially given the generational and gender-based differences in digital literacy, privacy sensitivity, and content preferences. In addition, there is a possibility of platform bias. While the study addressed general social media discontinuance, participants’ responses may have been disproportionately influenced by their primary platforms—such as Facebook, which is more prevalent among older users, as opposed to Instagram or TikTok, which are more popular among younger demographics. These platforms differ substantially in their personalization algorithms, content formats, and levels of user interaction, all of which may shape how users experience information overload, reactance, or disengagement. Future studies should consider collecting data across multiple platforms with clear identification of usage context to capture a more holistic and differentiated view of personalization-related user responses.

In response to these limitations, Research 2 aims to address the most pressing theoretical gap: the need to deepen our understanding of what “freedom” means to users in personalized environments, and how the erosion of perceived individuality contributes to psychological reactance and discontinuance. In response to these limitations, Research 2 aims to address the most pressing theoretical gap: the need to deepen our understanding of what “freedom” means to users in personalized environments, and how the erosion of perceived individuality contributes to psychological reactance and discontinuance.

Beyond this theoretical advancement, Research 2 also takes methodological steps to mitigate the biases identified in Research 1. Specifically, adjustments were made in both sample selection and analytical approach. The sample was designed to be more demographically balanced, with greater representation across gender and age groups, to better capture the diversity of user experiences across social media platforms. Moreover, refinements in the analytical framework—such as incorporating platform-specific factors and distinguishing between different types of personalization—were implemented to ensure more context-sensitive interpretation of user responses. These enhancements aim to provide a more valid and generalizable understanding of how perceived threats to freedom and individuality shape discontinuance behavior in algorithmic environments.

3.7 Conclusion

This research has provided a comprehensive understanding of the mechanisms driving social media discontinuance through the lens of PRT and the SSO framework. By surveying 327 users of Facebook and Instagram in Japan, we established that information overload and perceived threats to freedom are significant stressors leading to psychological reactance, which in turn fosters discontinuous usage intentions. Contrary to initial expectations, this research’s findings also revealed that personalized content recommendations can mitigate both information overload and perceived threats to freedom, challenging the traditional view of the personalization paradox.

This research contributes to the literature by empirically validating the direct relationship between information overload and reactance, thereby enriching the understanding of how cognitive stressors influence user behavior. Furthermore, by integrating PRT with the SSO framework, we have highlighted the motivational aspect of reactance as a critical factor in user disengagement from social media platforms.

Practically, these insights underscore the importance for social media platforms to carefully balance content personalization to enhance user satisfaction while avoiding the pitfalls of information overload and perceived autonomy threats. Future research should explore the cultural and contextual nuances that influence these dynamics to further optimize user engagement strategies.

In conclusion, this research underscores the complex interplay between personalization, information overload, and psychological reactance, offering valuable perspectives for both academia and industry to navigate the challenges of sustaining user engagement in the digital age.

4. Research 2: Freedom and Uniqueness in Social Media

Building upon the findings and limitations of Research 1, this chapter aims to refine the theoretical understanding of social media discontinuance by deepening the analysis of what “freedom” means to users in personalized environments. While Research 1 confirmed that perceived threats to freedom significantly predict psychological reactance and discontinuance intention, it left unresolved the critical question of how users conceptualize freedom under algorithmic mediation, and what specific design elements of personalized recommendations might constrain or support that perception.

Existing literature often frames freedom as a basic sense of choice or autonomy (Luqman et al., 2020). However, emerging critical perspectives suggest that digital freedom is increasingly shaped by more complex structural and psychological factors—such as surveillance, loss of self-determination, and algorithmic homogenization (Oldenbourg, 2024). These deeper concerns highlight that freedom is not only about having options, but also about feeling recognized as a unique individual in a system that continuously learns and predicts behavior.

To address the conceptual gap left by Research 1, Research 2 introduces the notion of uniqueness neglect—a psychological condition in which users feel that algorithmic personalization fails to recognize their individuality and instead reduces them to generalized behavioral patterns. In personalized social media environments, users are often positioned as passive recipients of algorithmically selected content, which raises concerns not only about restrictions to choice, but also about the erosion of identity and self-expression. Rather than perceiving personalization as empowering, some users interpret it as a subtle form of control that overlooks their uniqueness and, in doing so, threatens their autonomy and sense of self (Steindl et al., 2015).

This research re-examines the meaning of “freedom” in algorithmically mediated environments through the lens of the need for uniqueness—a fundamental psychological trait reflecting individuals’ desire to maintain a distinct identity. Drawing from psychological reactance theory and informed by literature in media psychology, consumer behavior, and digital sociology, the research proposes that when personalization is perceived to flatten one’s individuality, it can undermine the perceived sense of freedom, trigger psychological reactance, and ultimately lead to discontinuance behavior. In this way, personalization may paradoxically contribute to user alienation, despite its intended role in enhancing relevance and satisfaction.

This research aims to answer the following research questions:

1. How do users define and experience “freedom” in the context of personalized social media environments?
2. In what ways does personalization threaten or support users’ sense of freedom?
3. Does the need for uniqueness amplify users’ sensitivity to algorithmic personalization and perceived threats to freedom?

To explore these questions, we adopt a quantitative survey approach, collecting data from 316 active X users in Japan, with a focus on those who have encountered personalized recommendations on their feed. All measurement items were adapted from validated scales in prior research and assessed through a structural equation modeling (SEM) framework to test the proposed relationships and moderating effects. By focusing on the psychological significance of uniqueness and its interaction with personalization, this study seeks to refine our understanding of freedom in the digital age and extend the explanatory power of reactance-based models of discontinuance.

4.1 Ambiguity of Freedom

The preceding section introduced uniqueness neglect as a psychological mechanism through which personalization may paradoxically undermine user autonomy. Central to this argument is the notion of “freedom”—a concept widely invoked but rarely unpacked in the context of algorithmically mediated environments. To fully understand how users experience psychological reactance and discontinuance, it is first necessary to interrogate the meaning of freedom itself. In particular, how is freedom conceptualized, experienced, and possibly constrained within digital systems that claim to offer personalization and choice? This section begins by critically examining the ambiguity of freedom in social media environments and sets the theoretical foundation for identifying both external and internal sources of perceived freedom threats.

Traditional conceptualizations of user freedom in digital environments have largely equated freedom with the availability of choices—that is, whether users are presented with multiple options to select from. However, this perspective proves increasingly inadequate in algorithmically curated contexts such as social media. On the one hand, the rise of social media has empowered users to express their individuality online, with personal profiles often serving as digital extensions of one’s identity. On the other hand, this space for self-expression is embedded within a system governed by opaque

algorithmic infrastructures, surveillance practices, and behavioral nudging mechanisms that constrain user autonomy in less visible but more pervasive ways (Deibert, 2019). What appears to be user “freedom” may, in fact, be circumscribed by deeper structural conditions that limit genuine agency. Social media platforms provide users with technical tools for content curation, communication, and self-presentation, yet these affordances coexist with systemic limitations. Algorithms selectively prioritize certain content, influence interaction patterns, and steer engagement in ways that are often inscrutable to users.

To resolve this tension, emerging scholarship has called for a reconceptualization of freedom in algorithmic environments. Rather than defining freedom solely in terms of choice abundance, it should also be understood as freedom from domination, manipulation, and opaque influence (Deibert, 2019; Oldenbourg, 2024). Pettit’s (2018) theory of freedom as non-domination offers a particularly relevant lens: freedom entails the absence of arbitrary or uncontrolled interference, even if such interference is not actively exercised. Applying this view to social media, platforms may grant users surface-level autonomy while simultaneously exercising subtle structural and psychological control over users’ choices, actions, and self-conceptions.

Overall, this chapter is organized as follows: it begins by questioning the traditional assumptions of freedom in the context of algorithmic personalization (Section 4.1), then distinguishes between external and internal sources of freedom threats (Section 4.2). Section 4.3 presents the hypotheses development based on this revised conceptualization. This is followed by the detailed research methodology (Section 4.4), empirical results and interpretations (Section 4.5), and a discussion of the study’s implications and limitations (Sections 4.6–4.). Through this design, Research 2 aims to enhance our theoretical understanding of psychological reactance in the digital era and offer actionable insights into the personalization–autonomy paradox that increasingly characterizes social media usage.

4.2 The Dual Nature of Threats to Freedom in Social Media

In algorithmically mediated social media environments, users’ freedom is not only about having more choices—it is also about how those choices are shaped, presented, and interpreted. Building on both psychological and sociotechnical perspectives, this research identifies two core pathways through which recommendation systems threaten user freedom: external constraints and internal misrecognition. More specifically,

external constraints, rooted in cognitive overwhelm and control loss, and internal misrecognition, stemming from perceived identity flattening and symbolic misrepresentation.

External Constraints: Cognitive Overload and Loss of Control

One prominent threat comes from the volume and repetition of algorithmically curated content. Social media feeds often deliver a barrage of posts, ads, and suggestions, many of which feel redundant or irrelevant. Prior research has shown that such information overload undermines users' perceived autonomy by making it difficult to meaningfully navigate or manage choices (Sahebi & Formosa, 2022; Bui et al., 2022). In digital environments, autonomy is not defined by having many options, but by having the mental capacity and control to process them effectively (Hodgins & Knee, 2002). When this control is lost, users may experience psychological strain or even reactance, resisting the system's perceived manipulation.

Internal Misrecognition: Neglect of Uniqueness and Identity Flattening

The second threat is more symbolic and identity-related. Recommendation systems typically rely on pattern recognition and clustering to push "personalized" content. However, this process often reduces individuals to broad categories, neglecting the uniqueness of personal context, values, and evolving interests. Users may thus encounter content that, while statistically aligned, feels emotionally misaligned—generic, stereotyped, or irrelevant in deeper ways.

This form of uniqueness neglect threatens users' expressive autonomy and self-perception. As Stiglbauer & Kovacs (2019) and Knight & Kim (2007) show, users with strong needs for differentiation are particularly sensitive to algorithmic misrepresentation. What frustrates users is not just poor accuracy, but being misclassified by the system—a symbolic denial of individuality. This experience can generate reactance, as users seek to reassert control over how they are seen and understood (Oldenbourg, 2024). Such misrecognition may also constitute a form of epistemic injustice, where systems presume the authority to define users without their input. When users feel misrepresented by the very systems designed to "know" them, they may disengage or even deliberately manipulate their own data to disrupt algorithmic inference (Sahebi & Formosa, 2022).

Therefore, this chapter centers on these two forms of freedom threat. The next sections examine how (1) information overload, by overwhelming the user's sense of

control, and (2) uniqueness neglect, by eroding the recognition of individual identity, serve as core antecedents to perceived threats to freedom—and how these threats, in turn, may induce psychological reactance in the personalized media environment.

4.3 Hypotheses Development

Building upon the previous discussion of freedom as a multifaceted experience in digital environments, we argue that threats to autonomy in personalized social media can be understood through two distinct yet interrelated psychological pathways. The first involves the quantitative dimension—information overload—where an excess of algorithmically recommended content overwhelms users’ cognitive capacity and diminishes their perceived control. The second, more qualitative in nature, concerns how users’ identities are interpreted and responded to by the system. While informational burden may erode freedom by impairing the user’s ability to make meaningful choices, symbolic misrecognition—when users feel they are misunderstood, oversimplified, or flattened by algorithmic inferences—can equally threaten their sense of self-determination.

In this light, freedom is not merely about how much content is delivered, but also about how accurately that content reflects users’ self-concept. This distinction leads us to introduce the concept of uniqueness neglect, which captures a different kind of autonomy violation—one rooted not in volume, but in representation. When recommender systems fail to acknowledge users as complex, evolving individuals, and instead categorize them based on reductive behavioral cues or demographic profiling, users may experience a subtle but powerful erosion of agency. The following section further develops this concept and establishes hypotheses that articulate its psychological and behavioral consequences within the personalized media ecosystem.

In digital environments increasingly shaped by algorithmic decision-making, users’ sense of freedom is often challenged not only by the volume of information but also by how they are perceived and categorized by systems. Prior research on digital freedom has primarily focused on structural or cognitive constraints, such as information overload (IO), which occurs when users are exposed to more content than they can meaningfully process (Eppler & Mengis, 2004). However, recent scholarship has highlighted a second, more symbolic form of threat to autonomy: uniqueness neglect (UN).

Uniqueness neglect refers to the perceived failure of algorithmic systems—particularly those involving recommendation or personalization—to recognize and affirm individuals’ personal distinctiveness (Longoni et al., 2019). Grounded in uniqueness theory, this concept assumes that individuals are fundamentally motivated to maintain a distinct sense of self through their preferences, attitudes, and choices (Tian et al., 2001). When users feel reduced to behavioral stereotypes, demographic categories, or oversimplified preferences, this motivational need may be thwarted, leading to psychological discomfort. According to Psychological Reactance Theory, such discomfort can trigger a motivational state aimed at restoring threatened autonomy—known as psychological reactance (Brehm, 1966). Empirical studies across domains such as medical AI, chatbot interactions, and recommender systems have revealed that user resistance is not always driven by performance deficiencies, but often stems from deeper psychological concerns such as identity misrecognition and symbolic dehumanization (Longoni et al., 2019). These findings underscore that users may disengage from digital systems not because the technology fails functionally, but because it overlooks their individuality—a phenomenon we refer to as uniqueness neglect. Despite its relevance, this construct remains underexplored in the context of social media discontinuance.

Building on the insights from Research 1, which demonstrated that psychological stressors such as perceived freedom threat and cognitive overload significantly influence discontinuance behaviors, we propose a revised framework in Research 2. This framework introduces two key psychological antecedents—information overload and uniqueness neglect—and investigates how they contribute to users’ sense of threatened freedom and, subsequently, to psychological reactance and discontinuous usage. To better capture this process, we also consolidate cognitive and affective responses under a unified construct of threat-reactance, reflecting users’ mental strain in response to perceived constraints.

As a first step, we focus on information overload—a widely recognized stressor in digital environments characterized by an excess of content and diminished user processing capacity. One core function of recommendation systems is to mitigate this overload by filtering irrelevant information and surfacing content aligned with users’ preferences. When personalization is effective, it can reduce the cognitive burden associated with navigating content-dense platforms, thereby improving user experience (Eppler & Mengis, 2004). This aligns with the findings from Research 1, which

indicated that perceived personalization was associated with lower levels of information overload.

H1: Perceived personalization is negatively associated with information overload.

Ideally, personalization and uniqueness should go hand-in-hand: the more personalized the content, the more the system reflects one's individual preferences, thereby affirming the user's identity. However, in practice, this relationship is more complex and ambivalent, shaped by how users perceive the mechanisms and outcomes of personalization. On one end of the spectrum, a lack of personalization may lead to generic, undifferentiated content, which fails to distinguish between users altogether. In such environments, users may feel that their unique tastes and identities are not even considered—they are just another user in the crowd. This leads to a kind of structural neglect, where distinctiveness is absent by design.

On the other end, high levels of personalization may also result in uniqueness neglect, albeit through a different route. When personalization is implemented through rigid algorithmic classification, users may feel labeled, boxed in, or stereotyped. Rather than experiencing personalization as a recognition of who they are, they may perceive it as an oversimplified projection of who the system assumes them to be, based on prior behavior, aggregated norms, or demographic proxies (Longoni et al., 2019). This misalignment has been referred to as algorithmic misrecognition, wherein users feel the system fails to accurately reflect their dynamic identities (Alvarado & Waern, 2018). For example, users have expressed frustration when algorithms seem to reinforce unwanted stereotypes or overly narrow labels, rather than accommodate complexity and personal evolution (Karizat et al., 2021).

This is particularly problematic in identity-expressive platforms like social media, where users actively construct and present dynamic versions of themselves. If recommendation systems serve only to reinforce past behavior or narrow user interests, users may feel that their capacity for growth, complexity, and exploration is being ignored (Mou, Xu & Hu, 2023). For individuals with a strong need for uniqueness, this experience may feel especially constraining or misaligned. Therefore, perceived personalization can simultaneously signal recognition and misrecognition. It may affirm users' identities when executed well, but undermine them when perceived as reductive or overly deterministic. This dual nature reflects the inherent tension in algorithmic personalization: it intends to tailor, but often categorizes; it aims to serve

the individual, but operates through statistical generalization. As Złotowski et al. (2017) argue, identity threats can emerge when technological systems blur the boundary between personal agency and machine-determined representation—an insight that is equally relevant in the context of recommender systems.

Empirical studies further support this complexity. While users often appreciate personalization for improving relevance and usability, they may also disengage when recommendations become overly predictable or feel misaligned with their evolving interests. Over time, the system's persistent efforts to tailor content can paradoxically result in narrower and more repetitive outputs, reducing the sense of novelty and personal discovery. Nguyen et al. (2014) found that content diversity declines measurably with continued use, suggesting that even personalized systems may gradually constrain user experience rather than enhance it.

Given this nuanced landscape, we do not hypothesize a directional relationship between personalization and uniqueness neglect. Instead, we propose that the perception of personalization—whether affirming or reductive—plays a key role in shaping whether users feel uniquely understood or categorically flattened.

H2: Perceived personalization is significantly associated with uniqueness neglect

Information overload is not merely a cognitive strain—it often erodes perceived control, leading to psychological discomfort and behavioral resistance. Users confronted with excessive, rapid, or irrelevant content may feel their freedom of choice is compromised, especially when algorithmic systems dominate content curation (Pizzi et al., 2021; Lee & Lee, 2009). In alignment with reactance theory (Brehm, 1966), such constraint leads to motivational resistance aimed at regaining autonomy.

Findings from Research 1 supported this link: IO was a strong predictor of psychological reactance, reinforcing its role as a pathway to user disengagement.

H3: Information overload is positively associated with perceived reactance.

Beyond cognitive burdens like information overload, symbolic threats to identity have also emerged as powerful triggers of psychological reactance. In algorithmically mediated environments, users increasingly expect technologies to support not only efficient interaction, but also meaningful recognition of their individuality. When these expectations are violated—when users feel that the system ignores, misrepresents, or reduces their personal identity—they may perceive a threat to their expressive freedom:

the capacity to define and present themselves authentically in a digital space (Longoni et al., 2019).

This aligns with Pettit's (2018) conception of freedom as non-domination, where freedom is compromised not only by overt restrictions but also by subtle, uncontrolled influences that limit one's autonomy or self-expression. In this view, uniqueness neglect—the perception that an algorithmic system treats one as a generic, undifferentiated user—can constitute a symbolic form of domination. Even if the system offers choices, it fails to acknowledge the user's distinct identity, which can lead to a perceived loss of voice and agency. Such experiences are particularly salient in interactions with chatbots or recommender systems, where users report dissatisfaction due to the sense that “the system doesn't understand who I really am.” This misalignment between users' self-concept and the algorithmic representation can elicit strong emotional and cognitive resistance. Prior research has shown that algorithmic systems are often perceived as reductive—failing to account for users' nuanced identities and instead simplifying them into statistical profiles or behavioral categories. As one participant described, “It's reducing a human being to a percentage” (Binns et al., 2018). The system, in this case, is seen not merely as impersonal, but as intrusively shaping one's digital self in ways that conflict with internal identity cues, thereby undermining the user's sense of authenticity and autonomy.

Therefore, we argue that uniqueness neglect functions as a symbolic psychological stressor that undermines the perceived freedom to self-express and assert identity. This, in turn, generates psychological reactance—a defensive response to perceived constraints on autonomy and self-determination.

H4: Uniqueness neglect is positively associated with perceived reactance.

Finally, we argue that psychological reactance, triggered by either cognitive or symbolic constraints, leads to discontinuous usage behavior. Users experiencing reactance tend to reduce engagement, deactivate features, or abandon platforms altogether in an attempt to reassert autonomy (Ma et al., 2022). This was strongly supported in Research 1, where reactance emerged as a consistent predictor of platform abandonment or avoidance.

H5: Perceived reactance is positively associated with discontinuous usage behavior.

The proposed research model is illustrated in the following diagram (Fig. 4):

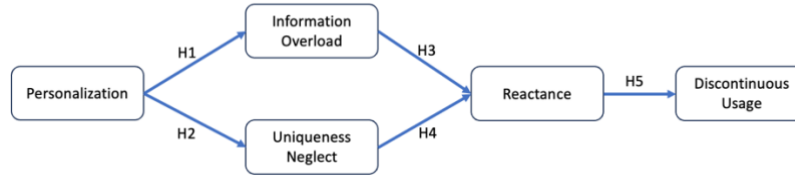


Fig.4 The research model (Research 2)

4.4 Research Methodology

4.4.1 Data Collection

To empirically test the proposed hypotheses, this study employed a quantitative survey approach using a structured questionnaire distributed online. Building on methodological insights from Research 1, where combining data from multiple platforms introduced platform-specific confounds, Research 2 refined the sampling strategy by focusing exclusively on one platform—X (formerly Twitter).

X was selected for three primary reasons. First, its content delivery is driven by real-time recommendation algorithms, which determine what users see based not only on who they follow, but also on behavioral patterns, trending data, and inferred interests. This makes X an ideal context for studying the effects of algorithmic personalization on user perception. Second, unlike traditional social networking platforms that prioritize relational content (e.g., posts from friends or family), X emphasizes feed-based content discovery, with a high proportion of information being algorithmically selected rather than user-initiated. This dynamic increases the visibility and salience of algorithmic influence, making constructs such as perceived uniqueness neglect and freedom threats more psychologically accessible to users. Third, X users frequently engage with recommended posts, accounts, and topics, offering rich ground for investigating the nuanced psychological responses to automated decision-making systems.

Survey data were collected on May 17, 2025, using the Yahoo! Crowdsourcing platform, a widely adopted crowdsourcing service in Japan. This platform enables access to a large pool of registered users who participate in tasks—such as completing online surveys—in exchange for PayPay points, a digital reward system. This incentive mechanism, combined with the platform’s broad demographic reach, ensured both high

response speed and a diverse sample composition. Prior to launching the survey, the questionnaire was pre-tested and then published as a task on the platform. A screening question was embedded to ensure that only active users of X could proceed. Additionally, a brief standardized explanation of the X platform's recommendation algorithm was provided at the beginning of the survey to ensure consistent baseline understanding among respondents.

Prior to launching the survey, the questionnaire was carefully designed and uploaded as a task on the platform. A filter question was embedded to ensure that only users of X could proceed with the survey. Participants were informed about the study's background and were explicitly asked about their prior experience with these platforms. After completing this screening process, data collection was automatically terminated once 350 valid responses were obtained.

The decision to collect 350 responses was based on methodological considerations. To ensure the statistical adequacy of covariance-based structural equation modeling (CB-SEM), a minimum sample size of 300 valid responses was targeted. According to Kline (2023), CB-SEM generally requires larger sample sizes than alternative estimation methods, particularly when involving multiple latent variables and complex paths. Likewise, Hair et al. (2017) recommend a sample size between 200 and 400 for models estimated using the maximum likelihood method, with 300 or more considered ideal for models of moderate complexity. By collecting 350 responses, we accounted for the possibility of low-quality data (e.g., patterned answers, inconsistent responses, or abnormally fast completion times) to ensure a robust final dataset.

Following data collection, a two-step screening process was conducted. First, responses were checked to confirm whether participants were indeed X users. Second, several attention-check items were embedded throughout the questionnaire. For example, respondents were asked to solve a simple arithmetic question ("200 + 300 = ?") or follow a specific instruction (e.g., "Please select 'Strongly Disagree' for this question"). Responses that failed these checks or demonstrated clear internal inconsistencies were removed. As a result, 34 responses were excluded, resulting in a final sample of 316 valid responses, yielding a usable response rate of 90.3%. Detailed demographic information is presented in Table 8.

Table 8. Demographic Information

Variable	Category	Frequency	Percentage
Gender	Male	208	65.82%
	Female	108	34.18%
Age	18-30	21	6.65%
	31-40	91	28.80%
	41-50	201	63.61%
	above 50	3	0.95%
Education Level	High School	69	21.84%
	University	185	58.54%
	Graduate School	14	4.43%
	Junior College	23	7.28%
	Middle School	8	2.53%
	Other	17	5.38%
Frequency of X Daily Usage	Less than once/week	16	5.06%
	1–5 times/week	44	13.92%
	Once/day	47	14.87%
	2–4 times/day	96	30.38%
	5+ times/day	113	35.76%

To minimize potential biases caused by nonresponse and common method variance (CMV), two post-hoc statistical tests were conducted to ensure the robustness of the data. First, an Early–Late Response Comparison was performed to assess potential nonresponse bias. This method, originally proposed by Armstrong and Overton (1977), assumes that late respondents are more similar to non-respondents than early ones. If no significant differences are observed between early and late respondents, it can be inferred that nonresponse bias is unlikely. Widely adopted in online survey research (Rogelberg & Stanton, 2007), this approach was implemented by dividing responses into early and late groups based on submission time. Independent sample t-tests were conducted for five key constructs: personalization (Per), uniqueness neglect (UN), freedom threat (Re), information overload (IO), and discontinuance (Dis). The results revealed no statistically significant differences between the two groups across any of the constructs (e.g., freedom threat: $t = 0.175$, $p = 0.861$; information overload: $t = -0.731$, $p = 0.466$; reactance: $t = 0.406$, $p = 0.686$), suggesting that nonresponse bias was not a major concern.

Second, to assess the risk of common method variance (CMV), the Harman's Single Factor Test was conducted following the recommendation of Podsakoff et al. (2003). All survey items—both independent and dependent variables—were entered into an exploratory factor analysis (EFA) using principal component analysis (PCA) without rotation in SPSS 23. The analysis revealed that the first unrotated factor accounted for 42.99% of the total variance. This value falls below the commonly accepted threshold of 50% (Podsakoff et al., 2003), indicating that CMV is unlikely to pose a serious threat to the validity of the results.

This carefully controlled sampling process and platform selection ensured that participants had adequate exposure to algorithmic recommendation systems, enabling reliable measurement of the key psychological constructs under investigation.

4.4.2 Survey Design and Measurements

The proposed research model was operationalized by capturing data on respondents' demographic characteristics, social media discontinuance intentions, and five theoretical constructs. All variables were assessed using a 7-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). Measurement items were adapted from validated scales in prior literature and reworded to fit the algorithmic recommendation context of the X platform. A pretest was conducted to ensure conceptual clarity, item relevance, and linguistic appropriateness for Japanese social media users.

The construct of Perceived Recommendation Personalization (Per) was measured using three items adapted from Chen, Sun, and Liu (2022). These items evaluated the extent to which users believed that the X platform's recommended content was personalized, relevant, and tailored to their preferences, capturing subjective perceptions of system accuracy and content fit.

Information Overload (IO) was measured using a three-item scale derived from Fu et al. (2020), focusing on users' cognitive responses to overwhelming volumes of recommended content. The items assessed feelings of informational fatigue, difficulty processing content, and being distracted by the platform's continuous updates.

Uniqueness Neglect (UN) was introduced as a theoretically novel construct in Research 2 and represents a key conceptual contribution of this research. It was assessed using a three-item scale adapted from Longoni, Bonezzi, and Morewedge (2019), which was originally developed in the context of AI-driven medical decision-

making but has since been extended to explain user resistance in algorithmic personalization. The scale measured the perceived failure of the recommendation system to recognize and account for one's unique personal traits, needs, or circumstances. Sample items included "The system would not recognize the uniqueness of my situation" and "The system would not tailor recommendations to my unique needs."

To capture the users' motivational and emotional responses to perceived threats, Reactance (Re) was modeled as a unified latent construct, combining perceived threats to freedom and psychological reactance. Items were adapted from Youn and Kim (2019) and Shen and Dillard (2005), reflecting both cognitive evaluations (e.g., constrained choice) and affective responses (e.g., frustration, defiance) toward the system. The final six-item scale was refined to reflect experiences unique to the X platform's algorithmic feed.

Discontinuous Usage Intention (DUI) was assessed using four items adapted from Zhang et al. (2016), measuring both short-term disengagement behaviors (e.g., avoiding platform content) and long-term exit intentions (e.g., considering deactivation or abandonment of the platform).

All measurement items were subjected to confirmatory factor analysis (CFA) to evaluate construct validity. Detailed results regarding reliability, convergent validity, and discriminant validity are presented in the next section.

4.4.3 Justification for Combining Threat to Freedom and Reactance

In this subsection, we elaborate the rationale and procedure for integrating the constructs of perceived Threat to Freedom (TTF) and psychological Reactance (Re) into a single latent dimension. This decision emerged from both theoretical considerations and empirical observations in the earlier phases of the research. As discussed in prior sections, users in algorithmically curated environments often report simultaneous experiences of constraint and motivational resistance, which challenges the traditional assumption of a sequential relationship between threat and reactance. To better capture this intertwined psychological process, the present study tests whether TTF and Re can be statistically modeled as a unified factor. The section proceeds by presenting the theoretical grounding for this integration, followed by a semantic and measurement-level justification, and concludes with empirical evidence from both exploratory and confirmatory factor analyses.

In the present research, the constructs of perceived threat to freedom (TTF) and psychological reactance (Re) are conceptually and empirically integrated into a single latent factor termed Reactance, which represents users' holistic psychological responses to perceived constraint in algorithmic environments. This decision is underpinned by theoretical rationale, semantic alignment in measurement items, empirical evidence from Research 1, and user-based interpretive insights. Theoretically, the decision is rooted in the foundational logic of Reactance Theory (Brehm, 1966), which asserts that psychological reactance is a motivational state directly triggered by perceived threats to one's autonomy. Although threat and reactance were originally viewed as occurring in sequence—with the perception of threat coming first and reactance following—it is increasingly difficult to separate the two in algorithm-driven personalized environments. The control exerted by algorithms is often subtle and continuous, making users feel both restricted and resistant at the same time. Recent studies have shown that in such digital settings, users tend to experience feelings of constraint and psychological pushback simultaneously, rather than in a clear step-by-step manner (Steindl et al., 2015; Pizzi et al., 2021; Mou et al., 2023). Given this overlap, it is reasonable to view threat and reactance as part of the same underlying psychological response.

Furthermore, semantic and measurement analysis reveals a high degree of content overlap between the two constructs. Items from the TTF scale (Youn & Kim, 2019) and the Reactance scale (Shen & Dillard, 2005) exhibit considerable redundancy in meaning, often tapping into the same psychological domain. Both sets of items assess users' sense of constrained autonomy, imposed content control, and motivational pushback. For instance, statements like “I feel the platform limits my choices” and “I want to oppose what the system recommends” differ in framing but converge in psychological implication. This overlap indicates that the constructs are not clearly distinguishable in user interpretation, but rather form a continuous experiential spectrum of constraint and resistance.

Empirical findings from Research 1 further support this integration. A high correlation ($r > 0.70$) was observed between TTF and Re, suggesting substantial conceptual proximity. Moreover, both exploratory and confirmatory factor analyses revealed that these items consistently loaded onto a single factor, failing to demonstrate discriminant validity when treated as separate constructs. When modeled as a unified latent variable, model fit improved significantly, providing statistical justification for

their consolidation into a single dimension representing users' psychological response to algorithmic restriction.

This measurement convergence is also supported by qualitative data. In a series of cognitive interviews and open-ended responses collected during the pilot phase, participants often described their emotional reactions to algorithmic content control in blended terms. Users expressed frustration, irritation, and resistance as immediate responses to perceived loss of choice, indicating that for them, the distinction between “feeling restricted” and “feeling resistant” was blurred or non-existent. This interpretation aligns with recent advances in AI-user interaction research, which increasingly treat control, discomfort, and rejection as co-occurring responses rather than separate emotional phases (Longoni et al., 2019).

Finally, to further examine the construct validity and dimensional structure of the psychological responses under investigation, an exploratory factor analysis (EFA) was conducted. Specifically, this analysis aimed to assess whether the items adapted from the two conceptually related constructs—Threats to Freedom (TTF) and Reactance (Re)—could be integrated into a unified latent factor representing users' psychological responses to algorithmic constraints.

The EFA was performed using Principal Component Analysis (PCA) with Varimax rotation and Kaiser normalization, a widely adopted approach for identifying distinct, orthogonal factors. Although all factor loadings above 0.40 were initially reported in Table 9 to ensure full transparency of the loading structure, the analysis revealed that all six items originally drawn from the TTF and Reactance scales exhibited strong loadings above 0.70 on a single dominant component (ranging from 0.712 to 0.799). According to Hair et al. (2017), loadings above 0.70 indicate that each item shares at least 49% of its variance with the latent construct, thus satisfying the more stringent threshold typically used in confirmatory factor analysis (CFA). This finding provides robust evidence that the TTF and Re items form a conceptually and statistically unified factor, with no significant cross-loadings observed on other components. As shown in Table 9, the resulting component also demonstrated high internal consistency (Cronbach's $\alpha > 0.70$) and strong convergent validity ($AVE > 0.50$). Together, these results support the decision to model Threats to Freedom and Reactance as a single, higher-order Reactance construct, reflecting users' integrated psychological response to algorithmic constraint in social media environments.

Based on these results, both theoretically and statistically, Threats to Freedom and Reactance were deemed to reflect a single, unified construct of psychological reactance in the context of algorithmic recommendation systems. This finding justifies the modeling decision to represent them jointly as a higher-order factor in subsequent structural analyses.

Table 9. Rotated Component Matrix

	Component				
	1	2	3	4	5
Per1				.881	
Per2				.903	
Per3				.842	
IO1					.757
IO2					.835
IO3					.791
IO4					<u>.412</u>
TTF1	.703				
TTF2	.776				
TTF3	.720				
TTF4	.717				
Re1	.743				
Re2	.712				
Re3	.751				
Re4	.799				
Re5	.798				
UN1			.749		
UN2			.795		
UN3			.809		
Dis1		.806			
Dis2		.765			
Dis3		.712			
Dis4		.721			

Note: All factor loadings ≥ 0.40 are reported. Extraction method: PCA with Varimax rotation.

4.4.4 Structural Model

To ensure the reliability and validity of the scales used in this research, SPSS 23 and AMOS 23 were employed for model assessment. Scale reliability was assessed using Cronbach's alpha (Nunnally, 1978), with all constructs exceeding the benchmark of 0.7 for acceptability. The composite reliability (CR) for each construct also surpassed the 0.8 threshold (Fornell & Larcker, 1981), indicating strong internal consistency.

In the measurement model, one loading item for Information Overload (Io4) was below the threshold of 0.5. Considering that the other three items for IO loaded above 0.7 and demonstrated good measurement consistency, Io4 was removed to improve model quality. After item refinement, all constructs met the criterion of average variance extracted (AVE) > 0.5 (Fornell & Larcker, 1981), confirming adequate convergent validity. These results, detailed in Table 10, meet all established criteria. The discriminant validity of the model was established by comparing the square roots of the AVEs with the squared inter-construct correlations, as shown in Table 11. All AVE square roots exceeded the correlations with other constructs, thereby satisfying the criterion.

Path analysis using AMOS 23.0 was conducted to test the structural model. The Maximum Likelihood (ML) estimation method was applied with a correlation matrix as input, in accordance with standard SEM procedures. The selection of the ML method was based on its robustness in estimating model parameters under conditions of approximate multivariate normality and its widespread use in theory testing (Byrne, 2016; Reinartz et al., 2009).

As shown in Table 12, the model demonstrated an acceptable level of fit, with the following indices: $\chi^2/df = 2.698$, CFI = 0.921, GFI = 0.866, AGFI = 0.834, and RMSEA = 0.074. While these values do not meet the most stringent cutoffs (e.g., CFI $\geq .95$, RMSEA $\leq .06$; Hu & Bentler, 1999), they fall within the commonly accepted range for reasonable fit (Schermelleh-Engel, Moosbrugger & Müller, 2003; Kline, 2016).

Table 10. Reliability and convergent validity analysis (Io4 was eliminated).

	Item	Standardized factor loading	CR	AVE	Cronbach's α
Personalization (Per)	Per1	0.846	0.960	0.755	0.726
	Per2	0.933			
	Per3	0.823			
Information overload (Io)	Io1	0.823	0.944	0.604	0.706
	Io2	0.810			
	Io3	0.692			
Uniqueness Neglect (Un)	Un1	0.913	0.977	0.783	0.744
	Un2	0.912			
	Un3	0.826			
Reactance (Re)	Free1	0.752	0.933	0.510	0.939
	Free2	0.681			
	Free3	0.707			
	Free4	0.775			
	Re1	0.845			
	Re2	0.721			
	Re3	0.788			
	Re4	0.896			
	Re5	0.838			
Discontinuous usage intention (DUI)	Dui1	0.796	0.959	0.535	0.752
	Dui2	0.710			
	Dui3	0.606			
	Dui4	0.797			

Table 11. Correlation matrix

	Mean	SD	Person	InfoOver	Unique	Reactance	Disuse
Person	4.557	1.050	0.869				
InfoOver	3.717	1.051	-0.005	0.777			
Unique	4.047	1.121	-0.524	0.406	0.885		
Reactance	3.572	1.085	-0.313	0.555	0.648	0.714	
Disuse	3.717	1.051	-0.314	0.375	0.511	0.627	0.731

Note: Diagonal numbers are the square root of AVE

Table 12. Model fit

Indicator	Criteria	Source	Result
Chi-square/d.f.	<3.0	Hayduk (1987)	2.698
GFI	>0.8	Baumgartner & Homburg (1996)	0.866
AGFI	>0.8	Baumgartner & Homburg (1996)	0.834
CFI	>0.9	Bagozzi (1988)	0.929
RMSEA	<0.08	Bagozzi (1988)	0.073

As with Research 1, this research adopts a flexible yet theory-driven approach to model evaluation. First, model fit was assessed using multiple indices from different classes—absolute, incremental, and residual-based—to capture different aspects of fit and avoid over-reliance on any single measure (West, Taylor & Wu, 2012). Second, the slightly lower fit values are justifiable given the model’s structural complexity, including multiple latent constructs and mediating paths, which make achieving “excellent fit” statistically difficult (Kenny, Kaniskan & McCoach, 2015). Third, moderate sample size may affect the sensitivity of certain indices such as RMSEA and GFI, both of which are known to be influenced by sample characteristics (MacCallum & Hong, 1997).

Taken together, these considerations support the use of more context-sensitive fit criteria, especially in applied behavioral research. The reported values thus indicate that the model is statistically sound and theoretically meaningful, in line with best practices in the field (Marsh, Hau & Wen, 2004).

4.4.5 Mediation Analysis

In this model, two indirect pathways to Discontinuous Usage Intention (DUI) were tested. The first pathway examined how Information Overload (IO) influences DUI through Reactance. The second focused on the effect of Uniqueness Neglect (UN) on DUI, also mediated by Reactance. Additionally, the effect of Perceived Personalization was evaluated through its influence on both IO and UN.

The mediation effects were tested using the bootstrap method, which is recognized for its accuracy in estimating indirect effects in complex mediation structures (Cheung & Lau, 2008). In this research, the number of bootstrap resamples was set to 5000, with a 95% confidence interval, and ML estimation was employed. The results of the mediation analysis are presented in Table 13. Two alternative pathways were tested to examine the psychological mechanisms linking perceived personalization (Per) to user

reactance (Re): one via information overload (Info), and the other via perceived uniqueness neglect (UN).

First, while information overload did not mediate the relationship between personalization and reactance (indirect effect = -0.001 , $p = .989$), it exhibited a significant direct effect on reactance (estimate = -0.352 , $p < .001$). This suggests that users who experience higher levels of information overload are more likely to develop psychological reactance, regardless of their perception of personalization.

In contrast, uniqueness neglect served as a significant and full mediator. The indirect effect of personalization on reactance via UN was significant (estimate = -0.397 , $p < .001$), while the corresponding direct effect of personalization on reactance was not statistically significant (estimate = 0.043 , $p = .549$). This pattern indicates that users' psychological responses to personalization are primarily shaped by whether they feel their individuality is acknowledged or overlooked.

Taken together, these findings suggest that cognitive overload and identity-related concerns function through distinct pathways. While information overload directly heightens user reactance, the impact of personalization on reactance is fully explained by its influence on perceived uniqueness neglect. In other words, algorithmic personalization that fails to reflect users' individual uniqueness may provoke stronger psychological reactance than one that simply presents too much information.

Table 13. Results of the mediation analysis

Path		Estimate	Lower	Upper	P
Per — Info — Re	Per indirect	-0.001	-0.088	0.095	0.989
	Per direct	-0.352	-0.502	-0.22	0
	Total	-0.352	-0.519	-0.191	0
Per — UN — Re	Per indirect	-0.397	-0.513	-0.297	0
	Per direct	0.043	-0.099	0.177	0.549
	Total	-0.354	-0.52	-0.192	0

Note: Info = Information Overload, Re = Reactance, Per = Personalization, UN = Uniqueness Neglect

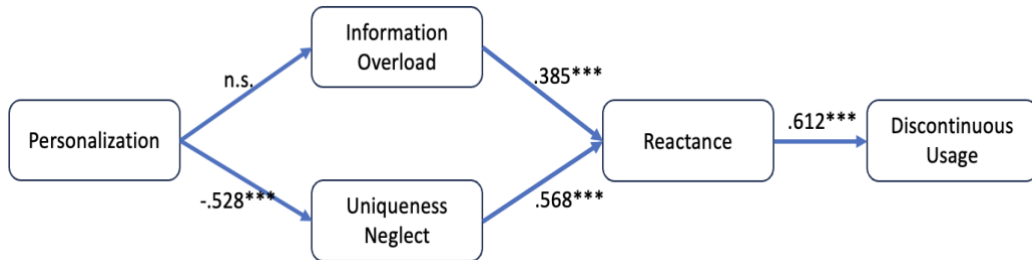
In sum, all proposed hypotheses were supported except for H2, which did not yield significant results. The final structural model, including the standardized path coefficients, is presented in Table 14 and visualized in Figure 5. These findings provide robust empirical support for the proposed framework and highlight the central role of

Reactance as a mediating mechanism linking platform experiences to disengagement intentions.

Table 14. Summary of hypotheses test.

	Hypothesis	Estimate	C.R.	P	Results
H1	Personalization → Information Overload	-0.028	-0.437	0.662	n.s.
H2	Personalization → Uniqueness Neglect	-0.528	-9.162	***	Support
H3	Uniqueness Neglect → Reactance	0.568	10.854	***	Support
H4	Information Overload → Reactance	0.385	7.139	***	Support
H5	Reactance → Discontinuous Usage Intention	0.612	9.76	***	Support

Note: * $p < .05$. ** $p < .01$. *** $p < .001$.



Note: * $p < .05$. ** $p < .01$. *** $p < .001$.

Fig. 5 Structural equation modeling results

4.4.6 Control Variable Analysis

In order to enhance the robustness and internal validity of the structural model, we conducted a comprehensive control variable analysis following established structural equation modeling (SEM) practices (Kline, 2023). This procedure aims to account for potential confounding influences from demographic or behavioral characteristics that might bias the relationships between the focal variables. Specifically, we selected age, educational background (education level), and frequency of platform usage as control variables, based on prior research suggesting their potential relevance in shaping user attitudes and technology-related behavioral responses.

To ensure the robustness of the structural model and to account for potential confounding influences, several demographic variables were included as control variables in the analysis. Specifically, age, education, and frequency of platform usage were incorporated following standard practices in SEM. Age was measured on a continuous scale and directly included in the model without transformation. Education,

originally collected as a categorical variable with six levels (“Junior high school,” “High school,” “Junior college,” “University,” “Graduate school,” and “Other”), was recoded into a five-point ordinal scale ranging from 1 (Junior high school) to 5 (Graduate school), allowing for ordered interpretation within the model. Responses marked as “Other” were treated as a separate category and coded as 0 to reflect their non-comparability with standard educational levels. Platform usage frequency was assessed through a five-point ordinal item ranging from “More than 5 times per day” to “Less than once per week.” Although this variable is not strictly continuous, it was treated as a pseudo-continuous ordinal covariate in the structural equation model. This approach aligns with methodological recommendations in behavioral SEM research, which suggest that ordinal variables with five or more categories can be treated as continuous when appropriate (Rhemtulla et al., 2012). This variable specification allowed for consistent and theoretically grounded incorporation of demographic controls into the model.

To assess the potential impact of background characteristics on the structural relationships of interest, this research incorporated age, education, and frequency of platform usage as control variables. These covariates were introduced to evaluate whether the hypothesized model remained robust after accounting for individual differences in demographic and behavioral attributes. All control variables were modeled in AMOS 23 as single-indicator observed variables, consistent with standard SEM practice (Kline, 2023). Each covariate was treated as an exogenous variable and specified with direct paths to all endogenous latent constructs in the model. This strategy allows for the statistical control of covariates while preserving the core theoretical structure.

Consistent with Spector and Brannick (2011), we treated control variables as theoretically neutral components and incorporated them into the structural model by specifying direct paths from each covariate to all endogenous constructs. Rather than assuming their necessity, we evaluated their empirical influence through a series of structured model comparisons, aligning with recommendations to avoid arbitrary statistical adjustments. Specifically, we constructed and compared three versions of the model: (1) a baseline model without any control variables; (2) a fully adjusted model that included age, education, and platform usage frequency simultaneously; and (3) models in which each control variable was added separately to examine their individual effects.

Model performance across these specifications was evaluated using five widely accepted fit indices: chi-square divided by degrees of freedom (χ^2/df), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). These indices were selected based on recommendations that no single fit statistic is sufficient to evaluate model adequacy (West, Taylor & Wu, 2012). CFI and RMSEA are particularly valued for their robustness to sample size and model complexity (Hu & Bentler, 1999; Kenny et al., 2015), while GFI and AGFI, though more sensitive to sample characteristics, are still commonly reported in consumer behavior research for consistency and interpretability (Baumgartner & Homburg, 1996).

Table 15. Comparison of Model Fit Indices With and Without Control Variables

Model	χ^2/df	GFI	AGFI	CFI	RMSEA
Baseline (no control)	2.785	0.883	0.848	0.928	0.074
With Frequency	2.624	0.865	0.832	0.927	0.072
With Age	2.54	0.869	0.837	0.93	0.07
With Education	2.564	0.868	0.835	0.928	0.07
Simultaneously (All)	2.419	0.864	0.831	0.925	0.067

Note: All models met conventional thresholds for acceptable model fit ($\chi^2/\text{df} < 3.0$; GFI $> .80$; AGFI $> .80$; CFI $> .90$; RMSEA $< .08$).

As shown in Table 15, model fit indices were compared across five specifications: the baseline model (no control variables), models with each control variable entered separately (age, education, and platform usage frequency), and a fully adjusted model with all three covariates included simultaneously. Across all versions, the model consistently met conventional thresholds for acceptable fit—CFI values remained above 0.92, RMSEA values stayed below 0.08, and GFI and AGFI both exceeded 0.83—demonstrating that the inclusion of demographic and behavioral control variables did not materially impair model performance. These results confirm that the hypothesized structural relationships were stable and theoretically meaningful regardless of background covariates.

In addition to model fit comparisons, we also examined the structural paths from each control variable to all endogenous latent constructs to evaluate their direct influence. Results showed that age and education did not exhibit any statistically significant relationships with the key constructs in the model. In contrast, platform usage frequency demonstrated one notable effect: it was significantly and negatively associated with disuse intention ($\beta = -0.296$, $p < .001$), indicating that heavier users

were substantially less likely to disengage from the platform. No other structural paths from frequency to latent variables (e.g., Uniqueness, Reactance, Information Overload) were found to be significant. These findings further confirm that while most covariates had limited influence, usage frequency may play a marginal role in shaping user retention behavior.

The negative association observed between platform usage frequency and discontinuance intention reflects a theoretically and behaviorally coherent pattern. Users with a stronger intention to leave are often already using the platform less frequently, suggesting that low usage is not merely a background trait but a behavioral manifestation of withdrawal intention. This finding supports the view that declining usage may be an outcome, rather than a cause, of disengagement intention. Importantly, frequency showed no significant effect on other key latent variables such as uniqueness, information overload, or reactance, indicating that its influence was limited to behavioral outcomes rather than psychological perceptions.

Taken together, these findings provide strong support for the structural validity and robustness of the model. The psychological processes linking personalization to discontinuance intention—via perceived threats to freedom and uniqueness neglect—are not artifacts of demographic bias. Instead, they appear to reflect generalizable mechanisms that operate independently of age, education level, or habitual platform use. The significant path from usage frequency to disuse intention can be reasonably interpreted as a behavioral manifestation of withdrawal, in which users with higher disengagement tendencies are already using the platform less. This behavioral link strengthens the theoretical plausibility of the proposed model, while also confirming its applicability across a diverse user base.

4.5 Discussion

4.5.1 Findings

Building upon the first research and guided by the frameworks of PRT and the SSO model, this second research aimed to further examine the psychological mechanisms underlying social media discontinuance. While Research 1 primarily emphasized the roles of information overload and threats to freedom, Research 2 introduced a novel construct—uniqueness neglect—to reflect deeper threats stemming from personalization processes. Based on 316 valid responses from X platform users, the

results provide nuanced insights into the double-edged nature of algorithmic personalization.

Finding 1: Reactance remains the core psychological driver of discontinuous usage behavior. Consistent with Research 1, this research confirmed that psychological reactance significantly and positively predicts discontinuous usage intention ($\beta = 0.612$, $p < .001$). This reinforces the notion that reactance functions as a critical strain in the SSO model. Once users perceive their freedom or autonomy is compromised—either directly or indirectly—they are more likely to disengage from the platform. The convergence across both studies strongly supports the theoretical centrality of reactance in explaining SM disengagement behavior, providing robust empirical validation for prior findings (e.g., Ma et al., 2022).

Finding 2: Both uniqueness neglect and information overload significantly heighten reactance, but they represent distinct forms of perceived constraint. In Research 1, perceived information overload was found to increase both threats to freedom and reactance, supporting prior literature that associates digital fatigue with excessive information exposure (Fu et al., 2020). Research 2 not only replicates the effect of information overload on reactance ($\beta = 0.385$, $p < .001$), but also introduces a more nuanced psychological stressor: uniqueness neglect. The analysis reveals that uniqueness neglect exerts an even stronger effect on reactance ($\beta = 0.568$, $p < .001$), suggesting that users may feel psychological resistance not only when overwhelmed by content volume, but also when their individual identity is overlooked by algorithmic categorization.

This finding represents a critical theoretical advancement. While prior research has often conceptualized threats to freedom in terms of external restriction—such as persuasive messaging or content overload—this research reveals that internal, identity-based mismatches can also generate a perceived loss of freedom. When algorithms ignore users' individuality, flattening their preferences into generic or stereotypical categories, it creates a subtle yet powerful sense of constraint. Users may not be aware of the volume of content per se, but may still feel a loss of self-expression and autonomy, triggering reactance. This research deepens our understanding of freedom-related stressors by showing that both quantitative excess (information overload) and qualitative neglect (uniqueness neglect) can undermine perceived freedom. This

distinction highlights the need for recommender systems to consider not just how much content is shown, but whether users feel recognized as individuals within that content.

Finding 3: Personalization reduces uniqueness neglect but not information overload. Contrary to Research 1—where personalization significantly reduced both information overload and threats to freedom—Research 2 shows a more differentiated pattern. Specifically, personalization was found to significantly reduce uniqueness neglect ($\beta = -0.528, p < .001$), confirming that algorithmically tailored content, when accurate, can make users feel understood and recognized as individuals. However, the effect of personalization on information overload was non-significant ($\beta = -0.028, p = .662$), suggesting that algorithmic curation may not always reduce content burden. This could reflect platform-specific design (e.g., X's hybrid chronological + algorithmic feed), or the fact that personalization increases relevance without necessarily reducing volume.

In addition to the main effects, we also tested the influence of control variables to ensure the robustness of the model. Specifically, age, education, and platform usage frequency were included as covariates. The results showed that these background factors had no substantial impact on the psychological constructs in the model. While usage frequency was negatively associated with discontinuance intention, it did not affect uniqueness neglect, information overload, or reactance. The structural relationships among the core variables remained stable across all model specifications, confirming the overall robustness and generalizability of the proposed framework.

4.5.2 Interpreting the Findings

While the preceding analysis confirmed the hypothesized relationships through robust empirical testing, it also revealed several theoretically intriguing patterns. For instance, the finding that perceived personalization significantly reduced uniqueness neglect—but not information overload—raises important questions about how users interpret algorithmic content in different psychological dimensions. This section therefore turns to a deeper examination of why these effects emerged, drawing upon relevant theories, platform-specific contexts, and user psychology to interpret the underlying mechanisms.

First, why did perceived personalization fail to reduce information overload on Platform X? The non-significant relationship between perceived personalization and information overload contrasts with the results observed in Research 1. This

discrepancy likely stems from platform-specific differences in content structure, user expectations, and algorithmic mechanisms.

Platform X presents users with an extremely high volume of real-time, text-based updates. Even when algorithmically curated, the feed remains densely populated with threads, reposts, and trending topics. In contrast to visual-oriented platforms like Instagram, where personalization can clearly filter and simplify consumption, Platform X's hybrid system—combining algorithmic and chronological timelines—may reduce the visibility of personalization effects. Users on X often engage with high-tempo information flows, which means that even tailored content may still feel overwhelming. Furthermore, personalization on X often functions as prioritization rather than reduction, thus failing to alleviate perceived information overload.

Second, why did perceived personalization significantly reduce uniqueness neglect? Interestingly, while personalization did not ease information overload, it significantly reduced users' sense of uniqueness neglect. This result suggests that personalization fulfills a fundamentally different psychological function: identity verification.

From the perspective of Self-Verification Theory (Swann, 2012), individuals are motivated to maintain consistency between their self-concept and how others (or systems) perceive and respond to them. Personalized recommendations that align with a user's preferences, values, or interests are more than just efficient—they serve as symbolic affirmations of the user's identity. When users feel that the system “understands them,” it satisfies their need for self-verification, reducing feelings of being generalized, stereotyped, or ignored. This aligns with recent research showing that users on social media platforms often balance between self-enhancement and self-verification motives (Zheng et al., 2020). In the context of personalization, when the algorithm reflects the user's own identity accurately, it not only enhances perceived relevance but also reduces psychological discomfort associated with “being misrepresented” or “lumped into a category.”

By contrast, lack of personalization—or inaccurate personalization—can generate identity mismatches, leading to a sense of semantic incongruence. Users may feel that the system is failing to recognize their individuality, thus increasing their perception of uniqueness neglect. Therefore, personalization plays a critical role not merely in content curation but in affirming users' self-concept.

4.5.3 Theoretical Implications

First, this research reinforces the theoretical centrality of psychological reactance (Ma et al., 2022) as a key explanatory mechanism for social media discontinuance. While prior research has established that perceived threats to freedom lead to resistance and disengagement (Youn & Kim, 2019), our findings further demonstrate that this psychological strain is consistently predictive of discontinuous usage across contexts ($\beta = 0.612$, $p < .001$), echoing previous results (Research 1). More importantly, by exploring the antecedents of this reactance, the research contributes to a deeper understanding of what constitutes a perceived threat to freedom in digital environments.

Second, the research introduces a dual-pathway conceptualization of freedom threats—one based on cognitive overload and the other on identity invalidation. While information overload captures the stress from excessive content exposure (Fu et al., 2020), uniqueness neglect reflects a subtler threat rooted in the user's sense of individuality being ignored by algorithmic curation (Longoni et al., 2019). The results show that both dimensions significantly intensify reactance, with UN exerting a stronger effect than IO ($\beta = 0.568$ vs. $\beta = 0.385$). This insight expands the current conceptualization of freedom threats beyond traditional external pressures to include internal, self-concept-based threats. It also aligns with recent calls in personalization and AI literature to consider psychological dimensions of user-system interaction (Pizzi et al., 2021).

Third, the research offers a novel theoretical contribution by identifying uniqueness neglect as a mediating mechanism between perceived personalization and psychological reactance. While prior studies have examined the direct negative effects of uniqueness neglect on user satisfaction or brand attitudes (Longoni et al., 2019), little attention has been paid to what causes this neglect to emerge. Our findings demonstrate that higher perceived personalization significantly reduces uniqueness neglect ($\beta = -0.528$, $p < .001$), and that UN fully mediates the relationship between personalization and reactance. This provides a theoretically grounded explanation of how personalization can alleviate or exacerbate freedom-related stressors, depending on whether it succeeds in recognizing users' individuality. Future research can build on this to further explore antecedents of uniqueness neglect and its interplay with algorithm design.

Fourth, the divergence in personalization effects across platforms—especially the non-significant effect on information overload in the X platform—offers an important

boundary condition for personalization theory. In contrast to Research 1 (conducted on Facebook/Instagram), where personalization reduced both IO and threats to freedom, the X platform context reveals a contextual limitation: personalization improved users' sense of uniqueness recognition but failed to alleviate content burden ($\beta = -0.028$, $p = 0.662$). This suggests that the effectiveness of personalization is not universal, and may depend on platform architecture, user goals, or content structures. These findings encourage future work to adopt a more context-sensitive lens when evaluating the psychological consequences of personalization.

4.6.4 Practical Implications

First, the research identifies two critical psychological pathways—information overload and uniqueness neglect—through which users may experience freedom threats and ultimately disengage from social media platforms. From a platform management perspective, these findings highlight the importance of avoiding reactance-triggering environments. On one hand, systems should monitor and minimize content oversaturation, which could overwhelm users and provoke defensive disengagement. On the other, platforms must avoid homogenizing users through overly generic or stereotypical recommendations, as this can signal a lack of recognition and reduce user satisfaction and retention.

Second, while personalization is widely considered a retention strategy, our findings suggest that its effectiveness is platform-dependent. On platforms like Facebook or Instagram, personalization may reduce both IO and uniqueness-related threats; however, on X, it appears to enhance individual recognition but not alleviate overload. This discrepancy implies that practitioners must carefully consider the specific platform context and user expectations when implementing or evaluating algorithmic personalization. A “one-size-fits-all” personalization logic may backfire if users continue to feel overwhelmed or misrepresented.

Third, our results provide actionable guidance for platform designers and marketers seeking to enhance personalization effectiveness. Systems should be designed not only to increase relevance, but also to signal individuality, e.g., through explainable recommendations, user-controlled filters, or personalization transparency. Emphasizing uniqueness could serve as a buffer against psychological reactance and increase user trust in the recommendation system (Pizzi et al., 2021). Additionally, content moderation strategies aimed at managing information volume—without

undermining personalization—could help reduce the cognitive burden, sustaining long-term engagement.

4.6 Limitations and Future Research

Despite offering valuable insights into the psychological mechanisms underlying social media discontinuance, this research is not without limitations. First, the findings are derived exclusively from users of the X platform, whose recommendation system architecture and user interaction norms may differ substantially from those of other platforms such as Instagram, Facebook, or TikTok. As platform design and usage motivation can influence user responses to personalization (Beyens et al., 2016), the generalizability of our findings to other social media contexts should be approached with caution.

Second, all variables in this research were measured through self-reported survey items, which may be subject to biases such as social desirability, memory distortion, or subjective interpretation. Although standardized scales were employed and statistical validation was performed, future research should incorporate behavioral data (e.g., usage logs, interaction histories) or physiological measures to triangulate users' psychological states and responses more objectively.

Third, while we combined perceived threats to freedom and psychological reactance into a unified construct based on theoretical reasoning and empirical evidence, such integration may obscure important conceptual distinctions. Reactance theory posits that perceived threat is the antecedent of emotional and behavioral resistance (Steindl et al., 2015), and although our exploratory factor analysis supported convergence, future studies should further test the multidimensional structure of reactance-related responses. Employing refined instruments or modeling strategies such as bifactor models could allow researchers to disentangle the nuanced differences between threat perception and motivational arousal.

Lastly, while this research found no significant relationship between perceived personalization and information overload, this non-significant result may be conditional on individual differences. One possible explanation is that users' algorithm awareness (AA)—their understanding of how content is selected, filtered, and presented—moderates how they cognitively respond to personalization. Individuals with higher algorithm awareness may be more sensitive to the potential for cognitive burden, even when content is tailored. This possibility is further examined in our

follow-up study (Research 3), which investigates the moderating role of algorithmic knowledge. Future research should continue to explore how users' awareness and mental models of algorithmic processes shape their psychological and behavioral responses to personalization.

4.7 Conclusion

Building on the theoretical and empirical foundations of Research 1, this research further explores the psychological underpinnings of social media disengagement in algorithmic environments by theoretically refining and expanding the concept of freedom threat. While Research 1 primarily focused on information overload as a cognitive stressor and its impact on user reactance and discontinuance, Research 2 introduces a dual-pathway conceptualization of freedom threat: one rooted in cognitive burden, and the other in identity-based misrecognition. This advancement led to the introduction of uniqueness neglect—a novel and theoretically grounded construct that captures users' perception of being reduced to oversimplified behavioral categories, and thereby deprived of identity affirmation in personalized content environments.

Using a new dataset collected from 316 users of the X platform, this research revealed several compelling findings. Most notably, while perceived personalization significantly reduced users' sense of uniqueness neglect, it had no significant impact on information overload—a result that diverges from Research 1 and highlights the platform-contingent effects of personalization. On platforms like X, where content velocity and heterogeneity are particularly high, personalization may not meaningfully reduce cognitive strain, but it can still serve as a mechanism for symbolic identity validation. This contrast provides a deeper and more nuanced understanding of how personalization interacts with different dimensions of perceived freedom and suggests that “being understood” may matter more than “seeing less” in certain digital contexts.

The research also makes a methodological contribution by empirically validating the unification of perceived threat to freedom and psychological reactance into a single latent construct—Reactance—capturing users' simultaneous experience of constraint and resistance within algorithmic systems. This modeling refinement reflects how users psychologically process algorithmic control: not as sequential cognitive stages, but as a fused emotional response to subtle forms of digital influence.

Theoretically, this study advances personalization and social media discontinuance research by distinguishing two psychological pathways—information overload and

uniqueness neglect—as distinct sources of perceived freedom threats. It highlights the central role of psychological reactance as a mediating mechanism and introduces uniqueness neglect as a critical identity-based strain that fully mediates the effect of personalization on resistance. Moreover, the findings enrich the SSO framework by integrating both volume-based and meaning-based stressors, and demonstrate that the psychological impact of personalization is context-dependent, varying across platform environments.

Practically, the results emphasize that effective personalization requires more than just reducing informational burden—it must also address users’ desire to feel individually recognized. Especially in high-noise platforms like X, where content volume remains high, acknowledging users’ uniqueness can serve as a key strategy to mitigate resistance. Platform designers are thus encouraged to adopt identity-aware personalization approaches and develop mechanisms such as transparent algorithms, explainable recommendations, and user-controlled filters to enhance perceived relevance and respect for individuality.

In conclusion, Research 2 deepens and sharpens the contributions of Research 1 by disentangling the multifaceted nature of perceived freedom threats in personalized environments. By proposing and validating a dual-pathway model—rooted in both cognitive load and identity misrecognition—this study highlights the evolving complexity of user-agency negotiations in algorithmic systems and sets the stage for more psychologically attuned research on social media discontinuance in the age of AI.

5. Research 3: Algorithm Awareness

In the previous chapter, we refined our measurement model and focused the investigation on users of the X platform. Unexpectedly, the results showed that perceived personalization had no significant effect on reducing information overload—an outcome that contrasts with existing findings suggesting personalization as a remedy for cognitive burden in digital contexts (Head et al., 2020). However, personalization was found to significantly reduce users’ perceived uniqueness neglect, suggesting that algorithmic content can indeed help users feel individually recognized.

This duality in results prompts an important theoretical question: why does personalization effectively address one psychological concern (uniqueness neglect) but not another (information overload)? Recent studies suggest that these benefits are not evenly distributed across users, but instead depend on individual differences in how people understand and interpret algorithmic systems (Eslami et al., 2015; Swart, 2021). In particular, users who possess a clearer awareness of how algorithms operate—what we term algorithm awareness (AA)—may be more capable of decoding personalized feeds and recognizing their structural logic. Others, with limited awareness, may perceive the same curated environment as intrusive, confusing, or arbitrary.

Algorithm awareness refers to users’ cognitive understanding and experiential sensitivity toward the operation of algorithmic recommendation systems. It encompasses both abstract knowledge about algorithmic processes and practical familiarity with how those processes affect one’s digital experience (Dogruel et al., 2022). In social media contexts, AA has been found to influence users’ trust, agency, and acceptance of personalized systems. Yet, few empirical studies have explored whether AA conditions the psychological outcomes of personalization—particularly in terms of users’ experiences of overload or individuality.

To address this gap, Research 3 investigates whether algorithm awareness moderates the effects of personalization on two key psychological outcomes: perceived information overload and perceived uniqueness neglect. Drawing on psychological reactance theory and the emerging literature on algorithmic literacy, this study argues that the effectiveness of personalization is contingent upon users’ level of algorithm awareness. While those with high AA may recognize personalization as a meaningful reduction in irrelevant content, those with low AA may fail to make such distinctions, thereby continuing to feel overwhelmed. At the same time, it remains unclear whether

a cognitive understanding of algorithms is necessary for users to feel individually recognized—or whether such recognition can occur through more intuitive, affective pathways.

This study aims to answer the following research questions:

RQ: How does algorithm awareness change the way people experience personalized recommendations?

Building on this notion, the present chapter investigates whether algorithm awareness serves as a moderating variable that explains the effectiveness of personalization. In particular, we explore whether higher AA enhances users' ability to perceive the benefits of personalization (e.g., reduced overload) and mitigates its potential psychological costs (e.g., perceived neglect of uniqueness).

To examine this question, we drew upon the dataset from Research 2, which includes responses from 316 active users of the X platform. Based on their levels of algorithm awareness, participants were categorized into high- and low-awareness groups. A multi-group analysis (MGA) was conducted to assess whether algorithm awareness moderates the effects of personalization on users' psychological perceptions. By leveraging this comparative framework, the study aims to illuminate how users' understanding of algorithms shapes their experiences with personalized content, and to provide a more nuanced account of user responses in algorithmically curated environments.

This chapter is structured as follows. Section 5.1 reviews the concept of algorithm awareness, its psychological and behavioral consequences, and its specific role in social media environments. Section 5.2 develops hypotheses regarding how algorithm awareness may condition users' responses to personalization. Section 5.3 outlines the methodology, including the use of Research 2 data, participant grouping by awareness levels, and the application of multi-group analysis. Section 5.4 presents the key findings and interprets their theoretical and practical implications. Finally, Section 5.5 discusses the limitations and future directions, followed by a brief conclusion in Section 5.6.

5.1 Literature Review on Algorithm Awareness

Algorithm Awareness, also known as algorithmic literacy or algorithmic knowledge, refers to the extent to which users recognize, comprehend, and critically reflect upon

the operation and implications of algorithms in digital environments. In this study, we adopt the definition of algorithmic media content awareness proposed by Zarouali et al. (2021), referring to the extent to which individuals possess accurate perceptions of how algorithms operate within a specific media environment and how these algorithms influence their media consumption and user experience. Eslami et al. (2015) were among the first to systematically examine this concept, demonstrating that many users are unaware of algorithmic filtering on platforms such as Facebook, and that such unawareness can lead to surprise or discomfort when they learn about it.

At its most basic level, AA includes two components: awareness of algorithmic presence (i.e., knowledge that algorithms exist and shape content delivery), and understanding of algorithmic logic (i.e., how algorithms function and make decisions). Building upon this foundation, recent scholars have expanded the concept into multi-dimensional frameworks. Several scholars have expanded algorithm awareness into multidimensional frameworks, including cognitive, affective, and behavioral dimensions (e.g., Dogruel et al., 2022; Swart, 2021). The affective responses—such as suspicion or frustration—resonate with Bucher’s (2019) findings, which highlight how users experience algorithms through moods and emotions, even without fully understanding their logic.

Taken together, these conceptualizations suggest that algorithm awareness is a complex and layered phenomenon, shaped by both cognitive understanding and affective experience. To further clarify how this awareness emerges and varies across users, we next review its antecedents.

Antecedents of Algorithm Awareness

Having established what constitutes algorithm awareness, it is equally important to consider how this awareness develops and what factors contribute to its formation. AA is influenced by several demographic, psychological, and contextual factors. Higher levels of education, digital literacy, and professional involvement in technology-related fields have been linked to greater algorithm awareness (Gran et al., 2021). Younger users also tend to exhibit greater adaptability in forming algorithmic mental models (Klawitter & Hargittai, 2018).

Psychological variables such as curiosity, skepticism, and digital self-efficacy contribute to AA development (Eslami et al., 2015). Contextual features of platforms—such as transparency of algorithmic operations or the presence of feedback

mechanisms—also affect awareness. For example, platforms like TikTok and Spotify, which offer cues about recommendation logic, often foster stronger algorithmic curiosity (Siles & Meléndez-Morán, 2021).

Consequences for Behavior and Attitudes

AA is linked to diverse behavioral and attitudinal outcomes. High-AA users often feel more empowered and in control of their digital environment, engaging in behaviors such as content filtering, algorithm training, or feedback provision (Oeldorf-Hirsch & Neubaum, 2023). However, increased awareness may also lead to critical or skeptical attitudes. For instance, Swart (2021) note that users with high AA may exhibit algorithm aversion when they perceive platform intentions as manipulative (Swart, 2021). Moreover, AA has been shown to influence perceptions of autonomy and privacy. Zarouali et al. (2021) found that high-AA users were more likely to identify privacy threats and resist algorithmic persuasion, particularly in advertising contexts. These findings suggest that AA plays a pivotal role in mediating the psychological impact of algorithmic personalization.

The Role of AA in Social Media Contexts

While algorithm awareness has been increasingly recognized as a crucial digital skill in various domains such as journalism, commerce, and public administration, its implications in the context of social media are particularly pronounced. As Gran et al. (2021) argue, algorithm awareness reflects a new layer of digital divide—beyond mere access or usage—shaping individuals’ ability to critically engage with and navigate algorithmic infrastructures that mediate everyday communication and participation.

In the social media ecosystem, AA plays a crucial role in shaping how users interact with algorithmic content. Social media platforms are prime sites for algorithmic influence, as they not only determine what content is shown, but also shape social visibility and interpersonal engagement. While prior work has emphasized algorithmic filtering as a cause of “filter bubbles” and ideological polarization, recent critiques argue that this overemphasizes algorithmic determinism and underestimates user agency (Cho et al., 2020). Swart (2021) argues that understanding algorithms can serve as a “filter bubble antidote”—enabling users to recognize and counteract echo chambers through deliberate action. Conversely, users with low AA may attribute negative experiences (e.g., boredom, overload) to the platform itself, rather than understanding the mechanisms behind content selection.

Furthermore, emerging evidence suggests that AA moderates users' emotional and cognitive reactions to personalization. Swart (2021) found that algorithm awareness mediates the effect of content overload on social media fatigue, indicating that users who understand algorithmic recommendations may experience less fatigue—but potentially more when they explicitly perceive manipulation.

In sum, AA is a dynamic and multi-faceted construct that not only shapes user understanding but also conditions user behavior and experience. It provides a meaningful lens through which to interpret the divergent effects of personalization observed in prior chapters—particularly regarding information overload and uniqueness neglect. In the next section, we develop hypotheses that explore how AA may moderate these relationships.

5.2 Hypotheses Development

Algorithm Awareness not only reflects users' understanding of algorithms but also functions as a moderating factor that shapes how they perceive and respond to personalized recommendations. As suggested by prior studies, users' understanding of algorithms significantly influences their reactions to personalized content, affecting both the benefits (e.g., perceived relevance, reduced information burden) and costs (e.g., privacy concern, loss of autonomy) of algorithm-driven systems (Zarouali et al., 2021). From a theoretical perspective, AA can be conceptualized as a moderator because it alters the strength or direction of the relationship between stimuli (e.g., personalization) and psychological responses (e.g., overload, reactance). This is aligned with the notion in media and communication research that awareness or knowledge functions as a meta-cognitive lens, through which users selectively interpret mediated experiences (Eslami et al., 2015). Individuals with higher AA are more likely to engage in reflective processing and exhibit differentiated responses to the same technological stimuli, compared to those with limited awareness. Thus, we hypothesize that AA moderates how personalization affects user perceptions and reactions.

Previous chapters have shown inconsistent evidence regarding the link between personalization and reduced information overload. Although personalization is often assumed to alleviate cognitive strain by filtering irrelevant content (Head et al., 2020), such benefits are not uniformly perceived across all users. One plausible explanation lies in users' algorithmic understanding.

Users with high levels of AA are more likely to appreciate the functional logic behind content curation. They recognize that algorithms select and prioritize information based on user preferences, relevance, and contextual engagement (Dogruel et al., 2022). As such, these users are more capable of perceiving personalization as a proactive mechanism that reduces clutter and enhances content relevance. They may also interpret reduced content volume not as a sign of censorship or randomness, but as intelligent filtering intended to improve user experience. By contrast, individuals with low AA may fail to connect personalization with algorithmic logic, perceiving their content feed as either random or overwhelming. In such cases, the intended benefit of overload reduction fails to materialize, not because the algorithm is ineffective, but because the user lacks the framework to recognize and appreciate its operation (Eslami et al., 2015). This interpretation gap may diminish the psychological efficacy of personalization.

Therefore, we propose the following hypothesis:

H6a: Algorithm Awareness strengthens the negative relationship between personalization and information overload. That is, when AA is high, the effect of personalization on reducing information overload becomes more pronounced.

In our prior findings, we observed that personalization reduced perceptions of uniqueness neglect—a form of psychological discomfort wherein users feel their individuality is not acknowledged. This result contrasts with earlier research suggesting that personalization, especially when overly homogenized, can evoke algorithm aversion by neglecting user uniqueness (Araujo et al., 2020). The divergence in outcomes again calls for a closer look at user-level differences—particularly AA.

Users with high AA may actively monitor how personalization reflects their preferences, and thus feel reassured when content is aligned with their identity. Because they understand the underlying personalization logic, they are less likely to interpret similarity in content as a disregard for their uniqueness. Instead, they may see it as validation of their expressed preferences. In other words, high AA may buffer against the perception of uniqueness neglect by increasing users' confidence in algorithmic competence. Conversely, users with low AA might interpret algorithmic content curation as intrusive or mechanical, especially if they cannot discern the reasoning behind recommendations. When exposed to repeated or similar content, such users may feel de-individualized, suspecting that the system is treating them as a

statistical category rather than a unique person (Bucher, 2019). This suspicion can intensify perceived uniqueness neglect.

Here, we hypothesize a dampening effect:

H6b: Algorithm Awareness strengthens the negative relationship between personalization and uniqueness neglect. That is, when AA is high, the effect of personalization on reducing uniqueness neglect becomes more pronounced.

This moderation effect is conceptually consistent with the notion that higher awareness leads to more analytical and less emotional interpretations of algorithmic output (Swart, 2021). It also aligns with findings that transparency and literacy mitigate overreactions to recommendation systems (Zarouali et al., 2021).

5.3 Research Methodology

5.3.1 Data Collection

To test the moderation hypotheses of Research 3, we used the same dataset collected for Research 2. As previously described, the data were obtained through an online survey administered via Yahoo! Crowdsourcing, one of Japan's most established crowdsourcing platforms. The survey focused exclusively on users of the X platform (formerly Twitter), which was selected due to its algorithm-driven content delivery and its emphasis on feed-based information exposure over social ties. This platform context provided an appropriate environment to examine users' psychological responses to algorithmic personalization.

All respondents were pre-screened to ensure active use of X, and were presented with a brief explanation of the platform's recommendation algorithm to establish a shared conceptual baseline. A total of 350 responses were collected, of which 316 were retained after quality screening, yielding a response validity rate of 90.3%, with an average age of 41.89 years ($SD = 7.05$), and 65.8% identifying as male. Educational attainment was varied, with the majority holding a four-year university degree.

5.3.2 Survey Design and Measurements

To measure participants' awareness of algorithmic processes, we adopted the Algorithmic Media Content Awareness Scale (AMCA-scale), developed and validated by Zarouali, Boerman and de Vreese (2021). The AMCA-scale captures users' cognitive understanding of how algorithms curate and shape online content. It comprises 13 items across four dimensions: (1) content filtering, which assesses

awareness that content is selected based on user data; (2) automated decision-making, which reflects recognition of algorithmic autonomy in content delivery; (3) human-algorithm interplay, which captures users' awareness of their role in influencing algorithmic outcomes; and (4) ethical considerations, which encompass concerns around privacy, transparency, and potential bias in algorithmic operations. Respondents rated their awareness on a 7-point Likert scale ranging 1 ("Strongly Disagree") to 7 ("Strongly Agree"). A composite score was computed by averaging responses to the 13 items. The AMCA-scale demonstrated high internal consistency in our sample (Cronbach's $\alpha = 0.91$), confirming its reliability.

To explore the potential moderating role of algorithm awareness, we employed a median split approach to categorize participants into two groups. The median score was 3.8, resulting in 148 respondents classified as having low algorithm awareness (AMCA < 3.8) and 168 respondents as having high algorithm awareness (AMCA $\geq$ 3.8). This grouping allowed for a comparative analysis of whether the effects of personalization on psychological outcomes varied as a function of algorithmic understanding.

The moderation analysis followed a two-step MGA procedure using structural equation modeling (SEM) in AMOS 23.0. First, the measurement model was validated using confirmatory factor analysis (CFA), which yielded acceptable model fit ($\chi^2/df = 2.167$, CFI = 0.901, RMSEA = 0.061), and all standardized factor loadings exceeded 0.70. Second, we conducted group-specific SEM analyses, where the structural paths from personalization to the outcome variables—information overload and uniqueness neglect—were compared across the high-AA and low-AA groups.

To statistically evaluate whether these relationships differed significantly between groups, we compared unstandardized path coefficients and calculated z-scores for each path using the standard error-based method. This approach aligns with the procedures recommended by Calvo-Mora et al. (2016) and applied in similar multi-group settings (Thaichon et al., 2014). A significant z-score ($|z| > 1.645$, $p < .05$) indicated a moderating effect of algorithm awareness.

This methodological design allowed us to rigorously test whether algorithm awareness acts as a boundary condition shaping the psychological effects of personalization, thereby offering empirical insight into the variability of user experiences across cognitive awareness levels.

5.3.3 Multi-group Analysis: Moderating Role of Algorithm Awareness

To examine whether users' awareness of algorithms influences the effects of personalization, a multi-group analysis was conducted using a median split on the AMCA-scale. The median value of algorithmic awareness was 3.8, yielding two groups: low algorithm awareness ($n = 148$) and high algorithm awareness ($n = 168$). This approach enables the investigation of whether the hypothesized paths react differently across awareness levels (Calvo-Mora et al., 2016).

The structural model was tested across the two groups, and group-specific path coefficients were compared. Table 16 and Figure 6 summarizes the key findings for the focal paths from personalization to information overload and uniqueness neglect. Results indicated that the path from personalization to information overload differed significantly between the two groups ($z = -1.808, p < .05$). Specifically, the relationship was non-significant in the low awareness group ($\beta = 0.023, p = .796$), but significantly negative in the high awareness group ($\beta = -0.231, p = .034$), suggesting that algorithmic awareness strengthens the negative impact of personalization on perceived information overload.

Conversely, the path from personalization to uniqueness neglect was consistently negative and statistically significant in both groups ($\beta_{\text{low}} = -0.531, p < .001$; $\beta_{\text{high}} = -0.686, p < .001$), with no significant difference between groups ($z = -1.237, \text{n.s.}$). This indicates that while personalization reduces perceived uniqueness neglect across all users, the strength of this effect is not significantly moderated by algorithmic awareness.

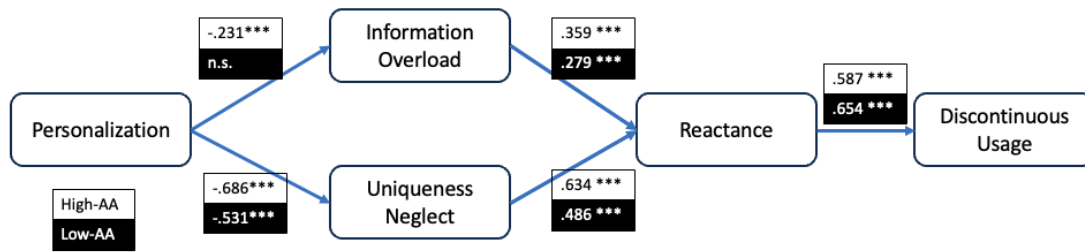
These findings support H6a, which posits that algorithm awareness enhances the effect of personalization in reducing information overload. However, H6b is not supported, as the moderating role of algorithm awareness on the relationship between personalization and uniqueness neglect was not statistically significant. This approach aligns with prior multi-group analysis studies where individual paths are compared after establishing model invariance to assess conditional effects of theoretical constructs.

Table 16. Results of the Multigroup analysis

Hypothesis		high		low		Z-score	Difference
		Estimate	P	Estimate	P		
H5a	Per → Info	0.023	0.796	-0.231	0.034	-1.808*	Support
H5b	Per → Un	-0.531	***	-0.686	***	-1.237	No difference

Note: *p < .05. **p < .01. ***p < .001.

Per = Personalization, Info = Information Overload, Un = Uniqueness Neglect

**Fig. 6** Multi-group SEM results comparing high and low AA groups

5.4 Discussion

5.4.1 Findings

This research examined whether algorithmic awareness moderates the effects of personalization on users' perceptions of information overload and uniqueness neglect. The multi-group analysis revealed that AA significantly moderated the impact of personalization on information overload (H6a supported), but not on uniqueness neglect (H6b not supported). These findings offer several insights into the psychological mechanisms through which personalization interacts with users' knowledge of algorithmic systems.

First, our findings support H6a, showing that algorithm awareness strengthens the negative relationship between personalization and perceived information overload. Specifically, only users with high algorithmic awareness perceived a significant reduction in overload as a result of personalization, whereas the effect was non-significant for low-awareness users. This result aligns with prior study suggesting that awareness of algorithmic processes provides users with a cognitive framework to interpret how content is filtered and curated (Eslami et al., 2015; Dogruel et al., 2022). Users who are more aware of algorithms likely recognize that their feeds are structured based on behavioral data and preferences, and thus interpret the reduced content volume as a purposeful effort to optimize relevance and minimize overload. This

matches the view that AA equips users with metacognitive skills that reduce uncertainty and foster trust in system operations (Swart, 2021).

In contrast, users with low algorithmic awareness may lack the necessary conceptual understanding to distinguish algorithmic curation from organic content flow. As a result, they may interpret the same recommendation environment as random or even excessive, thereby failing to perceive the intended benefit of information reduction (Eslami et al., 2015). This cognitive gap underscores the importance of AA in facilitating more favorable responses to personalized systems.

Second, H6b was not supported which means that algorithm awareness did not significantly moderate the negative relationship between personalization and perceived uniqueness neglect. This outcome suggests that the positive effect of personalization on alleviating uniqueness neglect may be broadly experienced across users, regardless of their level of algorithmic understanding. One plausible explanation is that uniqueness neglect, unlike information overload, operates at a more intuitive and emotional level. When users receive content that appears tailored to their interests or identities, it may elicit an immediate sense of recognition or validation—feelings that do not necessarily require a rational understanding of how the personalization occurred. This perspective is consistent with previous findings that highlight affective responses to algorithmic outputs as partially independent of cognitive awareness (Bucher, 2019).

Moreover, prior research has emphasized that personalization can implicitly convey a sense of “being seen” or “being known,” which may reduce feelings of being treated generically or stereotypically (Zarouali et al., 2021). Such experiences are likely to be emotionally salient and widely shared, regardless of whether users consciously attribute them to algorithmic filtering. Hence, AA may have limited additional explanatory power in this context.

Taken together, these findings suggest that the perceived informativeness and clarity of algorithmic processes (as in the case of overload reduction) depend more heavily on cognitive awareness, whereas perceived recognition or validation (as in the case of uniqueness neglect) may be more universal and less contingent upon awareness levels.

5.4.2 Theoretical Implications

This research makes several important contributions to the growing literature on algorithm awareness and its role in shaping user responses to algorithmic personalization. First and foremost, this research provide empirical support for AA as

a moderator—a function that, although conceptually suggested in previous literature, has rarely been formally tested in personalization research. While prior studies have often focused on the direct effects of AA, particularly in relation to trust, perceived fairness, or satisfaction (Zarouali et al., 2021; Swart, 2021), few have examined how differences in algorithmic literacy may alter the strength of structural relationships between technological features and user psychology. Our research extends this line of inquiry by demonstrating that algorithm awareness does not operate uniformly but instead conditions the cognitive effects of personalization, offering a more nuanced understanding of its role.

Second, and more critically, our findings suggest that algorithm awareness moderates different psychological mechanisms in distinct ways. Specifically, this research shows that while AA enhances the overload-reduction effect of personalization, it does not moderate its impact on perceived uniqueness neglect. This differential moderating effect has not been previously documented in the literature, marking an important theoretical advancement. Prior research has not sufficiently addressed the possibility that personalization outcomes vary not only in direction or magnitude but also in their dependence on user cognition. Our results suggest that algorithm awareness plays a selective role, strengthening cognitive interpretations (e.g., reduced overload) but not necessarily shaping affective responses (e.g., perceived recognition), thereby refining our understanding of the psychological pathways through which personalization operates.

Third, this research also offers an explanatory lens for when and why personalization may fail to deliver its intended benefits. In our earlier research (Research 2), the effect of personalization on information overload was found to be non-significant in the full sample, raising questions about the contextual boundaries of this relationship. By introducing AA as a moderator, we show that this “null effect” can be attributed to heterogeneity in user understanding: only users with high AA experience overload relief, while others do not. In doing so, we move beyond describing effects to explaining why some users do not benefit from personalization, and more broadly, how cognitive access to algorithmic logic conditions the user experience in algorithmic environments.

Finally, our research addresses a critical gap in the existing literature. As highlighted in our review of AA research, most prior work has focused on attitudinal or behavioral

outcomes, with limited attention to how algorithmic knowledge influences structural paths between system features and psychological constructs (Swart, 2021). Moreover, algorithm awareness has seldom been positioned as a boundary condition within broader conceptual models of human-algorithm interaction. By introducing and empirically validating AA as a moderator, this research helps integrate algorithm literacy into causal models of personalization, offering a framework that is both theoretically robust and empirically grounded.

5.4.3 Practical Implications

From a practical perspective, this research underscores the importance of algorithm awareness as a leverage point for enhancing the effectiveness of personalization strategies. While personalization is often assumed to benefit users uniformly, our findings suggest that its perceived effectiveness is contingent upon users' understanding of how algorithmic systems function. In particular, only those who are cognitively aware of algorithmic filtering mechanisms reported a reduction in perceived information overload. This implies that in the absence of algorithmic awareness, even technically sophisticated recommendation systems may fail to deliver meaningful psychological benefits.

For designers and platform managers, this highlights a critical consideration: personalization does not speak for itself. If users are unaware of the underlying logic guiding content delivery, they may perceive algorithmically curated feeds as arbitrary, intrusive, or even overwhelming. Therefore, fostering users' understanding and recognition of algorithmic operations should be a parallel goal alongside improving technical accuracy. Simple design features—such as “Why am I seeing this?” prompts, preference feedback tools, and transparent data usage indicators—can bridge the gap between algorithm function and user perception, thereby enhancing user trust and the perceived usefulness of personalization. This also aligns with recent research warning against algorithmic opacity, which has been shown to erode user trust and increase perceived manipulation or surveillance (Eslami et al., 2015). Our findings reinforce this concern by showing that algorithmic opacity not only undermines trust but also prevents users from recognizing the cognitive benefits that personalization systems are designed to offer.

Moreover, our results carry important implications for global social media platforms operating across diverse cultural and technological environments. Algorithm

awareness is unlikely to be uniformly distributed across user populations in different countries. For instance, in the Japanese context explored in this research, only a subset of users demonstrated sufficient understanding to benefit from algorithmic filtering. This suggests that national-level differences in digital literacy and media education may influence how personalization is received and interpreted. Consequently, global platforms should adopt a developmental and localized approach in designing their user interfaces and educational features—one that is sensitive to the varying stages of algorithm literacy across markets.

In sum, as algorithmic personalization becomes more central to user experience, firms must recognize that user cognition is a critical mediating factor. Investing in algorithmic transparency, user education, and context-sensitive interface design is not merely an ethical or regulatory requirement, but also a strategic move to ensure that personalization fulfills its promise across diverse user segments and cultural contexts.

5.5 Limitations and Future Research

Despite its contributions, this research has three notable limitations. First, the exclusive focus on the X platform limits the generalizability of the findings to other social media contexts. Unlike platforms such as Instagram or Facebook that emphasize visual self-presentation and curated social circles, X often serves as a hub for real-time information exchange, news aggregation, and public discourse. The nature of content consumption and users' expectations for timely, diverse information on X may shape how personalization is perceived and experienced. Therefore, the effects of algorithmic personalization and algorithm awareness observed in this research may not directly translate to other platforms with different user motivations and recommendation mechanisms.

Second, the measurement of algorithm awareness relied on self-reported data, which is subject to interpretation bias—especially among older respondents. Given the relatively high average age of the sample, there is a risk that some participants may not have fully understood the technical terminology or underlying concepts related to algorithmic functioning. This may lead to measurement inaccuracies or an overestimation of users' actual level of algorithm literacy. Future studies could benefit from incorporating more objective or behavioral assessments of algorithm awareness to better capture individual differences in understanding and engagement.

Third, this research employed a median split to categorize users into high and low algorithm awareness groups for multi-group comparison. While this approach facilitates intuitive group-based analysis, it also has methodological drawbacks. As Spiller et al. (2013) emphasize, dichotomizing continuous variables—particularly using arbitrary thresholds such as the median—can reduce statistical power, obscure true interaction effects, and create artificial group boundaries that may not reflect meaningful psychological distinctions. Therefore, future research is encouraged to adopt more refined moderation analysis techniques, such as spotlight analysis or the Johnson–Neyman method, which preserve the continuous nature of the moderator and offer more nuanced interpretations.

This research opens several directions for future research. First, although we focused on AA as a moderator of two psychological outcomes, future studies should explore whether AA also moderates other personalization effects—such as reactance, privacy concern, or continued engagement. This would help clarify when and for whom personalization is most effective.

Second, AA may interact with other individual traits. For example, users' platform usage motives (e.g., entertainment vs. information-seeking) or personality characteristics (e.g., need for cognition) may influence how algorithmic personalization is perceived. Future research could examine such combined effects to capture a more complete picture of user responses.

Third, cultural differences in algorithm understanding deserve further attention. As AA levels likely vary across countries, the same personalization system may produce different psychological effects. Future studies could compare how cultural values—such as individualism vs. collectivism or uncertainty avoidance—shape user interpretation of algorithmic recommendations.

Fourth, future research is encouraged to employ more refined techniques for probing moderation, such as spotlight analysis or the Johnson–Neyman procedure, which allow for examining the conditional effects across the full continuum of the moderator (Spiller et al., 2013). These methods retain the richness of the original data and provide more precise insights into when and how a moderator influences the focal relationship.

Finally, researchers should consider using behavioral or task-based measures of algorithm awareness, in addition to self-reports. More objective tools would improve

accuracy in assessing how well users actually understand and engage with algorithmic systems.

5.6 Conclusion

This research explored the moderating role of algorithm awareness in shaping users' responses to personalization on social media. Building on prior findings from Research 2—which revealed inconsistent effects of personalization on information overload and uniqueness neglect—we introduced algorithm awareness as a cognitive-level moderator to better understand when and why personalization exerts positive psychological effects.

Our analysis yielded two key findings. First, we confirmed that algorithm awareness strengthens the negative relationship between personalization and information overload, indicating that users with a clearer understanding of algorithmic processes are more likely to perceive cognitive relief when interacting with personalized content. Second, we found that AA did not moderate the relationship between personalization and uniqueness neglect, suggesting that affective experiences of being understood or “seen” may be less dependent on cognitive processing. This distinction between cognitive and emotional effects of personalization adds an important layer to current theoretical models of algorithmic influence.

These insights not only advance our conceptual understanding, but also help reinterpret previous findings. Critically, this research offers a compelling explanation for the non-significant effects observed in Research 2. While personalization appeared ineffective in reducing information overload across the full sample, our moderated model revealed that this null effect masked meaningful variation between users. Specifically, only those with high algorithm awareness benefited from the system's intended filtering functions. In this way, our research moves beyond identifying “what” effects personalization produces to explaining “for whom” and “under what conditions” these effects occur.

By establishing algorithm awareness as a boundary condition for the psychological impact of personalization, we contribute to a more nuanced and user-centered understanding of algorithmic systems. Furthermore, our findings underscore the value of integrating individual cognitive factors into the research of recommender technologies—highlighting that user outcomes are not only a function of system design, but also of user interpretation and understanding.

In sum, this research refines existing models by showing that personalization is not always effective—it depends on users' awareness of how algorithms work. This finding highlights the importance of AA and points to new directions for researching digital inequality and user differences in responses to recommend systems.

6. Conclusion

This final chapter synthesizes the key findings of the dissertation and discusses their broader theoretical and practical significance. While each previous chapter addressed a specific research question concerning personalization and user response, this chapter brings the insights together to construct a unified explanatory framework for social media discontinuance in algorithmically mediated environments. In doing so, it aims to clarify the psychological mechanisms by which personalized systems influence users' intentions to disengage, and to identify the conditions under which these mechanisms operate.

The chapter is organized into four sections. Section 6.1 summarizes the main findings across the three researches and outlines the proposed dual-pathway model of psychological reactance. Section 6.2 discusses the theoretical contributions and practical implications of the dissertation, offering guidance for scholars, platform designers, and policymakers. Section 6.3 outlines key limitations of the current work and suggests directions for future research. Together, these sections aim to consolidate the dissertation's contributions and highlight its relevance to ongoing debates about algorithmic influence, user agency, and digital well-being.

6.1 Summary

This dissertation set out to examine why and how users stop using social media platforms in the age of algorithmic personalization, addressing a critical yet underexplored issue at the intersection of technology design and consumer psychology. Amidst intensifying competition among social media (SM) platforms, retaining users has become imperative, and recommender systems (RS) play a central role in shaping users' interaction with digital content. However, while RSs are typically designed to enhance user satisfaction through content relevance, they can also induce unintended psychological costs—namely information overload, perceived threats to freedom, and identity invalidation—that may ultimately lead to platform discontinuance. Understanding these dynamics, from both theoretical and practical perspectives, has thus become urgent.

The theoretical positioning of this research bridges two complementary frameworks: the Stimulus-Strain-Outcome (SSO) model and Psychological Reactance Theory (PRT). While the SSO model has traditionally explained digital fatigue and withdrawal through passive strain responses, this study highlights psychological reactance—a

motivational response to perceived threats to autonomy—as a more proactive and nuanced mechanism that better accounts for resistance and discontinuous behavior. Against this backdrop, the following research questions guided the dissertation:

- Does the use of recommendation systems affect users' tendency to discontinue social media platforms? If so, how?
- What role does personalization play in influencing discontinuance behaviors?
- Does algorithmic awareness shape users' perceptions of recommendation systems and their psychological consequences?

To answer these questions, the dissertation employed a multi-method approach across three sequential empirical studies. Research 1 validated a foundational model in which personalization, information overload, and perceived threats to freedom interacted to predict psychological reactance and discontinuance intention. The results confirmed that both overload and freedom threats are key antecedents of reactance, while personalization—somewhat unexpectedly—was found to alleviate these stressors among Japanese users, likely due to cultural and contextual factors such as collectivist values and platform-specific affordances.

Building on these findings, Research 2 introduced a novel construct: uniqueness neglect. This study revealed that users' psychological resistance is not only triggered by cognitive strain (information overload) but also by emotional and identity-based stressors. When personalized content fails to reflect users' individuality, it generates a subtle yet potent sense of identity invalidation, which significantly intensifies psychological reactance. This dual-pathway model—one cognitive (through overload) and one affective (through uniqueness neglect)—provides a more holistic explanation of the psychological threats embedded in personalization systems.

Research 3 extended the model by incorporating algorithmic awareness (AA) as a boundary condition. The findings indicated that users with high AA were more likely to benefit cognitively from personalization, particularly in terms of reduced information overload. In contrast, the emotional relief from uniqueness recognition was found to be broadly shared across users, regardless of their awareness level. This suggests that algorithmic understanding moderates the cognitive route of personalization's effect, but not the affective one—an important distinction for future personalization design and digital literacy initiatives.

Taken together, the three studies converge into a comprehensive model that captures the psychological mechanisms driving social media discontinuance in the context of algorithmic personalization. At the core of this model is psychological reactance, a motivational state that arises when users perceive constraints on their autonomy. This reactance is shaped by two distinct but complementary pathways:

- Cognitive pathway: Personalization can reduce information overload, thereby lowering psychological reactance. However, this effect is conditional upon users' level of algorithmic awareness. Only users with a high degree of understanding about how recommendation systems work are able to interpret reduced information volume as intentional and beneficial, thus experiencing cognitive relief. In contrast, users with low awareness fail to perceive this benefit, maintaining or even amplifying their sense of overload.
- Affective/identity pathway: Personalization also alleviates uniqueness neglect, reducing the sense that users are being misrepresented or stereotyped by algorithmic systems. This recognition of individuality decreases feelings of identity invalidation and thus mitigates reactance. Importantly, this identity-based relief operates broadly across users, regardless of their level of algorithmic awareness, suggesting a more intuitive and emotionally accessible pathway.

This dual-pathway model, strengthened by the moderating role of algorithmic awareness, provides a robust and theoretically grounded framework for understanding when and why users disengage from social media platforms. It reveals that the effects of personalization are not universally positive: while it can reduce psychological strain in some cases, it may also fail to alleviate certain stressors—such as information overload—depending on users' interpretation of the system. The model further clarifies that algorithmic awareness acts as a selective amplifier, enhancing users' cognitive evaluation of personalization (e.g., informativeness or control), without necessarily improving its emotional effectiveness. These findings underscore the importance of considering both user psychology and system transparency when designing and evaluating personalized digital environments.

6.2 Theoretical Contributions and Practical Implications

Theoretical Contributions

This dissertation offers several key theoretical contributions to the literature on social media usage, psychological reactance, and algorithmic personalization.

First, it repositions psychological reactance as a central explanatory mechanism for social media discontinuance. While prior studies have predominantly emphasized fatigue or exhaustion as withdrawal triggers, this research demonstrates that user disengagement can also stem from motivational resistance to perceived threats to autonomy. By integrating reactance theory into the SSO framework, this work provides a more dynamic and agency-centered understanding of user withdrawal, expanding the conceptualization of “strain” beyond passive emotional states such as fatigue or others.

Second, the dissertation introduces and empirically validates a dual-pathway model of personalization-induced reactance. It identifies two distinct psychological routes through which recommendation systems may trigger user reactance: a cognitive pathway, driven by information overload, and an affective/identity-based pathway, rooted in uniqueness neglect. This distinction advances personalization research by emphasizing that user resistance is not solely about content quantity, but also about content quality and personal resonance. The model responds to recent calls for more psychologically nuanced approaches to algorithmic interaction, offering a more granular account of how personalization is experienced at the individual level.

Third, this work makes a novel contribution by establishing uniqueness neglect as a critical antecedent to reactance. Previous literature has largely focused on external restrictions or overt manipulation as sources of autonomy threat. In contrast, this research shows that users also experience reactance when algorithmic systems fail to recognize their individuality—a subtler but equally powerful form of perceived constraint. This identity-based dimension expands the theory of freedom threat by incorporating internal, self-concept-related mechanisms, with important implications for future personalization and AI research.

Fourth, the dissertation identifies algorithmic awareness as a boundary condition that shapes the cognitive interpretation of personalization. While personalization generally reduced uniqueness neglect across users, its effectiveness in reducing information overload depended on users’ understanding of how algorithms work. This finding introduces algorithmic literacy into the personalization literature as a moderating factor,

suggesting that technical awareness can significantly influence users' evaluations of system-generated content. By empirically validating this moderating role, the study offers a new perspective on user heterogeneity in digital environments and contributes to an emerging body of research on human-algorithm interaction.

Finally, this dissertation makes a forward-looking theoretical contribution by introducing AA as a moderator—an innovative application that reveals how personalization is perceived differently by users depending on their level of algorithmic understanding. Rather than assuming a uniform effect, this approach uncovers a cognitive divide: users with higher AA interpret personalization more analytically, benefiting from reduced uniqueness neglect and enhanced informational relevance, while users with lower AA may remain unaware of personalization mechanisms, limiting their ability to critically engage with or benefit from algorithmic curation. By positioning AA as a moderating factor, this study advances the personalization literature toward a more differentiated and user-centered paradigm, and sets the stage for future research on how literacy, transparency, and user knowledge shape algorithmic experience.

Practical Implications

Beyond theoretical advancement, this dissertation also yields actionable insights for platform designers, marketers, and policymakers seeking to enhance user retention in algorithm-driven environments.

First, the findings underscore the importance of reducing psychological reactance in social media design. Both information overload and uniqueness neglect were shown to intensify user resistance and discontinuance intention. Platforms should therefore strive not only to manage the volume of content delivered, but also to ensure that recommendations reflect users' individual identities and preferences. This entails avoiding generic, one-size-fits-all recommendation strategies and instead prioritizing personalization that signals recognition and respect for user individuality.

Second, the results highlight the strategic value of algorithmic transparency. Since users with higher algorithmic awareness experienced greater cognitive benefits (e.g., reduced overload), platforms should invest in features that foster user understanding of algorithmic processes. These may include explainable recommendation interfaces (“Why am I seeing this?”), preference customization options, or educational prompts

that demystify algorithmic logic. Enhancing users' algorithmic literacy not only builds trust but also amplifies the intended psychological benefits of personalization.

Finally, the study calls attention to the contextual nature of personalization effects. For instance, the impact of personalization on information overload varied across platforms, suggesting that platform-specific content structures, user expectations, and recommendation mechanisms all shape personalization outcomes. Designers should therefore adopt context-sensitive personalization strategies rather than assuming universal effectiveness. This includes continuously evaluating user feedback and adapting algorithmic parameters to better match platform characteristics and user needs.

6.3 Limitations and Suggestions for Future Studies

While this dissertation offers a theoretically grounded and empirically validated model of social media discontinuance in algorithmic environments, several meaningful limitations remain. Addressing these limitations can significantly advance future research on human–algorithm interaction and deepen our understanding of user disengagement.

First, the model incorporated algorithmic awareness (AA) as the sole moderating variable to explain variations in user responses to personalization. While the findings confirmed AA's conditional impact on cognitive outcomes such as information overload, a broader set of individual difference variables may further influence how users experience and interpret algorithmic environments. Future studies should explore other moderating factors, such as age, digital literacy, platform use motivations, privacy sensitivity, and personality traits (e.g., need for uniqueness or need for cognition). Examining these dimensions would allow researchers to construct a more granular and personalized understanding of when and for whom personalization systems trigger resistance or foster engagement.

Second, the current research relied exclusively on cross-sectional survey data analyzed through structural equation modeling (SEM). While SEM is powerful for testing theoretical relationships, it does not allow for robust causal inference. To establish the directionality and causality of the identified pathways—particularly those involving psychological states like reactance—future research should employ experimental designs or longitudinal studies. Experimental manipulation of variables such as algorithmic transparency, personalization level, or identity salience could offer

clearer evidence on how personalization processes trigger specific psychological and behavioral outcomes.

Third, the comparative analysis across three different social media platforms revealed substantial contextual differences in how users experience and interpret personalization. For instance, personalization reduced information overload on Instagram but not on X (formerly Twitter), likely due to differences in feed structure, content modality, and user expectations. However, this dissertation did not systematically investigate why such differences occur. Future studies should explore the mechanisms underlying platform-based variations, considering elements such as algorithm design, user interface features, content typologies, and usage culture. Such inquiry would help in refining platform-specific strategies for mitigating psychological strain.

Fourth, this dissertation predominantly adopted a stress-centered perspective, focusing on how algorithmic environments trigger negative psychological responses—particularly threats to freedom, information overload, and uniqueness neglect. While this approach has proven effective in explaining disengagement behaviors, it offers only a partial view of users' lived experiences. Future research should seek to balance the analysis by integrating positive psychological responses, such as satisfaction, enjoyment, or perceived relevance. Examining both the benefits and costs of algorithmic personalization will enable a more holistic assessment of how these systems shape user retention, experience, and well-being.

Another important limitation of the present research lies in its assumption of a uniform user response to algorithmic personalization, without accounting for individual differences in preferred levels of stimulation. Recent studies across social media and live streaming contexts suggest that individuals possess distinct Optimal Stimulation Levels (OSL)—a stable personality trait that influences how they evaluate and react to media stimuli (Gu et al., 2016; Zheng et al., 2023). Users with a high OSL are drawn to novelty, complexity, and variability, whereas low-OSL individuals tend to avoid excessive stimulation and prefer familiarity and simplicity. These preferences significantly shape how users experience personalized content. Therefore, future research should consider OSL as a potential moderator that influences users' cognitive and emotional responses to personalization. This perspective may help explain the inconsistent effects of personalization found in prior studies and provide a more user-

centered understanding of when and for whom personalization becomes effective or counterproductive.

Finally, another limitation concerns the study's cross-sectional design, which captures user attitudes and perceptions at a single point in time, rather than tracking how these perceptions develop into behaviors. However, the formation of behavioral intentions—such as reducing social media usage—is often a time-dependent process. Prior meta-analyses on persuasion effects (e.g., Kumkale & Albarracín, 2004) have demonstrated that attitude changes can exhibit a delayed impact, a phenomenon commonly referred to as the sleeper effect. This suggests that the influence of persuasive stimuli—such as personalized recommendations or platform experiences—may not manifest in observable behavior immediately, but instead take effect after a temporal delay, once initial resistance or counter-arguing weakens.

Given this, future studies should consider longitudinal or experimental time-lagged designs to examine whether short-term cognitive and emotional responses to personalization can predict longer-term disengagement or behavioral discontinuance. This would offer a more dynamic view of how social media usage patterns evolve and help validate whether initial psychological reactance leads to actual behavior change over time.

Reference

- Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6), 734–749.
- Aguirre, E., Mahr, D., Grewal, D., De Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of retailing*, 91(1), 34-49.
- Aichner, T., Grünfelder, M., Maurer, O., & Jegeni, D. (2021). Twenty-five years of social media: a review of social media applications and definitions from 1994 to 2019. *Cyberpsychology, behavior, and social networking*, 24(4), 215-222.
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211.
- Alvarado, O., & Waern, A. (2018, April). Towards algorithmic experience: Initial efforts for social media contexts. In *Proceedings of the 2018 chi conference on human factors in computing systems* (pp. 1-12).
- Araujo, T., Helberger, N., Kruijkemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & society*, 35(3), 611-623.
- Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of marketing research*, 14(3), 396-402.
- Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS quarterly*, 831-858.
- Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of The Academy of Marketing Science*, 16(1), 74-94.
- Bastani, H., Harsha, P., Perakis, G., & Singhvi, D. (2022). Learning personalized product recommendations with customer disengagement. *Manufacturing & Service Operations Management*, 24(4), 2010-2028.
- Baumgartner, H., & Homburg, C. (1996). Applications of structural equation modeling in marketing and consumer research: A review. *International journal of Research in Marketing*, 13(2), 139-161.
- Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly*, 29(3), 493–524.

- Beyens, I., Frison, E., & Eggermont, S. (2016). "I don't want to miss a thing": Adolescents' fear of missing out and its relationship to adolescents' social needs, Facebook use, and Facebook related stress. *Computers in human behavior*, 64, 1-8.
- Bilgin, Y. (2018). The effect of social media marketing activities on brand awareness, brand image and brand loyalty. *Business & management studies: an international journal*, 6(1), 128-148.
- Binns, R., Van Kleek, M., Veale, M., Lyngs, U., Zhao, J., & Shadbolt, N. (2018, April). 'It's Reducing a Human Being to a Percentage' Perceptions of Justice in Algorithmic Decisions. In *Proceedings of the 2018 Chi conference on human factors in computing systems* (pp. 1-14).
- Brehm, J. W. (1966). *A theory of psychological reactance*.
- Bright, L. F., & Logan, K. (2018). Is my fear of missing out (FOMO) causing fatigue? Advertising, social media fatigue, and the implications for consumers and brands. *Internet Research*, 28(5), 1213-1227.
- Brinson, N. H., Eastin, M. S., & Cicchirillo, V. J. (2018). Reactance to personalization: Understanding the drivers behind the growth of ad blocking. *Journal of Interactive Advertising*, 18(2), 136-147.
- Bucher, T. (2019). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. In *The social power of algorithms* (pp. 30-44). Routledge.
- Bui, M., Krishen, A. S., Anlamlier, E., & Berezan, O. (2022). Fear of missing out in the digital age: The role of social media satisfaction and advertising engagement. *Psychology & Marketing*, 39(4), 683-693.
- Byrne, B.M. (2016). *Structural Equation Modeling With AMOS: Basic Concepts, Applications, and Programming*, Third Edition (3rd ed.). Routledge.
- Calvo-Mora, A., Navarro-García, A., Rey-Moreno, M., & Periañez-Cristobal, R. (2016). Excellence management practices, knowledge management and key business results in large organisations and SMEs: A multi-group analysis. *European Management Journal*, 34(6), 661-673.
- Cao, X., & Sun, J. (2018). Exploring the effect of overload on the discontinuous intention of social media users: An SOR perspective. *Computers in human behavior*, 81, 10-18.
- Cao, X., Khan, A. N., Ali, A., & Khan, N. A. (2020). Consequences of cyberbullying and social overload while using SNSs: A study of users' discontinuous usage behavior in SNSs. *Information Systems Frontiers*, 22, 1343-1356.

- Cao, X., Masood, A., Luqman, A., & Ali, A. (2018). Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain-outcome perspective. *Computers in Human Behavior*, 85, 163-174.
- Chang, I. C., Liu, C. C., & Chen, K. (2014). The push, pull and mooring effects in virtual migration for social networking sites. *Information Systems Journal*, 24(4), 323-346.
- Chen, Q., Feng, Y., Liu, L., & Tian, X. (2019). Understanding consumers' reactance of online personalized advertising: A new scheme of rational choice from a perspective of negative effects. *International Journal of Information Management*, 44, 53-64.
- Chen, T., Li, X., & Duan, Y. (2024). The effects of cognitive dissonance and self-efficacy on short video discontinuous usage intention. *Information Technology & People*, 37(4), 1514-1539.
- Chen, X., Sun, J., & Liu, H. (2022). Balancing web personalization and consumer privacy concerns: Mechanisms of consumer trust and reactance. *Journal of consumer behaviour*, 21(3), 572-582.
- Cheung, G. W., & Lau, R. S. (2008). Testing mediation and suppression effects of latent variables: Bootstrapping with structural equation models. *Organizational research methods*, 11(2), 296-325.
- Chin, W. W., & Todd, P. A. (1995). On the use, usefulness, and ease of use of structural equation modeling in MIS research: a note of caution. *MIS quarterly*, 237-246.
- Chiou, L., & Tucker, C. (2017). Content aggregation by platforms: The case of the news media. *Journal of Economics & Management Strategy*, 26(4), 782-805.
- Cho, J., Ahmed, S., Hilbert, M., Liu, B., & Luu, J. (2020). Do search algorithms endanger democracy? An experimental investigation of algorithm effects on political polarization. *Journal of Broadcasting & Electronic Media*, 64(2), 150-172.
- Chung, D., Chen, Y., & Meng, Y. (2023). Perceived information overload and intention to discontinue use of short-form video: The mediating roles of cognitive and psychological factors. *Behavioral Sciences*, 13(1), 50.
- Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the national academy of sciences*, 118(9), e2023301118.
- Deibert, R. J. (2019). The road to digital unfreedom: Three painful truths about social media. *Journal of Democracy*, 30(1), 25-39.

- Dhir, A., Yossatorn, Y., Kaur, P., & Chen, S. (2018). Online social media fatigue and psychological wellbeing—A study of compulsive use, fear of missing out, fatigue, anxiety and depression. *International journal of information management*, 40, 141-152.
- Dijkstra, A. (2008). The psychology of tailoring-ingredients in computer-tailored persuasion. *Social and personality psychology compass*, 2(2), 765-784.
- Dillard, J. P., & Shen, L. (2005). On the nature of reactance and its role in persuasive health communication. *Communication monographs*, 72(2), 144-168.
- Do, D. K. X., Rahman, K., & Robinson, L. J. (2020). Determinants of negative customer engagement behaviours. *Journal of Services Marketing*, 34(2), 117-135.
- Dogruel, L., Masur, P., & Joeckel, S. (2022). Development and validation of an algorithm literacy scale for internet users. *Communication Methods and Measures*, 16(2), 115-133.
- Dolan, R., Conduit, J., Frethey-Bentham, C., Fahy, J., & Goodman, S. (2019). Social media engagement behavior: A framework for engaging customers through social media content. *European journal of marketing*, 53(10), 2213-2243.
- Dolega, L., Rowe, F., & Branagan, E. (2021). Going digital? The impact of social media marketing on retail website traffic, orders and sales. *Journal of Retailing and Consumer Services*, 60, 102501.
- Dong, Y., Li, W., & Chen, M. (2024). Personalization reactance in online medical consultations: effects of two-sided personalization and health topic sensitivity on reactance. *Human Communication Research*, 50(1), 66-78.
- Dwivedi, Y. K., Ismagilova, E., Rana, N. P., & Raman, R. (2023). Social media adoption, usage and impact in business-to-business (B2B) context: A state-of-the-art literature review. *Information Systems Frontiers*, 1-23.
- Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The information society*, 20(5), 325-344.
- Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., ... & Sandvig, C. (2015, April). "I always assumed that I wasn't really that close to [her]" Reasoning about Invisible Algorithms in News Feeds. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, 153-162.
- Fan, X., Jiang, X., Deng, N., Dong, X., & Lin, Y. (2021). Does role conflict influence discontinuous usage intentions? Privacy concerns, social media fatigue and self-esteem. *Information Technology & People*, 34(3), 1152-1174.

- Farhoomand, A. F., & Drury, D. H. (2002). Managerial information overload. Association for computing machinery. *Communications of the ACM*, 45(10), 127-127.
- Farooq, A., Dahabiyeh, L., & Maier, C. (2023). Social media discontinuation: A systematic literature review on drivers and inhibitors. *Telematics and Informatics*, 77, 101924.
- Fornell, C., & Larcker, D. F. (1981), "Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics," *Journal of Marketing Research*, 18(3), 382-388.
- Fu, S., Li, H., & Liu, Y. (2021). Why discontinue Facebook usage? An empirical investigation based on a push–pull–mooring framework. *Industrial Management & Data Systems*, 121(11), 2318-2337.
- Fu, S., Li, H., Liu, Y., Pirkkalainen, H., & Salo, M. (2020). Social media overload, exhaustion, and use discontinuance: Examining the effects of information overload, system feature overload, and social overload. *Information Processing & Management*, 57(6), 102307.
- Gan, C., Li, H., & Liu, Y. (2024). Understanding social media discontinuance behavior in China: a perspective of social cognitive theory. *Information Technology & People*, 37(3), 1185-1207.
- Gardner, L., & Leshner, G. (2016). The role of narrative and other-referencing in attenuating psychological reactance to diabetes self-care messages. *Health communication*, 31(6), 738-751.
- Ghasemaghahi, M., Hassanein, K., & Benbasat, I. (2019). Assessing the Design Choices for Online Recommendation Agents for Older Adults. *Mis Quarterly*, 43(1), 329-A6.
- Gollwitzer, P. M. (1999). Implementation intentions: strong effects of simple plans. *American psychologist*, 54(7), 493.
- Gran, A.-B., Booth, P., & Bucher, T. (2021). To be or not to be algorithm aware: A question of a new digital divide? *Information, Communication & Society*, 24(12), 1779–1796.
- Graupmann, V. (2020). Show me what threatens you, and I can tell who you are: Perception of threat and the self. In *Emerging Perspectives on Self and Identity* (pp. 41-51). Routledge.
- Grover, P., Kar, A. K., & Dwivedi, Y. (2022). The evolution of social media influence-A literature review and research agenda. *International Journal of Information Management Data Insights*, 2(2), 100116.

- Gu, R., Oh, L. B., & Wang, K. (2016). Multi-homing on SNSs: the role of optimum stimulation level and perceived complementarity in need gratification. *Information & Management*, 53(6), 752-766.
- Guo, Y., Lu, Z., Kuang, H., & Wang, C. (2020). Information avoidance behavior on social network sites: Information irrelevance, overload, and the moderating role of time pressure. *International Journal of Information Management*, 52, 102067.
- Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107-123.
- Hayduk, L. A. (1987). *Structural equation modeling with LISREL: Essentials and Advances*. Jhu Press.
- Head, A. J., Fister, B., & MacMillan, M. (2020). Information Literacy in the Age of Algorithms: Student Experiences with News and Information, and the Need for Change. *Project Information Literacy*.
- Heinonen, K., & Strandvik, T. (2015). Customer-dominant logic: foundations and implications. *Journal of Services Marketing*, 29(6/7), 472-484.
- Hodgins, H. S., & Knee, C. R. (2002). *The integrating self and conscious experience*.
- Hofstede, G. H., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind: Intercultural cooperation and its importance for survival* (3rd ed.). New York: McGraw-Hill.
- Hong, H., & Oh, H. J. (2020). Utilizing bots for sustainable news business: Understanding users' perspectives of news bots in the age of social media. *Sustainability*, 12(16), 6515.
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, 6(1), 1-55.
- Hu, T., Kettinger, W. J., & Poston, R. S. (2015). The effect of online social value on satisfaction and continued use of social media. *European journal of Information systems*, 24(4), 391-410.
- Huang, Z., Palvia, P., & Mehta, N. (2024). The social media discontinuance model: the trio of dark side, regret, and privacy control. *Behaviour & Information Technology*, 1-29.
- Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing?. *Journal of personality and social psychology*, 79(6), 995.

- Kang, I., Zhang, Y., & Yoo, S. (2020). Elaboration of social media performance measures: from the perspective of social media discontinuance behavior. *Sustainability*, 12(19), 7962.
- Karizat, N., Delmonaco, D., Eslami, M., & Andalibi, N. (2021). Algorithmic folk theories and identity: How TikTok users co-produce knowledge of identity and engage in algorithmic resistance. *Proceedings of the ACM on human-computer interaction*, 5(CSCW2), 1-44.
- Kian, T. P., Boon, G. H., Lian Fong, S. W., & Jian Ai, Y. (2017). Factors that influence the consumer purchase intention in social media websites. *International Journal of Supply Chain Management*, 6(4), 208-214.
- Kim, J., Choi, I., & Li, Q. (2021). Customer satisfaction of recommender system: Examining accuracy and diversity in several types of recommendation approaches. *Sustainability*, 13(11), 6165.
- Kim, S., Ma, I., & Son, J. (2024). How does stress experienced on instagram differ from threads? Comparing social media fatigue based on platform types. *Computers in Human Behavior*, 157, 108249.
- Kim, Y., Baek, T. H., Yoon, S., Oh, S., & Choi, Y. K. (2017). Assertive environmental advertising and reactance: Differences between South Koreans and Americans. *Journal of Advertising*, 46(4), 550-564.
- Klawitter, E., & Hargittai, E. (2018). “It’s like learning a whole other language”: The role of algorithmic skills in the curation of creative goods. *International Journal of Communication*, 12, 3490-3510.
- Kleijnen, M., Lee, N., & Wetzels, M. (2009). An exploration of consumer resistance to innovation and its antecedents. *Journal of economic psychology*, 30(3), 344-357.
- Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.
- Klug, K., & Strang, C. (2019). The filter bubble in social media communication: How users evaluate personalized information in the facebook newsfeed. *Media Trust in a Digital World: Communication at Crossroads*, 159-180.
- Knight, D. K., & Young Kim, E. (2007). Japanese consumers' need for uniqueness: Effects on brand perceptions and purchase intention. *Journal of Fashion Marketing and Management: An International Journal*, 11(2), 270-280.
- Ko, H., Lee, S., Park, Y., & Choi, A. (2022). A survey of recommendation systems: recommendation models, techniques, and application fields. *Electronics*, 11(1), 141.

- Koeske, G. F., & Koeske, R. D. (1993). A preliminary test of a stress-strain-outcome model for reconceptualizing the burnout phenomenon. *Journal of Social Service Research*, 17(3-4), 107-135.
- Kross, E., Verduyn, P., Sheppes, G., Costello, C. K., Jonides, J., & Ybarra, O. (2021). Social media and well-being: Pitfalls, progress, and next steps. *Trends in cognitive sciences*, 25(1), 55-66.
- Kumkale, G. T., & Albarracín, D. (2004). The sleeper effect in persuasion: a meta-analytic review. *Psychological bulletin*, 130(1), 143.
- LaRose, R., Lin, C. A., & Eastin, M. S. (2003). Unregulated Internet usage: Addiction, habit, or deficient self-regulation?. *Media psychology*, 5(3), 225-253.
- Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big data & society*, 5(1), 2053951718756684.
- Lee, Y. J., & Lee, E. J. (2009). Psychological reactance to online recommendation services. *Information & Management*, 46(5), 363–367.
- Levis, L., Ma, S. S., & Nava, E. (2024). *Journey to 1000 models: Scaling Instagram's recommendation system*. *Meta Engineering Blog*. Retrieved from <https://engineering.fb.com/2025/05/21/production-engineering/journey-to-1000-models-scaling-instagrams-recommendation-system/> (Accessed July 1, 2025)
- Li, C. (2016). When does web-based personalization really work? The distinction between actual personalization and perceived personalization. *Computers in human behavior*, 54, 25-33.
- Liang, H., & Fu, K. W. (2017). Information overload, similarity, and redundancy: Unsubscribing information sources on Twitter. *Journal of Computer-Mediated Communication*, 22(1), 1-17.
- Liang, T. P., Lai, H. J., & Ku, Y. C. (2006). Personalized content recommendation and user satisfaction: Theoretical synthesis and empirical findings. *Journal of Management Information Systems*, 23(3), 45-70.
- Lim, C., & Ahn, J. (2021). Social overload and discontinuance intention on facebook: A comparative study. *Sustainability*, 13(22), 12556.
- Lin, J., Lin, S., Turel, O., & Xu, F. (2020). The buffering effect of flow experience on the relationship between overload and social media users' discontinuance intentions. *Telematics and Informatics*, 49, 101374.

- Lin, S., Lin, J., Luo, X. R., & Liu, S. (2021). Juxtaposed effect of social media overload on discontinuous usage intention: the perspective of stress coping strategies. *Information Processing & Management*, 58(1), 102419.
- Lo, J. (2019). Exploring the buffer effect of receiving social support on lonely and emotionally unstable social networking users. *Computers in Human Behavior*, 90, 103-116.
- Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of consumer research*, 46(4), 629-650.
- Luqman, A., Cao, X., Ali, A., Masood, A., & Yu, L. (2017). Empirical investigation of Facebook discontinues usage intentions based on SOR paradigm. *Computers in Human Behavior*, 70, 544-555.
- Luqman, A., Masood, A., & Ali, A. (2018). An SDT and TPB-based integrated approach to explore the role of autonomous and controlled motivations in “SNS discontinuance intention”. *Computers in Human Behavior*, 85, 298-307.
- Luqman, A., Masood, A., Weng, Q., Ali, A., & Rasheed, M. I. (2020). Linking excessive SNS use, technological friction, strain, and discontinuance: the moderating role of guilt. *Information Systems Management*, 37(2), 94-112.
- Ma, X., Sun, Y., Guo, X., Lai, K. H., & Vogel, D. (2022). Understanding users’ negative responses to recommendation algorithms in short-video platforms: a perspective based on the Stressor-Strain-Outcome (SSO) framework. *Electronic Markets*, 1-18.
- Mahmud, I., Wen, L. H., Fern, Y. S., Ling, T. C., & Ramayah, T. (2023). Science behind social media discontinuance: An integrated model of stress and coping theory. *Information Development*, 02666669231213941.
- Maier, C., Laumer, S., Weinert, C., & Weitzel, T. (2015). The effects of technostress and switching stress on discontinued use of social networking services: a study of Facebook use. *Information Systems Journal*, 25(3), 275-308.
- Markus, M. L., & Robey, D. (1988). Information technology and organizational change: Causal structure in theory and research. *Management science*, 34(5), 583-598.
- Marsh, H. W., Hau, K. T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural equation modeling*, 11(3), 320-341.
- Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual review of psychology*, 52(1), 397-422.

- Miron, A. M., & Brehm, J. W. (2006). Reactance theory-40 years later. *Zeitschrift für Sozialpsychologie*, 37(1), 9-18.
- MIT Technology Review. (2022). *Recommendation engine market report*. Retrieved from <https://www.grandviewresearch.com/industry-analysis/recommendation-engine-market-report>. (Accessed June 1, 2025)
- Mou, Y., Xu, T., & Hu, Y. (2023). Uniqueness neglect on consumer resistance to AI. *Marketing Intelligence & Planning*, 41(6), 669-689.
- Ng, A. H., Kermani, M. S., & Lalonde, R. N. (2021). Cultural differences in psychological reactance: Responding to social media censorship. *Current Psychology*, 40, 2804-2813.
- Nguyen, T. T., Hui, P. M., Harper, F. M., Terveen, L., & Konstan, J. A. (2014). Exploring the filter bubble: The effect of using recommender systems on content diversity. *Proceedings of the 23rd International Conference on WWW*.
- Nieborg, D. B., & Helmond, A. (2019). The political economy of Facebook's platformization in the mobile ecosystem: Facebook Messenger as a platform instance. *Media, Culture & Society*, 41(2), 196-218.
- Nunnally, J. C. (1978). *Psychometric Theory 2nd ed*. McGraw-Hill, New York
- Oeldorf-Hirsch, A., & Neubaum, G. (2023). Attitudinal and behavioral correlates of algorithmic awareness among German and US social media users. *Journal of Computer-Mediated Communication*, 28(5), zmad035.
- Oldenbourg, A. (2024). Digital freedom and corporate power in social media. *Critical Review of International Social and Political Philosophy*, 27(3), 383-404.
- Pang, H., & Qiao, Y. (2023). Identifying the impact of WeChat interaction on college adjustment and academic performance among freshmen: The mediator role school connectedness. *Education and Information Technologies*, 28(2), 1987-2007.
- Pang, H., & Ruan, Y. (2023a). Can information and communication overload influence smartphone app users' social network exhaustion, privacy invasion and discontinuance intention? A cognition-affect-conation approach. *Journal of Retailing and Consumer Services*, 73, 103378.
- Pang, H., & Ruan, Y. (2023b). Determining influences of information irrelevance, information overload and communication overload on WeChat discontinuance intention: The moderating role of exhaustion. *Journal of Retailing and Consumer Services*, 72, 103289.
- Pariser, E. (2011). *The filter bubble: How the new personalized web is changing what we read and how we think*. Penguin.

- Park, J. H. (2014). The effects of personalization on user continuance in social networking sites. *Information processing & management*, 50(3), 462-475.
- Pavey, L., & Sparks, P. (2009). Reactance, autonomy and paths to persuasion: Examining perceptions of threats to freedom and informational value. *Motivation and Emotion*, 33, 277-290.
- Pettit, P. (2018). Freedom: psychological, ethical, and political. In *Exploring Republican Freedom* (pp. 27-41). Routledge.
- Pizzi, G., Scarpi, D., & Pantano, E. (2021). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot?. *Journal of Business Research*, 129, 878-890.
- Proulx, T., Inzlicht, M., & Harmon-Jones, E. (2012). Understanding all inconsistency compensation as a palliative response to violated expectations. *Trends in cognitive sciences*, 16(5), 285-291.
- Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of marketing*, 85(1), 131-151.
- Qaisar, S., Nawaz Kiani, A., & Jalil, A. (2024). Exploring discontinuous intentions of social media users: a cognition-affect-conation perspective. *Frontiers in Psychology*, 15, 1305421.
- Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information systems research*, 19(4), 417-433..
- Rains, S. A. (2013). The nature of psychological reactance revisited: A meta-analytic review. *Human communication research*, 39(1), 47-73.
- Ram, S., & Sheth, J. N. (1989). Consumer resistance to innovations: the marketing problem and its solutions. *Journal of consumer marketing*, 6(2), 5-14.
- Rassameeroj, I., & Wu, S. F. (2019, October). Reverse engineering of content delivery algorithms for social media systems. In *2019 Sixth International Conference on Social Networks Analysis, Management and Security (SNAMS)* (pp. 196-203). IEEE.
- Ravindran, T., Yeow Kuan, A. C., & Hoe Lian, D. G. (2014). Antecedents and effects of social network fatigue. *Journal of the Association for Information Science and Technology*, 65(11), 2306-2320.
- Reinartz, W., Michael, H., & Jörg, H. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Research in Marketing*, 26(4), 332-344.

- Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological methods*, 17(3), 354.
- Rosenberg, B. D., & Siegel, J. T. (2018). A 50-year review of psychological reactance theory: Do not read this article. *Motivation Science*, 4(4), 281.
- Saha, P., Sengupta, A., & Gupta, P. (2024). Influence of personality traits on Generation Z consumers' click-through intentions towards personalized advertisements: A mixed-methods study. *Heliyon*, 10.
- Sahebi, S., & Formosa, P. (2022). Social media and its negative impacts on autonomy. *Philosophy & Technology*, 35(3), 70.
- Shanahan, T., Tran, T. P., & Taylor, E. C. (2019). Getting to know you: Social media personalization as a means of enhancing brand loyalty and perceived quality. *Journal of Retailing and Consumer Services*, 47, 57-65.
- Shen, L. (2015). Antecedents to psychological reactance: The impact of threat, message frame, and choice. *Health communication*, 30(10), 975-985.
- Shen, L., & Dillard, J. P. (2005). Psychometric properties of the Hong psychological reactance scale. *Journal of personality assessment*, 85(1), 74-81.
- Siles, I., & Meléndez-Moran, A. (2021, May). The most aggressive of algorithms”: User awareness of and attachment to TikTok’s content personalization. *In annual meeting of the ICA*.
- Sittenthaler, S., Traut-Mattausch, E., & Jonas, E. (2015). Observing the restriction of another person: Vicarious reactance and the role of self-construal and culture. *Frontiers in psychology*, 6, 1052.
- Spector, P. E., & Brannick, M. T. (2011). Methodological urban legends: The misuse of statistical control variables. *Organizational research methods*, 14(2), 287-305.
- Spiller, S. A., Fitzsimons, G. J., Lynch Jr, J. G., & McClelland, G. H. (2013). Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of marketing research*, 50(2), 277-288.
- Statistic. (2024). *Social media penetration rate in the Asia-Pacific region as of January 2024*. Retrieved from <https://www.statista.com/statistics/255235/active-social-media-penetration-in-asian-countries/> (Accessed June 30, 2025).
- Steindl, C., Jonas, E., Sittenthaler, S., Traut-Mattausch, E., & Greenberg, J. (2015). *Understanding psychological reactance*. Zeitschrift für Psychologie.

- Stets, J. E., & Burke, P. J. (2000). Identity theory and social identity theory. *Social psychology quarterly*, 224-237.
- Stiglbauer, B., & Kovacs, C. (2019). Need for uniqueness determines reactions to web-based personalized advertising. *Psychological reports*, 122(1), 246-267.
- Sun, J., & Lee, S. K. (2022). Flooded with too many messages? Predictors and consequences of instant messaging fatigue. *Information Technology & People*, 35(7), 2026-2042.
- Swann Jr, W. B. (2012). Self-verification theory. *Handbook of theories of social psychology*, ed. P. Van Lang, A. Kruglanski & ET Higgins. Sage.[MLB, aWvH].
- Swart, J. (2021). Experiencing algorithms: How young people understand, feel about, and engage with algorithmic news selection on social media. *Social media+ society*, 7(2), 20563051211008828.
- Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS quarterly*, 865-890.
- Thaichon, P., Lobo, A., Prentice, C., & Quach, T. N. (2014). The development of service quality dimensions for internet service providers: Retaining customers of different usage patterns. *Journal of Retailing and Consumer Services*, 21(6), 1047-1058.
- Tian, K. T., Bearden, W. O., & Hunter, G. L. (2001). Consumers' need for uniqueness: Scale development and validation. *Journal of consumer research*, 28(1), 50-66.
- Tucker, C. (2014). Social Networks, Personalized Advertising, and Privacy Controls. *Journal of Marketing Research*, 51(5), 546–562.
- Turel, O. (2015). Quitting the use of a habituated hedonic information system: a theoretical model and empirical examination of Facebook users. *European Journal of Information Systems*, 24(4), 431-446.
- Vaghefi, I., Qahri-Saremi, H., & Turel, O. (2020). Dealing with social networking site addiction: A cognitive-affective model of discontinuance decisions. *Internet Research*, 30(5), 1427-1453.
- Wang, J., Zheng, B., Liu, H., & Yu, L. (2021). A two-factor theoretical model of social media discontinuance: role of regret, inertia, and their antecedents. *Information technology & people*, 34(1), 1-24.
- Weber, J., Angerer, P., & Apolinário-Hagen, J. (2022). Physiological reactions to acute stressors and subjective stress during daily life: A systematic review on ecological momentary assessment (EMA) studies. *PloS one*, 17(7), e0271996.
- Wicklund, R. A. (1974). *Freedom and reactance*. Lawrence Erlbaum.

- Wright, T. A., & Cropanzano, R. (1998). Emotional exhaustion as a predictor of job performance and voluntary turnover. *Journal of applied psychology*, 83(3), 486.
- Wu, C., Kao, S. C., & Chiu, H. Y. (2019). Determinants of discontinuous intention of attention to mobile instant message services. *Journal of Retailing and Consumer Services*, 49, 219-230.
- X Corp. (n.d.). *Recommendations on X*. Retrieved from <https://help.x.com/en/rules-and-policies/recommendations> (Accessed July 1, 2025)
- Xiao, L., & Mou, J. (2019). Social media fatigue-Technological antecedents and the moderating roles of personality traits: The case of WeChat. *Computers in Human Behavior*, 101, 297-310.
- Xie, X. Z., & Tsai, N. C. (2021). The effects of negative information-related incidents on social media discontinuance intention: Evidence from SEM and fsQCA. *Telematics and Informatics*, 56, 101503.
- Yi, X., Hong, L., Zhong, E., Liu, N. N., & Rajan, S. (2014, October). Beyond clicks: dwell time for personalization. *In Proceedings of the 8th ACM Conference on Recommender systems* (pp. 113-120).
- Youn, S., & Kim, S. (2019). Understanding ad avoidance on Facebook: Antecedents and outcomes of psychological reactance. *Computers in human behavior*, 98, 232-244.
- Zarouali, B., Boerman, S. C., & de Vreese, C. H. (2021). Is this recommended by an algorithm? The development and validation of the algorithmic media content awareness scale (AMCA-scale). *Telematics and Informatics*, 62, 101607.
- Zhang, S., Zhao, L., Lu, Y., & Yang, J. (2016). Do you get tired of socializing? An empirical explanation of discontinuous usage behaviour in social network services. *Information & Management*, 53(7), 904-914.
- Zhang, Y., He, W., & Peng, L. (2022). How perceived pressure affects users' social media fatigue behavior: a case on WeChat. *Journal of Computer Information Systems*, 62(2), 337-348.
- Zheng, A., Duff, B. R., Vargas, P., & Yao, M. Z. (2020). Self-presentation on social media: When self-enhancement confronts self-verification. *Journal of Interactive Advertising*, 20(3), 289-302.
- Zheng, S., Chen, J., Liao, J., & Hu, H. L. (2023). What motivates users' viewing and purchasing behavior motivations in live streaming: a stream-streamer-viewer perspective. *Journal of Retailing and Consumer Services*, 72, 103240.

- Złotowski, J., Yogeeswaran, K., & Bartneck, C. (2017). Can we control it? Autonomous robots threaten human identity, uniqueness, safety, and resources. *International Journal of Human-Computer Studies*, 100, 48-54.
- Zou, L., Xia, L., Ding, Z., Song, J., Liu, W., & Yin, D. (2019, July). Reinforcement learning to optimize long-term user engagement in recommender systems. *In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining* (pp. 2810-2818).

Appendix

Construct		Items
<i>Used in R1, 2, 3</i> Personalization (Per)	Per1	Facebook/Instagram/X は、私の活動状況に合わせておすすめコンテンツを提供してくれると思います。
Chen, Sun & Liu (2022)	Per2	Facebook/Instagram/X は、私の好みや個人的な興味に合わせたより関連性の高い内容を提供してくれると思います。
	Per3	Facebook/Instagram/X は、私が好むかもしれないおすすめコンテンツを提供してくれると思います。
<i>Used in R1, 2, 3</i> Threat to Freedom (Free)	Free1	私の好みに応じたおすすめコンテンツが Facebook/Instagram/X を使用し続ける自由を脅かしていると感じます。
Youn & Kim (2019)	Free2	私の好みに応じたおすすめコンテンツが私の代わりに決断しようとしていると感じます。
	Free3	私の好みに応じたおすすめコンテンツが Facebook/Instagram/X の使用を邪魔していると感じます。
	Free4	私の好みに応じたおすすめコンテンツが私が Facebook/Instagram/X の使用目的の達成を邪魔していると感じることがあります。
<i>Used in R1, 2, 3</i> Information overload (Io)	Io1	Facebook/Instagram/X に利用可能な情報量が多すぎて、しばしば気が散ります。
Fu et al. (2020)	Io2	毎日 Facebook/Instagram/X で処理しなければならない情報量に圧倒されることがあります。
	Io3	Facebook/Instagram/X に友人に関する情報が多すぎて、処理するのが負担に感じます。
	Io4	Facebook/Instagram/X にある情報のほんの一部だけが私のニーズに関連していると感じます。
<i>Used in R1, 2, 3</i> Reactance (Re)	Re1	Facebook/Instagram/X が私に影響しようとするのを、私は拒むようにしています。
Shen & Dillard (2005)	Re2	Facebook/Instagram/X がおすすめコンテンツを見せることを強いられた時、反対のことをしたくなります。
	Re3	Facebook/Instagram/X からたくさんのおすすめコンテンツが来ると、私はそれを受け入れないようにしています。

	Re4	Facebook/Instagram/X からのおすすめコンテンツを侵入だと感じます。
	Re5	Facebook/Instagram/X のおすすめコンテンツは、通常、私の自由が制限されているように感じさせます。
<i>Used in R1, 2, 3</i> Discontinuous Usage Intention (DUI)	Dui1	これからは、現在より Facebook/Instagram/X をかなり使わなくなると思っています。
Zhang et al. (2016)	Dui2	これからは、他のソーシャルネットワークを使うつもりです。
	Dui3	たまに Facebook/Instagram/X を少しの間使わない時期を設けます。
	Dui4	もし可能なら、Facebook/Instagram/X を使うのをやめます。
<i>Used in R2, 3</i> Uniqueness Neglect (Un)	Un1	X の推薦システムは、私の状況の独自性を認識していません。
Longoni, Bonezzi & Morewedge (2019)	Un2	X の推薦システムは、私自身の状況を踏まえて推薦を行っていません。
	Un3	X の推薦システムは、私の状況の独自性に応じた推薦を行っていません。
<i>Used in R3</i> Algorithmic Awareness (AA) Zarouali, Boerman & de Vreese (2021)	AA1	ソーシャルメディアでは、アルゴリズムがコンテンツを私に推薦しています。
	AA2	アルゴリズムは、私がソーシャルメディアで最初に見るコンテンツを決定します。
	AA3	アルゴリズムは、私にどの投稿を見せるかを選択しています。
	AA4	アルゴリズムは、私のソーシャルメディアで何が表示されるかを決めています。
	AA5	自動化された意思決定に基づき、アルゴリズムが私にコンテンツを表示しています。
	AA6	ソーシャルメディア上のコンテンツ表示は、自動プロセスに基づいています。
	AA7	自動化システムが、私がソーシャルメディアで見るものを決定しています。
	AA8	ソーシャルメディアでアルゴリズムが私に推薦するコンテンツは、私のオンライン行動に依存しています。
	AA9	私がどのコンテンツと関わったかが、後でアルゴリズムが私に何を見せるかに影響します。

- AA1
0 ソーシャルメディアでの私の行動は、私が何を見るかについてのアルゴリズムの判断に影響を与えます。
- AA1
1 なぜアルゴリズムが特定のコンテンツを表示するのが、常に明らかとは限りません。
- AA1
2 アルゴリズムは、表示するコンテンツの選択において偏りがある可能性があります。
- AA1
3 私は、ソーシャルメディアで私に見せられるコンテンツについてのアルゴリズムの決定が、公平であるかどうかを懸念しています。
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