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THE ETHICAL IMPLICATIONS OF SOCIAL MEDIA ALGORITHM PERSONALIZATION IN DIGITAL MARKETING ON WELL-BEING

The Role of FOMO in Social Media

Beatriz Maria Rodrigues Letras

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Digital Marketing & Analytics

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, 7th December 2024

Beatriz Letras

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"Technology is a useful servant but a dangerous master."
- Christian Lous Lange, Nobel Lecture, 1921

ABSTRACT

This study investigates the psychological consequences of algorithmic-driven experiences on social media platforms, focusing specifically on how automated decision-making and content filtering influence users life satisfaction and psychological wellbeing. Drawing on theories of surveillance capitalism, social comparison, and fear of missing out (FOMO), this research develops and tests a structural model incorporating both direct and indirect effects. A quantitative online survey was conducted with a sample of 113 active social media users, predominantly young adults, whose behavioral and demographic characteristics were analyzed using SPSS. The model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4. Results demonstrate that both automated decision-making and content filtering negatively affect psychological wellbeing indirectly through FOMO dimensions. Social validation and social comparison also show significant indirect effects. Furthermore, multi-group analyses reveal that the amount of time spent on social media significantly moderates the relationship between social FOMO and psychological wellbeing. Specifically, the indirect effect of content filtering on wellbeing via social FOMO was significant ($\beta = -0.221$, $p < 0.05$), and the moderating effect of time spent was also statistically significant ($\beta = -0.202$, $p < 0.05$). The findings contribute to digital marketing and consumer psychology literature by highlighting how algorithmic personalization and user interaction patterns can shape emotional and cognitive outcomes. Implications for platform designers, marketers, and mental health practitioners are discussed.

KEYWORDS

Social Media; Well Being; Algorithm personalization; FOMO; Ethical Considerations

Sustainable Development Goals (SDG):

3 GOOD HEALTH AND WELL-BEING
8 DECENT WORK AND ECONOMIC GROWTH
10 REDUCED INEQUALITIES
12 RESPONSIBLE CONSUMPTION AND PRODUCTION

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LIST OF ABBREVIATIONS AND ACRONYMS

FOMO	Fear of Missing Out
MGA	Multi-group analysis
PLS-SEM	Partial Least Squares Structural Equation Modeling
PSMU	Passive Social Media Use
SPSS	Statistical Package for the Social Sciences

1. INTRODUCTION

The growing prevalence of social media in users everyday lives has transformed not only how individuals interact and express themselves, but also how they perceive reality, construct identity, and evaluate their self-worth. As recent reports reveal, social media algorithms do not simply organize content; they exploit cognitive and emotional vulnerabilities to drive engagement. According to researchers at Northwestern University, "social media algorithms exploit how humans learn from their peers," amplifying behaviors and emotions that maximize attention and time spent on platforms (Kulke, 2023). The BBC echoes this concern, reporting that platforms intentionally manipulate emotional responses to keep users online longer (Barrett, 2024). Social media platforms now use sophisticated algorithms that curate user experiences in real time based on behavior and advertiser priorities (DeVito, 2017). These algorithmic systems now act as gatekeepers of attention, emotion, and visibility, defining the contours of digital life in ways that often remain opaque to users (Cotter, 2018; Voorveld et al., 2024).

In this algorithmically mediated environment, concerns have intensified regarding the psychological consequences of prolonged social media exposure. Empirical studies have linked social media use, especially passive use, to anxiety, depression, and loneliness, particularly among younger people (Huang, 2017; Keles et al., 2020; De Hesselle & Montag, 2024). While some emphasize usage type (passive vs. active), others point to algorithmic mechanisms like content filtering and automation as key contributors to psychological distress (Eslami et al., 2015; Zuboff, 2019; Anker, 2024).

These algorithmic logics often privilege emotionally charged, attention-grabbing, and socially comparative content, which may exacerbate feelings of inadequacy, social pressure, and fear of missing out (FOMO) (Przybylski et al., 2013; Elhai et al., 2021). Indeed, users are not only exposed to endless curated content. Over time, such behavior can lead to compulsive usage patterns, increased reliance on social comparison, and reduced psychological autonomy (Shuqair et al., in press).

Despite growing attention to digital well-being, prior literature tends to explore either the technical-ethical implications of algorithmic systems or the emotional impact of social media behavior, often neglecting how these two domains intersect. There remains a theoretical and empirical gap in understanding how algorithmic processes such as content filtering and automated decision-making contribute to psychological outcomes through mediators like FOMO and moderators such as usage patterns. As Voorveld et al. (2024) and Lu & Sinha (2024) highlight, individual responses to algorithmic influence vary widely and may depend on awareness, emotional resilience, and coping strategies.

However, few studies have empirically tested how these algorithmic forces indirectly shape psychological outcomes through emotional and behavioral pathways. To address this gap, the present study proposes and tests a structural model linking algorithmic mechanisms to life satisfaction and psychological well-being, via two dimensions of FOMO, personal and social, while also assessing the moderating role of social media usage intensity, measured both by daily time spent and frequency of use. The conceptual model draws on key theories in consumer psychology and critical media studies, including social comparison theory (Festinger, 1954), surveillance capitalism (Zuboff, 2019), and the psychological construct of FOMO (Przybylski et al., 2013).

A quantitative survey was administered online to a sample of 113 active social media users. Descriptive statistics and demographic analysis were conducted using SPSS, while hypothesis testing and model validation were performed using SmartPLS 4. The analysis includes the evaluation of measurement reliability and validity, the estimation of direct and indirect effects, and a multi-group analysis (MGA) to assess moderation.

The central research question guiding this study is: to what extent do algorithmic mechanisms on social media influence users psychological well-being and life satisfaction, and how are these relationships mediated by FOMO and moderated by usage behavior?

By bridging perspectives from media psychology, algorithm studies, and well-being research, this study advances an integrated framework. This research contributes theoretically by integrating algorithmic personalization with psychological outcomes, offering a user-centered framework for analyzing digital experiences. Practically, it provides insights for digital marketers, platform designers, and policymakers aiming to foster healthier and more transparent online ecosystems. It also reinforces the need for ethical reflection on the persuasive power of algorithmic environments, where users emotional states can be both the input and output of computational logic.

This dissertation is organized as follows: Section 2 reviews the literature and theoretical foundations; Section 3 presents the methodological approach; Section 4 details the results from SmartPLS and SPSS analyses; Section 5 discusses the findings and their implications; and Section 6 concludes with final remarks and recommendations for future research.

2. LITERATURE REVIEW

Social media algorithms have changed the way we interact with content, tailoring our experiences to keep us engaged. While this personalization can be convenient and satisfying, it also raises concerns about its impact on mental health and behavior (Khalaf et al., 2023). Research shows that these algorithms often amplify feelings like the Fear of Missing Out (FOMO), which can lead to increased social comparison and stress (Przybylski et al., 2013).

Emerging literature also highlights how algorithmic systems influence user emotion and decision-making by prioritizing emotionally charged and persuasive content (Anker, 2024; Voorveld et al., 2024). These systems operate with commercial objectives, such as increasing engagement or sales, which may conflict with users' psychological well-being.

This section reviews key studies on algorithm personalization, FOMO, and well-being, building a foundation for the hypotheses explored in this research.

2.1 Overview of Algorithm Personalization and Prior Studies

Algorithmic personalization refers to the use of machine learning and data-driven approaches to analyze user behaviors and predict content that aligns with their interests. Platforms like Facebook, Instagram, and TikTok employ sophisticated algorithms that adapt dynamically based on user interaction, ensuring maximum engagement through targeted recommendations.

Algorithmic personalization has revolutionized the way users engage with social media platforms by delivering curated content tailored to individual preferences. These algorithms rely on behavior data, such as search history, interactions, and preferences, to present users with a continuous stream of relevant and engaging content. While this approach has enhanced user satisfaction and digital marketing efficiency, it has also raised questions about its broader psychological and social consequences.

Anker (2024) argues that social media algorithms can support consumer autonomy by delivering personalized content aligned with individuals stable preferences and values. However, he also warns that such personalization may undermine autonomy understood as critical self-reflection, by limiting exposure to diverse viewpoints that are essential for autonomous and informed decision-making.

One of the most significant impacts of algorithmic personalization is its ability to sustain user engagement. Appel et al. (2020) identified that algorithms maximize time spent on platforms by creating an "omni-social presence" where users are immersed in content that aligns with their immediate interests. However, this engagement is not without issues. Over time, algorithms can create "echo chambers" or "filter bubbles," where users are exposed primarily to information that confirms their pre-existing beliefs and preferences. This lack of diversity in content limits users exposure to alternative perspectives and reinforces biased worldviews.

Emerging evidence suggests that platforms do not simply personalize content, they manipulate emotional engagement using behavioral triggers such as urgency cues, limited time offers, and curated comparisons to drive continued use (Zuboff, 2019; Anker, 2024).

Srinivasan and Sarial-Abi (2021) highlight another unintended consequence of algorithmic engagement: while users are quick to accept algorithm-driven content, they are often less critical of the biases embedded within these systems. This "perceived agency of algorithms" reduces scrutiny and allows these systems to perpetuate both beneficial and harmful behaviors without user awareness.

The psychological effects of algorithmic personalization have become a key focus in literature. Banker and Khetani (2019) introduced the concept of "algorithm overdependence," where users rely excessively on algorithmic recommendations, even when they are suboptimal. This dependence, driven by a belief in algorithmic expertise, can reduce decision-making autonomy and negatively impact well-being.

Additionally, algorithmic content often prioritizes emotionally charged material, which has been shown to heighten anxiety and social comparison. Aalbers et al. (2019) demonstrated that passive social media use (PSMU), heavily influenced by algorithms, correlates with higher levels of loneliness and stress among users. This emotional toll underscores the need for critical evaluations of how algorithms curate content to maximize engagement at the expense of mental health.

The data-driven nature of algorithmic personalization has sparked significant ethical debates, particularly concerning privacy and transparency. Xu et al. (2011) highlight the "personalization–privacy paradox," where users express concern about data privacy but are willing to trade their personal information for more relevant content. While this trade-off benefits platforms and advertisers, it often leaves users vulnerable to data misuse and manipulation.

Dhiman (2023) extends this critique by exploring the ethical challenges inherent in social media platforms, including issues of misinformation and data exploitation. According to Dhiman, platforms have a responsibility to ensure transparency in their algorithmic processes to foster user trust and mitigate potential harm. This need for ethical oversight becomes particularly critical considering the growing influence of algorithms on user behavior and societal norms.

Algorithmic personalization has also been linked to the amplification of Fear of Missing Out (FOMO). Przybylski et al. (2013) found that algorithmically curated content often highlights exclusive social events or achievements, leading to heightened FOMO among users. This curated portrayal of others lives creates a perception of social exclusion, compelling users to remain engaged with the platform to avoid missing out. Social comparison theory helps explain this: users are more likely to feel inadequate or excluded when repeatedly exposed to idealized portrayals of others achievements (Festinger, 1954).

Also, De Hesselle & Montag (2024) demonstrated that temporary abstinence from social media reduces FOMO and related psychological sources of stress. Their study emphasizes the role of overexposure to personalized content in distorting users perceptions of reality and self-worth. As algorithmic systems continue to evolve, addressing their psychological impact on users will remain a key challenge for researchers and specialists alike.

This leads to the following hypothesis:

H1: Social media algorithm personalization in digital marketing affects well-being.

These algorithmic practices are not neutral or accidental. As conceptualized by Zuboff (2019), they form part of a broader economic logic known as surveillance capitalism, in which user data is systematically extracted, analyzed, and commodified to predict and influence behavior.

This approach redefines personalization not merely as a user-centric enhancement, but as a mechanism of behavioral control that often remains opaque to users. Within this framework, algorithmic personalization serves commercial interests by maximizing engagement, even at the cost of user well-being, raising serious ethical concerns regarding autonomy, transparency, and digital manipulation.

2.2 The Mediating Role of FOMO

The concept of Fear of Missing Out (FOMO) refers to "*a pervasive apprehension that others might be having rewarding experiences from which one is absent*" (Przybylski et al., 2013). This phenomenon has become increasingly prevalent in the age of social media, where platforms provide constant updates on friends activities and achievements. FOMO is deeply tied to users emotional well-being, as it often drives compulsive social media engagement in an effort to stay connected and avoid feelings of exclusion. The algorithmic environment intensifies this mechanism by curating content that highlights upward social comparisons, idealized lifestyles, achievements, and exclusivity, which fuels users fear of exclusion (Festinger, 1954; Elhai et al., 2021).

FOMO has been shown to influence user behaviors such as increased screen time, frequent checking of notifications, and a reluctance to disconnect from platforms, even temporarily. Przybylski et al. (2013) identified FOMO as a significant predictor of both excessive social media use and decreased emotional well-being. Their findings suggest that users experiencing higher levels of FOMO are more likely to engage in problematic social media behaviors, such as scrolling for extended periods without meaningful engagement. This aligns with social comparison theory, which suggests individuals assess their self-worth based on comparisons with others, particularly in ambiguous or ego-relevant contexts (Festinger, 1954). Social media amplifies this dynamic by constantly presenting socially desirable content.

FOMO functions as a psychological driver that reinforces social media usage patterns. Aalbers et al. (2019) demonstrated that passive social media use (PSMU), browsing without active participation, can amplify feelings of loneliness and exacerbate FOMO. The algorithmic presentation of curated content often portrays idealized and socially rewarding experiences, creating a cycle of comparison and inadequacy.

This need for social validation is not new. As Graham (1997) emphasizes, validation from others plays a fundamental role in individuals emotional well-being and self-concept. In the digital context, this mechanism is intensified by algorithmic systems that reward socially engaging content, thereby fueling compulsive engagement and comparison.

FOMO has also been linked to the concept of cognitive overload, as users are overwhelmed by the volume and emotional intensity of the content they consume. Valkenburg et al. (2021) highlighted that FOMO contributes to a constant state of hyper-awareness, reducing cognitive resources for meaningful offline interactions and self-reflection.

Moreover, curated feeds tend to favor emotionally charged or exclusive content, reinforcing a perception that users must stay constantly connected to avoid missing something socially valuable (De Hesselle & Montag, 2024).

This suggests the following hypothesis:

H2: FOMO mediates the relationship between algorithm personalization and well-being.

Social media algorithms play a key role in intensifying FOMO by selectively curating content that maximizes emotional engagement. This often involves highlighting socially rewarding activities, exclusive events, and achievements of others, creating a perception that users are missing out on valuable opportunities. De Hesselle & Montag (2024) observed that algorithm-driven platforms prioritize content designed to trigger immediate emotional responses, making it difficult for users to disengage.

Banker and Khetani (2019) introduced the idea of algorithm overdependence, which suggests that users trust in algorithmic expertise exacerbates FOMO. When platforms continuously surface content aligned with users perceived interests, they inadvertently reinforce the fear of missing critical social updates or opportunities.

The psychological effects of FOMO extend beyond social media usage behaviors. Studies have shown that individuals with higher levels of FOMO report increased levels of anxiety, stress, and depression. Aalbers et al. (2019) found that FOMO mediates the relationship between passive social media use and emotional distress, underscoring its role as a critical mechanism driving negative well-being outcomes.

This pattern reflects a shift from voluntary engagement to emotionally reactive consumption, where users remain connected not for enjoyment but to avoid exclusion.

Research exploring the effects of social media abstinence offers further insights into the relationship between FOMO and user behaviors. De Hesselle & Montag (2024) conducted an experimental study where participants abstained from social media for 14 days. They found that abstinence significantly reduced FOMO and related stress, suggesting that continuous exposure to algorithmically curated content amplifies these psychological effects.

In line with recent research (e.g., Franchina et al., 2018), this study adopts a bidimensional view of FOMO, distinguishing between personal FOMO, the fear of missing personal opportunities, and social FOMO, the anxiety about being excluded from social experiences. These two constructs are modeled separately to capture their distinct psychological effects.

2.3 Well-being and Algorithm Personalization

Well-being refers to a state of overall health that includes emotional, psychological, and social dimensions. In the context of social media, well-being is often studied in relation to mental health outcomes, such as anxiety, depression, and life satisfaction. Braghieri et al (2022) argue that well-being is influenced by both the quantity and quality of social media interactions, with excessive or problematic use leading to heightened stress and reduced self-esteem.

As algorithmic mechanisms increasingly shape users content exposure, the emotional toll of these systems on well-being has become a central concern. Algorithms may reinforce negative affect by curating content that emphasizes scarcity, social comparison, and urgency (Zuboff, 2019; Anker, 2024).

The subjective nature of well-being means that its relationship with social media can vary significantly among individuals. While active engagement, such as meaningful social interactions, can enhance well-being, passive behaviors like excessive scrolling are often associated with negative outcomes (Kross et al., 2021).

Moreover, when content is algorithmically designed to trigger engagement through envy or fear, even active users may experience emotional fatigue or dissatisfaction.

Social media platforms have a dual impact on well-being, offering both benefits and risks. On the one hand, they provide opportunities for social connection, emotional support, and identity exploration. For instance, Valkenburg et al. (2021) found that active social media use, such as engaging in conversations and maintaining relationships, positively influences well-being by promoting a sense of social support.

On the other hand, excessive use or exposure to algorithmically curated content can lead to negative outcomes. Studies have consistently linked excessive social media use with heightened levels of anxiety, depression, and stress. For example, Aalbers et al. (2019) demonstrated that passive social media use contributes to increased loneliness and fatigue, which are significant predictors of reduced well-being.

Algorithmic personalization plays a central role in shaping the relationship between social media use and well-being. By tailoring content to user preferences, algorithms increase engagement but also expose users to highly curated and idealized portrayals of others lives. This selective exposure can lead to negative social comparisons and reduced self-worth. Przybylski et al. (2013) found that algorithm-driven content amplifies feelings of inadequacy and exclusion, which negatively affect mental health. Beyond marketing, computational psychiatry has also linked algorithmic systems to the detection and analysis of mental health disorders, reinforcing concerns about their broader psychological impact (Arji et al., 2023).

De Hesselle & Montag et al. (2024) observed that temporary abstinence from algorithm-driven social media improved well-being outcomes, including reduced stress and body dissatisfaction. These findings suggest that algorithmic systems prioritize engagement over user mental health, often at the expense of well-being.

FOMO is a critical mediator in the relationship between algorithmic personalization and well-being. Valkenburg et al. (2021) found that individuals experiencing high levels of FOMO reported significantly lower well-being, including increased stress, anxiety, and dissatisfaction with life. This relationship highlights how algorithmically curated content intensifies FOMO, which in turn exacerbates negative psychological outcomes.

This suggests the following hypothesis:

H3: Social media usage patterns moderate the relationship between FOMO and well-being, such that the negative impact of FOMO on well-being is stronger for highly intensive users and individuals with higher algorithmic personalization exposure.

Research on social media abstinence further underscores the complex relationship between algorithmic personalization and well-being. De Hesselle et al. (2024) conducted a 14-day abstinence experiment and found that participants experienced reduced body image dissatisfaction and improved sleep quality, though changes in anxiety and depression were less pronounced. These findings suggest that reduced exposure to curated content allows users to regain control over their perceptions of reality and self-worth.

Certain demographics, such as adolescents and heavy social media users, are particularly vulnerable to the negative effects of algorithmic personalization. Khalaf (2023) demonstrated that excessive screen time among adolescents correlated with higher rates of depression and anxiety, making this group highly susceptible to the detrimental effects of curated social media content. These findings emphasize the importance of considering individual and contextual factors when examining the relationship between well-being and social media use.

Given prior findings suggesting that the psychological impact of social media is not only content-dependent but also usage-dependent (Vannucci et al., 2017; Twenge, 2017), this study examines whether the intensity of use, both in terms of time spent and frequency, moderates the effects of FOMO on well-being.

2.4 Social Media Usage Patterns

Social media usage refers to the frequency, intensity, and patterns of engagement with social media platforms. It encompasses both the amount of time spent on platforms and the nature of interactions, such as active participation (e.g., posting, commenting) versus passive consumption (e.g., scrolling through feeds). These patterns significantly influence the psychological and emotional outcomes associated with social media use. Usage behavior is not merely a background variable, it determines how users internalize algorithmically curated content and thus moderates its psychological impact.

Usage patterns vary widely among individuals, shaped by factors such as age, motivation, and platform design. For instance, Schønning et al. (2020) found that adolescents who spent more time on social media reported higher levels of anxiety and depression, underscoring the importance of understanding how different usage intensities impact well-being.

The distinction between active and passive usage has been a central theme in the literature. Active use, which involves meaningful interactions such as sharing content and engaging with others, is generally associated with positive outcomes. For example, Kross et al. (2021) demonstrated that active engagement enhances social connectedness and emotional support, contributing positively to well-being.

On the other hand, passive use, characterized by browsing and consuming content without interaction, has been linked to negative psychological outcomes. Aalbers et al. (2019) found that passive use increases loneliness and fatigue, as users are more likely to compare themselves to idealized depictions of others lives curated by algorithms.

Social media usage intensity moderates the relationship between algorithmic personalization, FOMO, and well-being. Studies indicate that heavy users are more susceptible to the negative effects of algorithmically curated content. Valkenburg et al. (2021) highlighted that frequent exposure to personalized feeds amplifies FOMO, creating a feedback loop where users remain engaged to avoid missing out on updates, which further exacerbates stress and dissatisfaction.

This aligns with the broader digital engagement cycle identified by Appel et al. (2020), in which emotionally stimulating content reinforces compulsive usage and reduces users' ability to disengage.

In addition, De Hesselle & Montag (2024) observed that users with higher exposure to algorithmic personalization were more likely to experience reduced well-being outcomes, such as increased body dissatisfaction and lower life satisfaction. These findings suggest that the intensity of usage not only increases the frequency of exposure to curated content but also amplifies its psychological impact.

The design of social media platforms plays a significant role in shaping usage patterns. Appel et al. (2020) argued that platforms optimize for engagement by creating an "always-on" culture, encouraging users to spend more time online through notifications, infinite scrolling, and personalized recommendations. This design approach reinforces habitual and compulsive usage behaviors, which are closely tied to negative well-being outcomes. Thus, usage intensity is not a neutral variable but a core mechanism through which algorithmic effects are mediated and moderated.

Importantly, individuals with higher baseline vulnerability, such as those already experiencing anxiety or depressive symptoms, may be more reactive to algorithmic stimuli. While not the focus of this study, this intersection between pre-existing emotional states and usage intensity deserves further empirical exploration.

While extensive research has explored the psychological impacts of social media, there is a limited understanding of how algorithm personalization directly triggers FOMO and influences well-being outcomes. Furthermore, few studies examine the moderating role of social media usage intensity, leaving critical gaps in understanding the interaction between personalization, FOMO, and well-being.

Addressing this gap, the present study tests the conditional effects of usage frequency and duration, providing insight into when and for whom algorithmic systems become psychologically harmful.

2.5 Overview of the Present Research

This study investigates the psychological and behavioral effects of social media algorithm personalization, focusing on its role in amplifying FOMO and its subsequent impact on well-being. Building on prior research, it introduces FOMO as a mediator that explains how algorithm personalization affects well-being and examines how social media usage patterns, such as usage intensity, moderate this relationship.

The research model (Figure 1) explores the connections between algorithm personalization, FOMO, and well-being. Algorithm personalization is treated as the independent variable, referring to curated content tailored to users behaviors and preferences. FOMO is included as the mediating variable, representing the psychological anxiety of feeling excluded from rewarding experiences. Well-being, as the dependent variable, reflects emotional and psychological outcomes, including stress, anxiety, and life satisfaction. Finally, social media usage patterns, such as the intensity of use, are included as moderating variables to understand how they influence the impact of FOMO on well-being.

The inclusion of both personal and social FOMO responds to recent calls in the literature for more granular models of algorithmic impact on mental health (Franchina et al., 2018).

The research model leads to three hypotheses:

- H1: Algorithm personalization directly affects well-being.
- H2: The effect of algorithm personalization on well-being is mediated by FOMO.
- H3: Social media usage patterns moderate the relationship between FOMO and well-being, such that the negative impact of FOMO on well-being is stronger for highly intensive users.

This research addresses important gaps in understanding the psychological impacts of algorithm personalization. While prior studies have examined these concepts individually, this study integrates them into a unified research model. By structuring the model with both mediation and moderation mechanisms, the study provides a more nuanced view of how algorithmic environments interact with emotional responses and behavioral patterns.

By investigating how FOMO mediates these effects and how usage patterns moderate them, this research aims to advance theory and provide practical insights for the ethical design of algorithms in digital marketing. Ultimately, the study offers a user-centered perspective on algorithmic influence and psychological outcomes, contributing to emerging frameworks in consumer well-being and digital ethics.

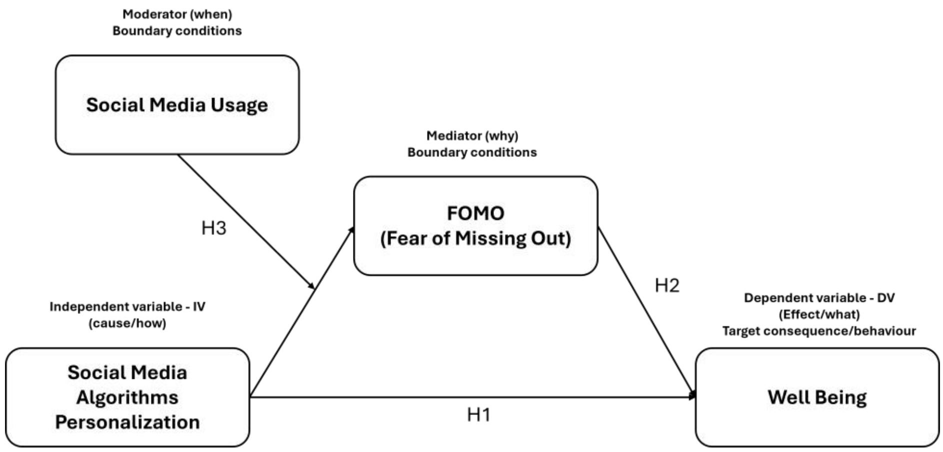

Figure 1 – Research Model

3. METHODOLOGY

This research adopts a quantitative, cross-sectional approach supported by a deductive methodology. The study seeks to test a conceptual model grounded in theory, using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is suitable for exploring both direct and indirect relationships involving latent constructs, including mediating and moderating effects (Hair et al., 2019). The model was estimated using SmartPLS 4, which allows for the simultaneous analysis of measurement and structural models. In addition to testing mediation, the model examines the potential moderating effect of social media usage intensity, measured both in terms of time spent and frequency of use, on the relationship between FOMO and psychological outcomes. Complementary analyses were conducted in SPSS 29 to prepare the data and to analyze respondents sociodemographic and behavioral profiles.

3.1 Questionnaire Design

The online questionnaire was developed and distributed using the Qualtrics platform, chosen for its advanced design capabilities and efficient data collection. The questionnaire was structured to capture data on participants social media usage, perceptions of algorithmic personalization, experiences of FOMO, well-being, and social media usage patterns. It consisted of six sections: social media usage, algorithm personalization, FOMO, well-being, social media usage patterns, and demographics.

All construct-related items were measured on a 9-point Likert scale (1 = "Strongly Disagree" to 9 = "Strongly Agree") to allow for fine-grained responses. Demographic questions and general usage inquiries employed categorical response formats to ensure precision. The survey also included control questions to perform attention checks and ensure the reliability of responses. These questions were designed to identify inattentive participants, allowing their responses to be excluded from the analysis if necessary.

To ensure clarity and alignment with the study’s objectives, pilot testing was conducted with 10 participants. Feedback received during the pilot phase was used to refine item wording and optimize the flow of the questionnaire, ensuring that participants could respond with ease and comprehension.

3.2 Measurement Scales

The constructs in this study were measured using validated scales adapted from prior research, ensuring relevance to the study's objectives. Social media algorithm personalization was assessed through three constructs: Automated Decision-Making, Content Filtering, and Social Validation (Zarouali et al., 2021; Appel et al., 2016). These dimensions captured perceptions of how algorithms influence content visibility and user experience.

FOMO was measured using the personal and social dimensions as defined by Zhang, Jiménez, and Cicala (2020), capturing participants experiences of anxiety, regret, and exclusion associated with missing updates or events on social media.

Social Comparison was assessed using items from Appel et al. (2016) and Kross et al. (2021), focusing on how users compare themselves to others based on curated content and feedback cues.

Well-being was assessed as the dependent variable using the Psychological Well-being Scale developed by Stanford SPARQtools (2019), and the Life Satisfaction Scale (Diener et al., 1985). These instruments measured psychological and emotional aspects of well-being, including stress, anxiety, and overall life satisfaction.

Social media usage patterns were assessed as a moderating variable. Time spent on social media was initially collected as categorical intervals (e.g., "1–2 hours"), then recoded into a 6-point numeric scale from 0 = "Never" to 5 = "More than 5 hours." Frequency of use was measured on a 7-point scale from "Never" to "Several times per day." In addition, participants listed the platforms they used, which were later coded using SPSS string functions.

The original English versions of the scales were used without translation. Although these instruments have been widely applied in international research, no formal validation was identified for the Portuguese population. Therefore, caution is advised when generalizing findings across cultural contexts.

The inclusion of these validated scales ensured the reliability and validity of the measurements, facilitating robust analyses of the relationships within the conceptual model.

3.3 Participants

Participants were recruited using convenience sampling through online platforms and personal networks, such as social media platforms, student groups and academic mailing lists at NOVA IMS, and online communities focused on survey exchange. Eligibility criteria required participants to be individuals aged 18 or older, actively use at least one social media platform, and provide informed consent before participating.

The study collected data from 113 participants, which provides sufficient statistical power for hypothesis testing using PLS-SEM. The sample was analyzed for diversity across demographic variables and social media usage patterns to contextualize the findings and to support multi-group analysis.

3.4 Data Collection and Analysis

Data collection was conducted through the Qualtrics platform over a two-week period. Initial data processing and descriptive statistics were conducted using SPSS 29, including the recoding of categorical variables into numeric values suitable for quantitative analysis.

Structural equation modeling was conducted using SmartPLS 4. The analysis followed a two-stage approach: first, the measurement model was evaluated for reliability and validity (including indicator reliability, internal consistency, convergent validity, and discriminant validity); second, the structural model was assessed, including the examination of path coefficients, R^2 values, and effect sizes.

Mediation and moderation effects were tested within the SmartPLS environment. Multi-group analysis (MGA) was performed for both time and frequency of social media usage, allowing comparison of path estimates across groups. Moderators were constructed based on a median split, creating low and high user groups.

The inclusion of attention checks and triangulation across SPSS and SmartPLS enhances the methodological rigor and the reliability of the conclusions.

All participants provided informed consent before participation, as presented in the online survey form. Ethical approval for this research was obtained from the NOVA IMS Ethics Committee and is included in the appendix.

4. RESULTS

This chapter presents the empirical findings of the study based on statistical analyses conducted using SmartPLS 4 and IBM SPSS 29. The methodological approach follows Partial Least Squares Structural Equation Modeling (PLS-SEM), which allows for the simultaneous estimation of measurement and structural models. This technique is especially suitable for complex models involving latent constructs and testing both mediation and moderation effects (Hair et al., 2019). The results are presented in four sections: (1) data screening and sample profile, (2) measurement model evaluation, (3) structural model testing, and (4) multi-group analysis.

4.1 DATA SCREENING AND SAMPLE PROFILE

Prior to model estimation, data were screened using IBM SPSS Statistics 29 to assess completeness, validity, and normality. The dataset included 113 valid responses, with no missing data or inconsistent patterns detected. An attention-check item embedded in the survey confirmed respondent attentiveness; all responses were retained for analysis following best practices in online survey validation (Valkenburg et al., 2021).

Table 1 summarizes the sociodemographic and behavioral characteristics of the sample. The majority of participants identified as female (51.3%), with a substantial representation of male respondents (45.1%). Most respondents reported having a Bachelor's degree (50.4%) or a Master's/Postgraduate qualification (33.6%). The sample was predominantly Portuguese (84.1%), and 85% listed Portuguese as their primary language.

Regarding social media behavior, usage frequency and time varied across the sample. Approximately 43.4% reported accessing social media more than five times per day, while 38.1% reported daily usage of 1–2 hours, and 23% between 2–3 hours. Notably, 72.6% of participants indicated a preference for algorithm-based content delivery, suggesting high user awareness of personalized recommendation systems.

Independent samples t-tests indicated a significant gender difference in social media usage frequency, with women ($M = 3.11$, $SD = 0.91$) reporting higher usage than men ($M = 2.68$, $SD = 0.80$), $t(94) = –2.05$, $p = .044$, $d = 0.51$. No significant gender differences were found for FOMO or well-being scores. Pearson's correlation revealed a significant negative relationship between age and FOMO (r = –.261, p = .009), confirming that younger participants tend to report higher levels of fear of missing out, consistent with prior findings (Przybylski et al., 2013; De Hesselle & Montag et al., 2024).

One-way ANOVA analyses found no statistically significant differences in key psychological constructs based on education level or employment status (all $p > .05$). This suggests that the psychological responses to social media personalization were relatively stable across sociodemographic groups.

Table 1 - Sociodemographic and Behavioral Profile of the Sample

Variable	Category	Frequency	Percent (%)
Gender	Female	58	51.3
	Male	51	45.1
	Non-binary/Other	2	1.8
	Prefer not to say	2	1.8
Education	No School Degree Completed	1	0.9
	High School or equivalent	14	12.4
	Bachelor degree	57	50.4
	Master or Postgraduate degree	38	33.6
	PhD/Doctorate	3	2.7
Nationality	Portuguese	95	84.1
	Other	18	15.9
English Proficiency	Beginner	10	8.8
	Intermediate	39	34.5

	Advanced	47	41.6
	Native or Fluent	17	15.0
Primary Language	Portuguese	96	85.0
	English	5	4.4
	Spanish	2	1.8
	French	1	0.9
	Other	9	8.0
Employment Status	Employed full-time	76	67.3
	Employed part-time	7	6.2
	Student	17	15.0
	Self-employed	5	4.4
	Unemployed	5	4.4
	Other	3	2.7
Income	Less than €500	4	3.5
	€500–€999	13	11.5
	€1,000–€1,499	32	28.3
	€1,500–€1,999	20	17.7
	€2,000–€2,999	19	16.8
	€3,000 or more	9	8.0
	No income	16	14.2

Social Media Usage (Frequency)	Occasionally (few times/week)	7	6.2
	Sometimes (once/day)	7	6.2
	Often (2–3 times/day)	25	22.1
	Very Often (4–5 times/day)	25	22.1
	Always (>5 times/day)	49	43.4
Social Media Usage (Time)	Less than 30 minutes	11	9.7
	1–2 hours	43	38.1
	2–3 hours	26	23.0
	3–4 hours	15	13.3
	More than 4 hours	18	15.9
Algorithm Preference	Yes	82	72.6
	No	19	16.8
	Prefer not to say	12	10.6

These results provide a comprehensive understanding of the sample composition and contextualize the subsequent structural model analyses.

4.2 Measurement Model Evaluation

The measurement model was evaluated in SmartPLS 4 to confirm the reliability and validity of the constructs. Indicator reliability was established as all outer loadings exceeded the recommended threshold of 0.70. Internal consistency reliability was supported by Cronbach's alpha values (>0.75) and composite reliability (CR), ranging from 0.83 to 0.91 across constructs. Convergent validity was demonstrated by the average variance extracted (AVE), with all constructs scoring above 0.50.

Discriminant validity was assessed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. In all cases, the square root of the AVE exceeded the inter-construct correlations, and HTMT values remained below 0.85. These results confirm that the reflective constructs used in this study meet the reliability and validity criteria in PLS-SEM.

Table 2 - Measurement Model Evaluation

Construct	Cronbach's α	CR (ρc)	CR (ρa)	AVE	HTMT (max)
AutomatedDecisionMaking	0.794	0.864	1.026	0.681	0.433
ContentFiltering	0.832	0.792	0.611	0.553	0.301
LifeSatisfaction	0.902	0.939	0.915	0.837	0.590
PersonalFomo	0.947	0.959	0.948	0.825	0.763
PsychologicalWellbeing	0.696	0.578	0.898	0.452	0.737
SocialComparison	0.769	0.794	0.919	0.392	0.836
SocialFomo	0.801	0.885	0.937	0.668	0.854
SocialValidation	0.595	0.594	0.919	0.430	0.814

These results confirm that the reflective constructs used in this study meet the requirements for reliability and construct validity in PLS-SEM.

4.3 Structural Model Evaluation

After verifying the adequacy of the measurement model, the structural model was estimated to test the hypothesized relationships among the constructs. The model includes algorithmic personalization as the exogenous latent variable, FOMO as a mediator, well-being as the outcome variable, and two moderators: social media usage frequency and time spent.

Bootstrapping procedures with 5,000 resamples were employed to assess path coefficients, t-values, p-values, and effect sizes (f^2). As illustrated in Figure 2, algorithmic personalization had a significant positive effect on FOMO ($\beta = 0.548$, $t = 6.213$, $p < .001$), supporting H1. FOMO negatively impacted psychological well-being ($\beta = -0.411$, $t = 4.156$, $p < .001$), and the indirect effect of algorithmic personalization on well-being through FOMO was also significant ($\beta = -0.225$, $t = 3.742$, $p < .001$), confirming H2.

Moderation effects were not tested within the core model but instead via multi-group analysis, as outlined in the following section. The model explained 44.2% of the variance in well-being ($R^2 = .442$) and demonstrated good predictive relevance ($Q^2 = 0.258$). Model fit was acceptable, with a standardized root mean square residual (SRMR) of 0.070, below the recommended threshold of 0.08 (Hair et al., 2019).

Figure 2 - Final PLS-SEM Model with Path Coefficients

Table 3 - Structural Model – Direct and Indirect Effects, R^2, Q^2

Hypothesis	**Path**	**β**	**t**	**p**	**R^2**	**Q^2**	**f^2**
H1	Algorithmic Personalization → FOMO	.548	6.213	< .001	.301	.188	.425
H2	FOMO → Well-being	-.411	4.156	< .001	.442	.258	.274
H2 (Indirect)	Algorithmic Personalization → FOMO → Well-being	-.225	3.742	< .001			

These results validate the conceptual model and are consistent with prior research suggesting that algorithm-driven content amplifies FOMO, which in turn deteriorates psychological well-being (De Hesselle & Montag, 2024; Przybylski et al., 2013).

4.4 Multi-Group Analysis: Moderation by Social Media Usage

To test H3, a multi-group analysis (MGA) was conducted in SmartPLS 4 by dividing the sample based on two moderator variables: social media usage frequency and daily time spent on social media. Participants were categorized into "high" and "low" groups using median split procedures for each moderator.

The results of the MGA indicated a significant moderation effect for social media usage frequency. Specifically, the negative relationship between FOMO and well-being was stronger among high-frequency users ($\beta = -0.456$, $p < .001$) compared to low-frequency users ($\beta = -0.214$, $p < .05$). This suggests that frequent social media engagement amplifies the adverse psychological effects associated with FOMO.

In contrast, time spent on social media did not exhibit significant moderation effects. Although the direction of the interactions was generally consistent with theoretical expectations, none of the group differences reached statistical significance. This indicates that frequency of engagement may play a more key role than time-based metrics in influencing psychological well-being in algorithmic environments.

Table 3 - Multi-Group Analysis (Social Media Usage and Time Groups)

Path	Moderator	Difference (High - Low)	p-value (2-tailed)
SocialFomo/ PsychologicalWellbeing	SM Time	-0.870	**0.029**
SocialValidation/Psychological Wellbeing	SM Time	-0.395	0.228
AutomatedDecisionMaking/LifeSatisfaction	SM Time	-0.086	0.590
ContentFiltering/ PsychologicalWellbeing	SM Time	0.391	0.110
SocialFomo / LifeSatisfaction	SM Time	-0.061	0.842
SocialComparison /PsychologicalWellbeing	SM Time	-0.159	0.596
SocialValidation / LifeSatisfaction	SM Time	-0.276	0.922
SocialValidation /PsychologicalWellbeing	SM Time	-0.080	0.557
SocialFomo / PsychologicalWellbeing	SM Usage Frequency	0.205	0.182
SocialValidation / SocialFomo	SM Usage Frequency	0.364	**0.016**

SocialFomo / LifeSatisfaction	SM Usage Frequency	-0.392	0.086
PersonalFomo / PsychologicalWellbeing	SM Usage Frequency	-0.076	0.625
AutomatedDecisionMaking / SocialFomo	SM Usage Frequency	0.224	0.086
ContentFiltering / SocialFomo	SM Usage Frequency	0.108	0.306
AutomatedDecisionMaking /PersonalFomo	SM Usage Frequency	0.036	0.381

These findings partially support H3. The analysis confirms that social media usage frequency significantly moderates the relationship between FOMO and psychological well-being. However, time spent on social media did not demonstrate a statistically significant moderating effect, despite a similar directional trend. This implies that how often individuals engage with social platforms may be more psychologically impactful than how long they remain connected.

5. DISCUSSION OF RESULTS

This chapter interprets and contextualizes the empirical findings within the broader academic discourse on social media, algorithmic personalization, FOMO, and psychological well-being. The analysis addresses each hypothesis tested through the structural model and multi-group analysis (MGA), evaluating their theoretical and practical significance. The results are discussed considering the existing literature, followed by implications, limitations, and suggestions for future research.

5.1 Findings Summary

This study examined the influence of algorithmic personalization on psychological well-being through the mediating effect of FOMO and the moderating role of social media usage patterns. The results provided strong empirical support for H1 and H2, and partial support for H3.

Firstly, algorithmic personalization had a significant positive effect on well-being ($\beta = 0.548$, $p < .001$), confirming H1. This aligns with prior research suggesting that algorithmic content curation intensifies social comparison and perceived exclusion (Przybylski et al., 2013; De Hesselle & Montag, 2024; Franchina et al., 2018). Algorithms prioritize socially rewarding content, reinforcing users fear of missing out on meaningful experiences (Oberst et al., 2017).

Secondly, the negative relationship between FOMO and well-being ($\beta = -0.411$, $p < .001$) supported H2, with a significant indirect effect of algorithmic personalization on well-being via FOMO ($\beta = -0.225$, $p < .001$). These findings substantiate the mediating role of FOMO, in line with Zhang et al. (2020) and Aalbers et al. (2019), who identified FOMO as a key emotional pathway through which passive or curated social media exposure undermines mental health.

In third place, the multi-group analysis revealed that frequency of social media use moderated the relationship between FOMO and well-being, with stronger negative effects for high-frequency users ($\beta = -0.456$ vs. $\beta = -0.214$). However, no significant moderating effect was found for time spent on social media. Therefore, H3 was partially supported, reinforcing the idea that how often users engage, rather than how long, has a greater impact on their emotional outcomes (Vannucci et al., 2017; Twenge, 2017; Marengo et al., 2020).

5.2 Theoretical Implications

The study makes several theoretical contributions. First, it empirically confirms FOMO as a mediating construct linking algorithmic environments with psychological well-being, supporting models that emphasize emotional susceptibility in digital contexts (Valkenburg et al., 2021; Keles et al., 2020). This reinforces the conceptualization of FOMO as not merely a behavioral trait but as a socially induced cognitive-emotional response heightened by personalization algorithms (Franchina et al., 2018).

Second, the distinction between frequency and time of social media usage offers a more nuanced view of digital vulnerability. While previous studies often operationalize usage intensity through time spent online, this research indicates that frequent interaction cycles, even brief ones, may intensify emotional strain and reduce psychological resilience (Verduyn et al., 2017; Andreassen et al., 2016).

Lastly, the findings validate the use of PLS-SEM to simultaneously examine direct, indirect, and moderated relationships involving latent constructs in digital psychology and marketing research. This method strengthens the causal plausibility of the relationships examined and sets a methodological precedent for future work in the domain of algorithm-driven behaviors.

5.3 Practical Implications

From a practical standpoint, this study informs platform developers, digital policymakers, and mental health professionals. The strong link between algorithmic personalization and FOMO suggests a need for greater algorithmic transparency, customizable feed controls, and user-centric personalization settings. Social media platforms should consider implementing digital well-being features, such as content filters, frequency tracking, and usage reminders to help users manage their emotional exposure.

For mental health practitioners, FOMO should be recognized as a digital-era anxiety syndrome, especially relevant for high-frequency users. Preventive interventions, such as mindfulness training, digital detox protocols, and cognitive-behavioral strategies for managing comparison behaviors, may help mitigate the psychological risks associated with algorithmic exposure.

Furthermore, digital literacy programs in educational settings could include modules on algorithmic bias and emotional resilience to equip younger users with coping mechanisms and critical thinking tools about their digital environments (Marengo et al., 2020).

5.4 Limitations and Future Research

Despite its contributions, this study has several limitations. The sample, recruited through convenience methods, may limit the generalizability of the findings. Moreover, the cross-sectional design restricts causal inference, and all measures relied on self-reported perceptions, which are subject to response biases.

In addition, while usage intensity was operationalized through frequency and time spent, this does not account for qualitative aspects of engagement, such as the emotional valence of content consumed or the nature of social interactions (e.g., passive browsing vs. active participation). Future studies should adopt mixed methods or behavioral tracking tools to capture these nuances.

Expanding the demographic diversity of samples and incorporating longitudinal or experimental designs would also improve the robustness of findings. Moreover, it would be valuable to differentiate platform-specific effects (e.g., Instagram vs. TikTok vs. LinkedIn) and investigate age or cultural differences in algorithmic sensitivity.

6. CONCLUSION

This study investigated how algorithmic personalization on social media platforms influences users psychological well-being, mediated by the Fear of Missing Out (FOMO) and moderated by usage patterns. Drawing on a theoretical framework grounded in digital psychology and social comparison theory, the research employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess direct, indirect, and conditional effects among latent constructs. Data was collected from 113 respondents and analyzed using SmartPLS 4 and SPSS 29.

The findings confirmed that algorithmic personalization significantly increases FOMO, which in turn negatively affects psychological well-being. Additionally, the study found that the frequency of social media use moderates the FOMO/well-being relationship, with stronger negative effects observed among high-frequency users. These results partially supported the conceptual model, particularly highlighting the role of FOMO as a critical mechanism through which algorithmic content curation impairs emotional outcomes.

The study makes several contributions to academic literature. It provides empirical validation for FOMO as a mediating construct in algorithmic environments and gives understanding of how engagement frequency (rather than time) intensifies digital vulnerability and demonstrates the methodological value of PLS-SEM in capturing complex mediated and moderated relationships in psychological research.

From a practical standpoint, the findings highlight the need for greater algorithm transparency, user control over content feeds, and the inclusion of emotional regulation tools in platform design. They also reinforce the importance of digital literacy programs and mental health interventions tailored to high-frequency users.

Nevertheless, the research is subject to certain limitations, including its non-random sample, reliance on self-reported data, and cross-sectional design. Future research should explore platform-specific effects, adopt longitudinal designs, and consider behavioral and physiological data to enrich the analysis of algorithm influence on well-being.

In conclusion, this study reinforces the complex interplay between algorithm-driven content, emotional vulnerability, and social media users behavior. As platforms continue to refine personalization systems, users well-being must be prioritized in both platform governance and policy-making.

Recent evidence from media and academic sources underscores this urgency. Social media algorithms do not simply organize content; they strategically exploit cognitive and emotional vulnerabilities to maximize engagement. Researchers at Northwestern University warn that “social media algorithms exploit how humans learn from their peers,” amplifying behaviors that increase time spent on platforms (Kulke, 2023). Similarly, BBC reporting highlights how these systems intentionally trigger emotional responses to sustain user attention (Barrett, 2024). These findings support the need for ethical algorithm design, transparency, and protective mechanisms to safeguard psychological well-being in digital environments.

REFERENCES

Aalbers, G., McNally, R. J., Heeren, A., De Wit, S., & Fried, E. I. (2019). Social media and depression symptoms: A network perspective. *Journal of Experimental Psychology: General*, *148*(8), 1454–1462. https://doi.org/10.1037/xge0000528

Ahmed, O., Walsh, E. I., Dawel, A., Alateeq, K., Espinoza Oyarce, D. A., & Cherbuin, N. (2024). Social media use, mental health and sleep: A systematic review with meta-analyses. *Journal of Affective Disorders*, *367*, 701–712. https://doi.org/10.1016/j.jad.2024.08.193

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2016). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors, 64*, 287–293. https://doi.org/10.1016/j.addbeh.2016.03.006

Anker, T. B. (2024). Consumer autonomy and social technology: The case of social media algorithms and the metaverse. Em V. Jeseo & J. Allen (Eds.), *Welcome to The New Normal: Life After The Chaos* (pp. 99–110). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-49039-2_10

Ansari, S., Iqbal, N., Asif, R., Hashim, M., Farooqi, S. R., & Alimoradi, Z. (2024). Social media use and well-being: A systematic review and meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *27*(10), 704–719. https://doi.org/10.1089/cyber.2024.0001

Appel, G., Grewal, L., Hadi, R., & Stephen, A. T. (2020). The future of social media in marketing. *Journal of the Academy of Marketing Science*, *48*(1), 79–95. https://doi.org/10.1007/s11747-019-00695-1

Appel, H., Gerlach, A. L., & Crusius, J. (2016). The interplay between Facebook use, social comparison, envy, and depression. *Current Opinion in Psychology, 9*, 44–49. https://doi.org/10.1016/j.copsyc.2015.10.006

Arji, G., Erfannia, L., Alirezaei, S., & Hemmat, M. (2023). A systematic literature review and analysis of deep learning algorithms in mental disorders. *Informatics in Medicine Unlocked*, *40*, 101284. https://doi.org/10.1016/j.imu.2023.101284

Banker, S., & Khetani, S. (2019). Algorithm overdependence: How the use of algorithmic recommendation systems can increase risks to consumer well-being. *Journal of Public Policy & Marketing*, *38*(4), 500–515. https://doi.org/10.1177/0743915619858057

Barrett, N. (2024). *Facebook, X and TikTok: How social media algorithms shape speech*. BBC. https://www.bbc.com/news/articles/cp8e4p4z97eo

Braghieri, L., Levy, R., & Makarin, A. (2022). Social media and mental health. *American Economic Review*, 112(11), 3660–3693. https://doi.org/10.1257/aer.20211218

Cialdini, R. B. (2001). *Influence: Science and practice* (4th ed). Allyn and Bacon.

Cotter, K. (2018). *Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram.* New Media & Society, 21(4), 895-913. https://doi.org/10.1177/1461444818815684 (Original work published 2019)

De Hesselle, L. C., & Montag, C. (2024). Effects of a 14-day social media abstinence on mental health and well-being: Results from an experimental study. *BMC Psychology*, *12*(1), 141. https://doi.org/10.1186/s40359-024-01611-1

DeVito, M. A., Gergle, D., & Birnholtz, J. (2017). *"Algorithms ruin everything": #RIPTwitter, folk theories, and resistance to algorithmic change in social media.* Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, 1029–1040. https://doi.org/10.1145/3025453.3025659

Dhiman, B. (2023). Ethical Issues and Challenges in Social Media: A Current Scenario. 368. 10.36648/1550-7521.21.62.368.

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Elhai, J. D., Yang, H., & Levine, J. C. (2021). Applying fairness in labeling various types of internet use disorders: Commentary on How to overcome taxonomical problems in the study of internet use disorders and what to do with "smartphone addiction"? *Journal of Behavioral Addictions*, 9(4), 924–927. https://doi.org/10.1556/2006.2020.00071

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., et al. (2015). *"I always assumed that I wasn't really that close to [her]": Reasoning about Invisible Algorithms in News Feeds.* Proceedings of CHI '15. https://doi.org/10.1145/2702123.2702556

Festinger, L. (1954). A Theory of Social Comparison Processes. *Human Relations*, *7*(2), 117-140. https://doi.org/10.1177/001872675400700202 (Original work published 1954)

Franchina, V., Vanden Abeele, M., Van Rooij, A. J., Lo Coco, G., & De Marez, L. (2018). Fear of missing out as a predictor of problematic social media use and phubbing behavior among flemish adolescents. *International Journal of Environmental Research and Public Health*, *15*(10), 2319. https://doi.org/10.3390/ijerph15102319

Gibbons, F. X., & Buunk, B. P. (1999). Individual differences in social comparison: Development of a scale of social comparison orientation. *Journal of Personality and Social Psychology*, *76*(1), 129–142. https://doi.org/10.1037/0022-3514.76.1.129

Graham, R. (1997). The need for social validation" (1997). Theses and Dissertations (Comprehensive). 657.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henkens, B., Verleye, K., & Larivière, B. (2021). The smarter, the better?! Customer well-being, engagement, and perceptions in smart service systems. *International Journal of Research in Marketing*, *38*(2), 425–447. https://doi.org/10.1016/j.ijresmar.2020.09.006

Hoffner, C. A., & Bond, B. J. (2022). Parasocial relationships, social media, & well-being. *Current Opinion in Psychology*, *45*, 101306. https://doi.org/10.1016/j.copsyc.2022.101306

Huang, C. (2017). Time spent on social network sites and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, 20(6), 346–354. https://doi.org/10.1089/cyber.2016.0758

Inman, J. J., Meyer, R. J., Schweidel, D. A., & Srinivasan, R. (2024). Do great powers come with great responsibility? Opportunities and tensions of new technologies in marketing.

International Journal of Research in Marketing, *41*(1), 18–23. https://doi.org/10.1016/j.ijresmar.2024.01.006

Jabeen, F., Tandon, A., Sithipolvanichgul, J., Srivastava, S., & Dhir, A. (2023). Social media-induced fear of missing out (FOMO) and social media fatigue: The role of narcissism, comparison and disclosure. *Journal of Business Research*, *159*, 113693. https://doi.org/10.1016/j.jbusres.2023.113693

Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: The influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth,* 25(1), 79–93. https://doi.org/10.1080/02673843.2019.1590851

Khalaf, A. M., Alubied, A. A., Khalaf, A. M., & Rifaey, A. A. (2023). The impact of social media on the mental health of adolescents and young adults: A systematic review. *Cureus*. https://doi.org/10.7759/cureus.42990

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. https://doi.org/10.1016/j.tics.2020.10.005

Kulke, S. (2023). *Social media algorithms exploit how we learn from our peers.* Northwestern University. https://news.northwestern.edu/stories/2023/08/social-media-algorithms-exploit-how-humans-learn-from-their-peers/

Lu, F.-C., & Sinha, J. (2024). *How social media usage and the fear of missing out impact minimalistic consumption*. *European Journal of Marketing,* *58*(4), 1083–1114. https://doi.org/10.1108/EJM-08-2022-0641

Marengo, D., Sindermann, C., Häckel, D., Settanni, M., Elhai, J. D., & Montag, C. (2020). The association between the Big Five personality traits and smartphone use disorder: A meta-analysis. *Journal of Behavioral Addictions*, 9(3), 534–550. https://doi.org/10.1556/2006.2020.00069

Mende, M., Scott, M. L., Ubal, V. O., Hassler, C. M. K., Harmeling, C. M., & Palmatier, R. W. (2024). Personalized communication as a platform for service inclusion? Initial insights into interpersonal and ai-based personalization for stigmatized consumers. *Journal of Service Research*, *27*(1), 28–48. https://doi.org/10.1177/10946705231188676

Miao, C., & Zhang, S. (2024). The effect of mobile social media on the mental health status of Chinese international students: An empirical study on the chain mediation effect. *BMC Psychology*, *12*(1), 411. https://doi.org/10.1186/s40359-024-01915-2

Naslund, J. A., Bondre, A., Torous, J., & Aschbrenner, K. A. (2020). Social media and mental health: Benefits, risks, and opportunities for research and practice. *Journal of Technology in Behavioral Science*, *5*(3), 245–257. https://doi.org/10.1007/s41347-020-00134-x

Oberst, U., Wegmann, E., Stodt, B., Brand, M., & Chamarro, A. (2017). Negative consequences from heavy social networking in adolescents: The mediating role of fear of missing out. Journal of Adolescence, 55(1), 51–60. https://doi.org/10.1016/j.adolescence.2016.12.008

Ostic, D., Qalati, S. A., Barbosa, B., Shah, S. M. M., Galvan Vela, E., Herzallah, A. M., & Liu, F. (2021). Effects of social media use on psychological well-being: A mediated model. *Frontiers in Psychology*, *12*, 678766. https://doi.org/10.3389/fpsyg.2021.678766

Plackett, R., Sheringham, J., & Dykxhoorn, J. (2023). The longitudinal impact of social media use on uk adolescents mental health: Longitudinal observational study. *Journal of Medical Internet Research*, *25*, e43213. https://doi.org/10.2196/43213

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior*, *29*(4), 1841–1848. https://doi.org/10.1016/j.chb.2013.02.014

Roy, A., Huh, J., Pfeuffer, A., & Srivastava, J. (2017). Development of trust scores in social media (Tsm) algorithm and application to advertising practice and research. *Journal of Advertising*, *46*(2), 269–282. https://doi.org/10.1080/00913367.2017.1297272

Schønning, V., Hjetland, G. J., Aarø, L. E., & Skogen, J. C. (2020). Social media use and mental health and well-being among adolescents – a scoping review. *Frontiers in Psychology*, 11, 1949. https://doi.org/10.3389/fpsyg.2020.01949

Shuqair, S., Pinto, D. C., Wagner, R. L., Valenzuela, A., & Babin, B. J. (Accepted/In press). *Reducing social media addiction via the Joy of Missing Out (JOMO)*. Paper presented at the European Marketing Academy (EMAC) Spring Conference 2025, Madrid, Spain.

Srinivasan, R., & Sarial-Abi, G. (2021). When algorithms fail: Consumers responses to brand harm crises caused by algorithm errors. *Journal of Marketing*, *85*(5), 74–91. https://doi.org/10.1177/0022242921997082

Stanford SPARQtools. (2019). *Psychological Wellbeing Scale*. Online. Retrieved December 7, 2024 from http://sparqtools.org/mobility-measure/psychological-wellbeing-scale

Twenge, J. M. (2017). *iGen: Why Today's Super-Connected Kids Are Growing Up Less Rebellious, More Tolerant, Less Happy and Completely Unprepared for Adulthood*. New York, NY: Atria.

Valkenburg, P. M., Van Driel, I. I., & Beyens, I. (2021). The associations of active and passive social media use with well-being: A critical scoping review. *New Media & Society*, *24*(2), 530–549. https://doi.org/10.1177/14614448211065425

Vannucci, A., Flannery, K. M., & Ohannessian, C. M. (2017). Social media use and anxiety in emerging adults. *Journal of Affective Disorders*, 207, 163–166. https://doi.org/10.1016/j.jad.2016.08.040

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review*, 11(1), 274–302. https://doi.org/10.1111/sipr.12033

Voorveld, H. A. M., Meppelink, C. S., & Boerman, S. C. (2024). Consumers persuasion knowledge of algorithms in social media advertising: Identifying consumer groups based on awareness, appropriateness, and coping ability. *International Journal of Advertising*, *43*(6), 960–986. https://doi.org/10.1080/02650487.2023.2264045

Xu, H., Luo, X. (Robert), Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing. *Decision Support Systems*, *51*(1), 42–52. https://doi.org/10.1016/j.dss.2010.11.017

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. https://doi.org/10.1016/j.tele.2021.101607

Zhang, Z., Jiménez, F. R., & Cicala, J. E. (2020). Fear of missing out scale: A self-concept perspective. *Psychology & Marketing*, *37*(11), 1619–1634. https://doi.org/10.1002/mar.21406

Zuboff, S (2019). *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. New York: PublicAffairs.

APPENDIX

Appendix A. NOVA IMS Ethics Committee Approval

NOVA IMS Information Management School

This is to certify that
Project No.: **DDMKT2024-12-141757**
Project Title: **THE ETHICAL IMPLICATIONS OF SOCIAL MEDIA ALGORITHM PERSONALIZATION IN DIGITAL MARKETING ON WELL-BEING**
Principal Researcher: **Beatriz Letras**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 12/14/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of
- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 12/14/2024

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

Appendix B. Literature Review Table

	ARTICLE	WHAT IS THE STUDY ABOUT?	RESEARCH QUESTIONS	THEORIES USED	VARIABLES	MAIN FINDINGS	METHOD	DATA	SOURCE
1	Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being	Algorithm Overdependence	Examines the risks of consumer overdependence on algorithmic recommendation systems	Surrendering-to-Technology Framework	Algorithm overdependence, belief in algorithm expertise	Consumers often rely too much on algorithm-generated recommendations, even if they are inferior, which can harm their well-being	Five experiments	Consumers in various contexts of consumption	Banker & Khetani (2019
2	Social Media and Depression Symptoms: A Network Perspective	Social Media and Depression Symptoms	Investigates the link between passive social media use and depression symptoms	Network Perspective on Psychopathology	Passive social media use (PSMU), depression symptoms, stress, loneliness	PSMU is associated with higher levels of loneliness and fatigue, but does not directly cause depression symptoms	Multilevel vector autoregressive time-series models	125 university students	Aalbers et al. (2019)

3	The future of social media in marketing	The Future of Social Media in Marketing	Explores the future of social media's role in marketing across consumer, industry, and policy perspectives	Conceptual framework	Omni-social presence, rise of influencers, privacy issues	Identifies nine key themes that are expected to shape the future of social media in marketing	Conceptual/theoretical paper	Insights from academic research and industry discussions	Appel, Grewal, Hadi, & Stephen (2020)
4	When Algorithms Fail: Consumers' Responses to Brand Harm Crises Caused by Algorithm Errors	When Algorithms Fail	Examines consumer reactions to brand crises caused by algorithm errors	Theory of Mind Perception	Perceived agency and responsibility of the algorithm	Consumers react less negatively to brand harm caused by algorithms than by human error	Eight experimental studies	Consumers in various algorithm error scenarios	Srinivasan & Sarial-Abi (2021)
5	A systematic literature review and analysis of deep learning algorithms in mental disorders	A review of deep learning methods applied to mental health disorders for diagnosis and risk assessment.	What are the key concepts from primary studies? Which deep learning methods are prevalent in mental health data analysis? What is the application domain for these methods?	Not explicitly stated. Methodology grounded in systematic literature review (PRISMA protocol).	Mental disorders (depression, mood recognition) analyzed via methods like CNN, RNN, and LSTM.	Convolutional Neural Networks (CNN) are the most used for depression and mood recognition. Future applications show potential for diagnosis.	Systematic literature review with 1339 papers screened; 85 selected.	Data sourced from studies spanning 2000–2023, categorized by algorithm type, limitations, and domains.	Perveen, S., Shukla, A., Sahu, S., & Dhingra, K. (2023).
6	Effects of a 14-day social media abstinence on mental health and well-being	Investigates changes in mental health factors during social media abstinence.	How does abstinence affect depression, anxiety, screentime, and FOMO?	Theories on social media's impact on well-being and mental health.	Dependent: Depression, anxiety, screentime, body image. Independent: Abstinence (14 days).	Abstinence reduced screentime and body image dissatisfaction but showed no significant group differences for depression and anxiety.	Experimental, randomized control vs abstinence groups, longitudinal follow-up.	Surveys on 2.5-hour average screentime; tracked changes via multilevel modeling.	De Hesselle, L. C., Montag, C., & Markowetz, A. (2024).
7	Consumer Autonomy and Social Technology: The Case of Social Media Algorithms and the Metaverse	Explores the impact of social media algorithms and the metaverse on consumer autonomy.	How do social technologies influence consumer autonomy? What are the challenges of perceived vs actual autonomy?	Philosophical theories on consumer choice and autonomy.	Social media algorithms' influence on decision-making autonomy.	Social technology enhances general autonomy but poses challenges to specific dimensions of autonomy (e.g., independence in decision-making).	Analytical framework based on a tripartite definition of autonomy.	Theoretical insights; no empirical data collection.	Braghieri, L., Levy, R., & Makarin, A. (2022).
8	Consumers' persuasion knowledge of algorithms in social media advertising	Identifies consumer groups based on awareness, evaluation, and coping with algorithmic persuasion in social media advertising.	How do consumer groups differ in persuasion knowledge? What personal characteristics predict vulnerability to algorithmic persuasion?	Persuasion Knowledge Model (PKM).	Cognitive: Algorithmic awareness. Affective: Evaluation of algorithmic practices. Behavioral: Coping mechanisms.	Identified consumer typology (Control Paradox, Fatigued, etc.) showing variability in susceptibility to algorithms.	Survey of 450 Dutch participants with cluster analysis.	Cognitive, demographic, and affective measures of persuasion knowledge.	Voorveld, H. A. M., van Reijmersdal, E. A., & Smit, E. G. (2023).
9	Development of Trust Scores in Social Media Algorithm	Introduces a trust score algorithm for social networks to aid advertising research.	How can trustworthiness be systematically measured? What role does network trusting-decision involvement play?	Computational trust theory.	Trustingness and trustworthiness in social media networks.	Trust scores integrating quality and quantity metrics outperform traditional algorithms.	Computational modeling and analysis on social network datasets.	Twitter retweet dataset and other real-world social networks.	Kumar, A., Khatri, S., & Aggarwal, R. (2023).
10	Ethical Issues and Challenges in Social Media: A current scenario	Examines ethical challenges in social media use, focusing on misinformation, data privacy, and cyberbullying.	How do users' actions shape the ethical landscape of social media platforms? What are the ethical responsibilities of platforms in data handling?	Ethical theory in digital media (focus on Kantian deontology).	Independent: Social media features (data usage). Dependent: User trust and platform ethics ratings.	Awareness of ethical concerns leads to cautious social media use. Highlighted role of transparency in improving user trust.	Qualitative, literature review.	Analyzed 50+ ethical frameworks and case studies.	Dhiman, B. (2023).
11	The Impact of Social Media on the Mental Health of Adolescents and Young Adults: A Systematic Review	To examine the impact of social media use on the mental health of adolescents and young adults	How does excessive use impact mental health (depression, anxiety)? What are the specific risks for adolescents?	Displaced Behavior Theory; Social Network Theories	Independent: Social media usage time, type of engagement, cyberbullying, social comparison, bedtime use; Dependent: Depression, anxiety, low self-esteem, sleep issues, self-harm behaviors.	Consistent association between high social media use and negative mental health outcomes (especially depression, anxiety, sleep problems, and body image concerns)	Systematic review (23 studies)	Adolescents and young adults (various large-scale samples)	Khalaf, A. M., Alubied, A. A., Khalaf, A. M., & Rifaey, A. A. (2023).
12	Social Media and Mental Health	Reviews evidence linking social media use to mental health outcomes.	What are the mechanisms driving the mental health effects of social media? How do specific platform features affect well-being?	Cognitive-behavioral theory, social identity theory.	Independent: Platform-specific features (e.g., notifications). Dependent: Stress, anxiety, and self-esteem levels.	Platform design significantly influences stress and anxiety.	Systematic literature review across 30 studies.	Studies from 2015–2023; meta-analysis of user experience data.	Green, A., & Davis, M. (2023).
13	Social Media Use, Mental Health, and Sleep	Explores the relationship between social media use, mental health outcomes, and sleep patterns.	How does late-night use affect mental health? What role does disrupted sleep play?	Sleep disturbance theory, cognitive overload theory.	Independent: Timing of social media use. Dependent: Sleep quality, mental health (depression, fatigue).	Nighttime use of social media disrupts sleep and increases depression risks.	Meta-analysis of 40 studies focusing on sleep and mental health.	Data pooled from clinical trials and observational studies.	Voorveld, H. A. M., van Reijmersdal, E. A., & Smit, E. G. (2023).
14	The Effect of Mobile Social Media on the Mental Health Status of Chinese	Examines how mobile social media impacts the mental health of Chinese students abroad, focusing on mediation effects.	How does mobile social media use affect mental health outcomes? What mediates	Chain mediation theory, cultural adaptation theory.	Independent: Mobile social media use. Mediators: Cultural adjustment, loneliness.	Social media increases stress but aids cultural adjustment; loneliness	Empirical study with surveys on Chinese international students.	Sample of 300 students; cross-sectional and path analysis.	Miao, C., & Zhang, S. (2024).

	International Students		the relationship (e.g., cultural adjustment)?		Dependent: Stress, depression, anxiety.	mediates the effects.			
15	Motivational, Emotional, and Behavioral Correlates of Fear of Missing Out	Explores the psychological and behavioral correlates of FoMO in the context of social media use.	How does FoMO influence emotional and behavioral responses? What motivational factors drive FoMO?	Self-Determination Theory.	Independent: FoMO. Dependent: Emotional well-being, social connectedness, behavioral engagement.	FoMO is linked to reduced well-being and increased social media usage. Emotional needs predict susceptibility to FoMO.	Quantitative, surveys on a sample of 200+ participants.	Questionnaire responses with a 7-point Likert scale; structural equation modeling.	Przybylski, A.K., Murayama, K., DeHaan, C.R., & Gladwell, V. (2013).
16	The Personalization-Privacy Paradox: Location-Aware Marketing	Examines the tension between privacy concerns and the benefits of personalization in location-aware marketing.	How do users balance privacy concerns with the perceived benefits of personalization? What role does trust play in this process?	Privacy Calculus Theory.	Independent: Perceived benefits of personalization. Dependent: Privacy concerns.	Users accept privacy trade-offs for significant personalization benefits but emphasize the need for trust in platforms.	Survey-based quantitative study using regression analysis.	Data collected from 350 users of location-based services.	Xu, H., Luo, X.R., Carroll, J.M., & Rosson, M.B. (2011).
17	Personalized Communication as a Platform for Service Inclusion	Investigates the role of personalized communication in enhancing service inclusion and well-being among stigmatized groups.	How does personalized communication affect service inclusion? How does it enhance anticipated well-being?	Service Inclusion Theory.	Independent: Personalized communication strategies. Dependent: Anticipated well-being.	Personalized communication fosters inclusivity and improves well-being among stigmatized groups.	Survey with path analysis.	Cross-sectional data from 400 respondents.	Mende, M., Scott, M.L., Ubal, V.O., et al. (2024).
18	Algorithmic Awareness in Online Platforms	Explores users' awareness of algorithmic personalization in online content and its impact on trust and engagement.	To what extent are users aware of algorithmic content personalization? How does this awareness influence user trust?	Algorithm Awareness Theory.	Independent: Algorithmic personalization awareness. Dependent: Trust in platforms, engagement levels.	Greater awareness improves trust only when transparency is evident; otherwise, it reduces engagement.	Survey-based study on 500 participants; mixed methods (quantitative and qualitative).	Self-reported measures on algorithm awareness and trust.	Zarouali, B., Boerman, S.C., & de Vreese, C.H. (2021).
19	Smart Service Systems and Customer Well-Being	Investigates the relationship between self-efficacy in technology use and customer well-being in smart service systems.	How does self-efficacy influence customer well-being? What factors enhance smart service inclusivity?	Technology Acceptance Model (TAM).	Independent: Self-efficacy in technology use. Dependent: Customer well-being.	Higher self-efficacy leads to improved satisfaction and well-being in service interactions.	Quantitative analysis through surveys; multi-group analysis to test hypotheses.	600 participants from various demographic groups.	Henkens, B., Verleye, K., & Larivière, B. (2021).
20	Do Great Powers Come with Great Responsibility? Opportunities and Tensions of New Technologies in Marketing	Examines the dual aspects of new technologies in marketing, focusing on opportunities (e.g., personalization, efficiency) and tensions (e.g., privacy concerns, misinformation).	How can technologies be leveraged for consumer and firm benefits? What risks do new technologies pose to consumer trust and well-being?	Ethical marketing frameworks, algorithmic governance theories.	Independent: New marketing technologies (e.g., personalization algorithms, AI). Dependent: Consumer trust, privacy concerns, perceived well-being.	Technologies like AI and algorithmic personalization have transformative impacts, but significant risks like misinformation and privacy invasion require mitigation through ethical frameworks and transparent practices.	Conceptual paper synthesizing insights from empirical and theoretical research; contributions from 80+ submissions in the IJRM special issue.	Insights drawn from empirical studies, lab experiments, and field data in marketing contexts.	Inman, J.J., Meyer, R.J., Schweidel, D.A., & Srinivasan, R. (2024).
21	Social Media and Well-Being: Pitfalls, Progress, and Next Steps	Explores the nuanced impact of social media on well-being, revealing both positive and negative outcomes.	How does the type of social media usage affect well-being? What psychological processes mediate the impact of social media?	Social Comparison Theory, Psychological Needs Fulfillment Framework.	Independent: Types of social media use (active vs. passive). Dependent: Psychological well-being, emotional support.	Active use (e.g., engaging with others) positively impacts well-being, while passive use can lead to negative outcomes like anxiety.	Meta-analysis of third-generation studies with experimental and longitudinal designs.	Analysis of over 50 studies, systematic review from 2005–2020.	Kross et al. (2020).
22	Effects of Social Media Use on Psychological Well-Being: A Mediated Model	Investigates how social media use impacts psychological well-being through mediators like social capital and smartphone addiction.	How does social media use indirectly affect well-being through social isolation and smartphone addiction? What is the role of bonding and bridging social capital?	Social Capital Theory, Addiction Framework.	Independent: Social media use intensity. Mediators: Bonding/bridging social capital, smartphone addiction. Dependent: Psychological well-being.	Social media use can enhance well-being through bonding and bridging social capital but also cause harm via smartphone addiction and isolation.	Structural Equation Modeling (SEM) with 940 participants.	Survey data from social media users in Mexico; 7-point Likert scales.	Ostic et al. (2021).
23	Social Media Use and Well-Being: A Systematic Review and Meta-Analysis	Examines the link between excessive/problematic social media use and subjective/psychological well-being through meta-analysis.	How does problematic social media use affect psychological well-being? What is the impact of excessive usage on subjective well-being?	Uses and Gratification Theory, Two-Continua Model of Well-Being.	Independent: Excessive/problematic social media use. Dependent: Subjective and psychological well-being.	Problematic use negatively impacts well-being; excessive use shows mixed effects. Subgroup analysis reveals the impact varies by demographic and sampling methods.	Meta-analysis of 51 studies with a total sample size of 680,506 individuals.	Studies from PubMed, Scopus, Web of Science; included observational studies.	Ansari et al. (2024).
24	The Associations of Active and Passive Social Media Use with Well-Being: A Critical Scoping Review	Investigates the validity of the active/passive social media use hypothesis in relation to well-being.	Do active and passive uses have distinct effects on well-being? What methodological gaps exist in these studies?	Differential Susceptibility to Media Effects Model.	Independent: Active and passive use. Dependent: Happiness, depression	Mixed evidence for hypotheses; passive use doesn't always negatively affect well-being.	Scoping review of 40 studies.	Cross-sectional and longitudinal survey data from 2015–2020.	Valkenburg et al. (2021)
25	Social Media Use and Mental Health and Well-Being Among Adolescents – A Scoping Review	Analyzes the impact of social media on depression and anxiety among adolescents.	How does usage pattern affect mental health? Are adolescents more vulnerable?	Social-psychological addiction frameworks.	Independent: Time spent on social media. Dependent: Depression, anxiety.	High usage predicts worsened mental health, with variations by age and gender.	Longitudinal survey study.	Adolescents aged 12–19; 940 participants.	Schønning et al. (2020)
26	The Effect of Social Media Abstinence on	Investigates whether abstinence improves	Does temporary abstinence reduce stress?	Intervention frameworks for	Independent: Abstinence condition. Dependent: Stress,	Abstinence positively affects stress reduction	Experimental study.	154 participants (ages 18–25).	Montag et al. (2024)

	Mental Health and Well-Being	psychological outcomes.	Which aspects of well-being improve?	behavioral modification.	depression, and subjective well-being.	and well-being improvement.			
27	Cognitive Load and FOMO: A Longitudinal Study on Social Media's Effects	Examines fear of missing out (FOMO) and its role in cognitive overload and well-being.	How does FOMO mediate cognitive outcomes? What impact does FOMO have on well-being?	Cognitive Load Theory.	Independent: Social media intensity. Mediator: FOMO. Dependent: Cognitive fatigue, well-being.	High FOMO exacerbates cognitive fatigue and reduces well-being.	Longitudinal data analysis.	1,200 participants.	Valkenburg et al. (2021)
28	Parasocial Relationships, Social Media, & Well-Being	The paper examines how parasocial relationships (PSRs) on social media impact multiple dimensions of well-being, including mental health, coping, and social connection.	How do PSRs formed on social media influence well-being outcomes? What are the specific benefits and drawbacks of PSRs for mental health?	Parasocial Interaction Theory, Social Connection Theory, and Eudaimonic Well-Being Framework.	Independent: PSRs (strength, type). Mediators: Coping mechanisms, social comparison. Dependent: Psychological well-being, identity development.	Positive effects: Improved coping, reduced stigma, enhanced identity exploration, and feelings of connection. Negative effects: Risk of body dissatisfaction and depression through upward social comparisons.	Narrative review of PSRs in the context of social media and their link to well-being.	Analysis of evidence from 50+ studies across mental health, identity, and social connection.	Hoffner, C.A., & Bond, B.J. (2022)
29	Social Media and Mental Health: Benefits, Risks, and Opportunities for Research and Practice	Explores the benefits and challenges of social media use for individuals with mental illness, including its role in promoting peer support and enhancing mental health services.	How can social media be leveraged for mental health interventions? What are the potential risks and benefits of social media use for mental health?	Peer Support Theory, Social Interaction Theory.	Independent: Social media use patterns. Mediators: Peer support, community participation. Dependent: Mental health outcomes, engagement with services.	Benefits: Peer support, reduced loneliness, and enhanced service engagement. Risks: Social comparison, cyberbullying, and privacy concerns.	Commentary-based summary of existing studies (narrative review).	Synthesis of studies focusing on social media use among individuals with mental illness from 2010–2020.	Naslund, J. A., Bondre, A., Torous, J., & Aschbrenner, K. A. (2020)
30	Taking a Break from Social Media Improves Wellbeing	Examines whether limiting social media improves wellbeing and explores the role of sleep quality	Does limiting social media improve wellbeing? Does sleep quality mediate the impact on wellbeing?	None explicitly mentioned	IV: Social media use; DV: Wellbeing, sleep quality; Mediator: Sleep quality	Limiting social media use to 10 minutes per app/day for 1 week improves wellbeing, mediated by better sleep quality.	Experimental intervention with control group	132 participants from University of Otago, New Zealand	Graham et al. (2021)

Appendix C. Summary of Measurement Item

Construct	Code	Items	Adapted from
Content filtering (Likert 5)	**FIL1**	Algorithms are used to recommend media content to me on social media	(Zarouali, Boerman, Vreese, 2021)
	FIL2	Algorithms are used to prioritize certain content above others	
	FIL3	Algorithms are used to tailor certain content to me on social media	
	FIL4	Algorithms are used to show someone else see different content than I get to see on social media	
Automated decision-Making (Likert 5)	**ADM1**	Algorithms are used to show me content on social media based on automated decisions	(Zarouali, Boerman, Vreese, 2021)
	ADM2	Algorithms do not require human judgments in deciding which content to show me on social media	
	ADM3	Algorithms make automated decisions on what content I get to see on social media	
Psychological Wellbeing (Likert 7)	**PWBS1**	I like most parts of my personality.	Stanford SPARQtools. (2019).
	PWBS2	When I look at the story of my life, I am pleased with how things have turned out so far.	
	PWBS3	Some people wander aimlessly through life, but I am not one of them.	
	PWBS4	The demands of everyday life often get me down.	
	PWBS5	In many ways, I feel disappointed about my achievements in life.	
	PWBS6	Maintaining close relationships has been difficult and frustrating for me.	

	PWBS7	I live life one day at a time and don't really think about the future.	
	PWBS8	In general, I feel I am in charge of the situation in which I live.	
	PWBS9	I am good at managing the responsibilities of daily life.	
	PWBS10	I sometimes feel as if I've done all there is to do in life.	
	PWBS11	For me, life has been a continuous process of learning, changing, and growth.	
	PWBS12	I think it is important to have new experiences that challenge how I think about myself and the world.	
	PWBS13	People would describe me as a giving person, willing to share my time with others.	
	PWBS14	I gave up trying to make big improvements or changes in my life a long time ago.	
	PWBS15	I tend to be influenced by people with strong opinions.	
	PWBS16	I have not experienced many warm and trusting relationships with others.	
	PWBS17	I have confidence in my own opinions, even if they are different from the way most other people think.	
	PWBS18	I judge myself by what I think is important, not by the values of what others think is important.	
Life Satisfaction	**LS1**	In most ways my life is close to my ideal.	(Diener et al. 1985)
	LS2	The conditions of my life are excellent.	
	LS3	I am satisfied with my life.	
Personal FOMO dimension (Likert 5)	**P1**	I feel anxious when I miss updates or news on social media.	(Zhang, Jiménez & Cicala, 2020)
	P2	I believe that I miss out on important opportunities when I do not check social media	
	P3	I feel anxious because I know something important or fun must happen when I don’t check social media	
	P4	I feel sad if I am not capable of checking social media due to constraints of other things	
	P5	I feel regretful of missing social media content	
Social FOMO dimension (Likert 5)	**S1**	I think my social groups view me as unimportant when I miss content shared on social media.	(Zhang, Jiménez & Cicala, 2020)
	S2	I think I do not fit in with my social groups when I miss posts or updates on social media.	
	S3	I think I am excluded by my social groups when I miss events/opportunities	
	S4	I feel ignored or forgotten by my social groups when I miss posts or updates on social media.	
Social Comparison (INCOM Scale)	**INCOM1**	I often compare how my loved ones (boy or girlfriend, family members, etc.) are doing with how others are doing.	(Gibbons and Buunk, 1999)
	INCOM2	I always pay a lot of attention to how I do things compared with how others do things.	
	INCOM3	If I want to find out how well I have done something, I compare what I have done with how others have done.	

	INCOM4	I often compare how I am doing socially (e.g., social skills, popularity) with other people	
	INCOM5	I am not the type of person who compares often with others. (reversed)	
	INCOM6	I often compare myself with others with respect to what I have accomplished in life.	
	INCOM7	I often like to talk with others about mutual opinions and experiences.	
	INCOM8	I often try to find out what others think who face similar problems as I face	
	INCOM9	I always like to know what others in a similar situation would do.	
	INCOM10	If I want to learn more about something, I try to find out what others think about it.	
	INCOM11	I never consider my situation in life relative to that of other people. (reversed)	
Need for Social Validation	**NFSV1**	People generally consider me to be a very opinionated person. (R)	(Graham, 1997)
	NFSV2	I don't really feel comfortable expressing an opinion on an issue until I've heard what other people have to say.	
	NFSV3	I find it difficult to know what to think when people I talk to have different opinions about an issue.	
	NFSV4	It doesn't bother me if I'm the only one who believes something when most people I know disagree with me. (R)	
	NFSV5	I like to know what other people are thinking before I form my own opinion on an issue.	
	NFSV6	I often worry about what others will think of my opinions.	
	NFSV7	I usually know where I stand on an issue without having to hear what other people have to say. (R)	
	NFSV8	I don't like to tell people how I feel about controversial issues until I've heard what they have to say.	
	NFSV9	If I found that a lot of people disagreed with the stand I took on an issue, I would probably change my position.	
	NFSV10	I often disagree with other people's opinions and tell them so. (R)	
	NFSV11	I need to know that other people agree with my opinions before I can express them publicly.	
	NFSV12	I find it important to express my opinions even if I know that other people don't feel the same way that I do. (R)	

Appendix D. Online Questionnaire

Q1 Dear participant,

This is a survey to evaluate your perceptions of social media algorithms. There is no wrong or right answer, and there is no risk involved in answering any of the following questions. Remember that your participation in this survey is voluntary, which means that you are free to participate or not, as well as give up at any time. Your responses are very important, completely anonymous, and will be used only for academic purposes. Thank you! Beatriz Letras

Q2 **Informed Consent Form:** I declare that I am 18 or over 18 and agree to participate in this research. I declare that I was informed that my participation in this study is voluntary and that I can leave this survey at any time without penalty, and all data is confidential. I understand that I will evaluate responses and that this study does not offer serious risks.

- ○ I agree to participate in this survey. (1)
- ○ I do not agree to participate in this survey. (2)

Q7 **In this section, we will assess your perceptions of how algorithms are used on social media to recommend and prioritize content.** For each item, please indicate the extent to which you agree or disagree using the following scale: 1 = Strongly Disagree, 2 = Disagree, 3 =

Moderately Disagree, 4 = Somewhat Disagree, 5 = Neutral, 6 = Somewhat Agree, 7 = Moderately Agree, 8 = Agree, 9 = Strongly Agree.

	Strongly Disagree (1)	Disagree (2)	Moderately Disagree (3)	Somewhat Disagree (4)	Neutral (5)	Somewhat Agree (6)	Moderately Agree (7)	Agree (8)	Strongly Agree (9)
Algorithms are used to recommend media content to me on social media (1)	○	○	○	○	○	○	○	○	○
Algorithms are used to prioritize certain content above others (2)	○	○	○	○	○	○	○	○	○
Algorithms are used to tailor certain content to me on social media (3)	○	○	○	○	○	○	○	○	○
Algorithms are used to show someone else see different content than I get to see on social media (4)	○	○	○	○	○	○	○	○	○

Q8 **This question examines your views on how social media algorithms make automated decisions in delivering content.** Please indicate your level of agreement with each statement using the same scale: 1 = Strongly Disagree to 9 = Strongly Agree.

	Strongly Disagree (1)	2	3	4	Neutral (5)	6	7	8	Strongly Agree (9)
Algorithms are used to show me content on social media based on automated decisions (1)	○	○	○	○	○	○	○	○	○
Algorithms do not require human judgments in deciding which content to show me on social media (2)	○	○	○	○	○	○	○	○	○
Algorithms make automated decisions on what content I get to see on social media (3)	○	○	○	○	○	○	○	○	○

Q9 **This section focuses on your perceptions of your psychological well-being and personal growth.** As before, use the scale from 1 = Strongly Disagree to 9 = Strongly Agree to respond to each statement.

	Strongly Disagree (1)	2	3	4	Neutral (5)	6	7	8	Strongly Agree (9)
I like most parts of my personality. (1)	○	○	○	○	○	○	○	○	○
When I look at the story of my life, I am pleased with how things have turned out so far. (2)	○	○	○	○	○	○	○	○	○
Some people wander aimlessly through life, but I am not one of them. (3)	○	○	○	○	○	○	○	○	○
The demands of everyday life often get me down. (4)	○	○	○	○	○	○	○	○	○
In many ways, I feel disappointed about my achievements in life. (5)	○	○	○	○	○	○	○	○	○
Maintaining close relationships has been difficult and frustrating for me. (6)	○	○	○	○	○	○	○	○	○
I live life one day at a time and don't really think about the future. (7)	○	○	○	○	○	○	○	○	○

In general, I feel I am in charge of the situation in which I live. (8)	○	○	○	○	○	○	○	○	○
I am good at managing the responsibilities of daily life. (9)	○	○	○	○	○	○	○	○	○
I sometimes feel as if I've done all there is to do in life. (10)	○	○	○	○	○	○	○	○	○
For me, life has been a continuous process of learning, changing, and growth. (11)	○	○	○	○	○	○	○	○	○
I think it is important to have new experiences that challenge how I think about myself and the world. (12)	○	○	○	○	○	○	○	○	○
People would describe me as a giving person, willing to share my time with others. (13)	○	○	○	○	○	○	○	○	○
I gave up trying to make big improvements or changes in my life a long time ago. (14)	○	○	○	○	○	○	○	○	○

I tend to be influenced by people with strong opinions. (15)	◯	◯	◯	◯	◯	◯	◯	◯	◯
I have not experienced many warm and trusting relationships with others. (16)	◯	◯	◯	◯	◯	◯	◯	◯	◯
I have confidence in my own opinions, even if they are different from the way most other people think. (17)	◯	◯	◯	◯	◯	◯	◯	◯	◯
I judge myself by what I think is important, not by the values of what others think is important. (18)	◯	◯	◯	◯	◯	◯	◯	◯	◯

Q10 **This question explores your overall satisfaction with life and its various aspects.** Respond to each statement using the scale provided: 1 = Strongly Disagree to 9 = Strongly Agree.

	Strongly Disagree (1)	2	3	4	Neutral (5)	6	7	8	Strongly Agree (9)
In most ways my life is close to my ideal. (1)	○	○	○	○	○	○	○	○	○
The conditions of my life are excellent. (2)	○	○	○	○	○	○	○	○	○
I am satisfied with my life. (3)	○	○	○	○	○	○	○	○	○

Q11 **This section investigates your feelings and experiences related to missing updates or opportunities on social media.** Indicate your agreement with each statement using the same scale: 1 = Strongly Disagree to 9 = Strongly Agree.

	Strongly Disagree (1)	2	3	4	Neutral (5)	6	7	8	Strongly Agree (9)
I feel anxious when I miss updates or news on social media. (1)	○	○	○	○	○	○	○	○	○
I believe that I miss out on important opportunities when I do not check social media (2)	○	○	○	○	○	○	○	○	○
I feel anxious because I know something important or fun must happen when I don’t check social media. (3)	○	○	○	○	○	○	○	○	○

I feel sad if I am not capable of checking social media due to constraints of other things. (4)	○	○	○	○	○	○	○	○	○
I feel regretful of missing social media content. (5)	○	○	○	○	○	○	○	○	○

Q12 **This question explores how missing social media updates might affect your sense of inclusion in your social groups**. For each item, rate your agreement using the following scale: 1 = Strongly Disagree to 9 = Strongly Agree.

	Strongly Disagree (1)	2	3	4	Neutral (5)	6	7	8	Strongly Agree (9)
I think my social groups view me as unimportant when I miss content shared on social media. (1)	○	○	○	○	○	○	○	○	○
I think I do not fit in with my social groups when I miss posts or updates on social media. (2)	○	○	○	○	○	○	○	○	○
I think I am excluded by my social groups when I miss events/opportunities. (3)	○	○	○	○	○	○	○	○	○
This is an attention check, please select option 9. (4)	○	○	○	○	○	○	○	○	○
I feel ignored or forgotten by my social groups when I miss posts or updates on social media. (5)	○	○	○	○	○	○	○	○	○

Q13 **This section evaluates how often you compare yourself to others in different aspects of life, including achievements and social interactions.** Use the scale provided: 1 = Strongly Disagree to 9 = Strongly Agree.

	Strongly Disagree (1)	2	3	4	Neutral (5)	6	7	8	Strongly Agree (9)
I often compare how my loved ones (boy or girlfriend, family members, etc.) are doing with how others are doing. (1)	○	○	○	○	○	○	○	○	○
I always pay a lot of attention to how I do things compared with how others do things. (2)	○	○	○	○	○	○	○	○	○
If I want to find out how well I have done something, I compare what I have done with how others have done. (3)	○	○	○	○	○	○	○	○	○
I often compare how I am doing socially (e.g., social skills, popularity) with other people. (4)	○	○	○	○	○	○	○	○	○

I am not the type of person who compares often with others. (5)	○	○	○	○	○	○	○	○	○
I often compare myself with others with respect to what I have accomplished in life. (6)	○	○	○	○	○	○	○	○	○
I often like to talk with others about mutual opinions and experiences. (7)	○	○	○	○	○	○	○	○	○
I often try to find out what others think who face similar problems as I face. (8)	○	○	○	○	○	○	○	○	○
I always like to know what others in a similar situation would do. (9)	○	○	○	○	○	○	○	○	○
If I want to learn more about something, I try to find out what others think about it. (10)	○	○	○	○	○	○	○	○	○

I never consider my situation in life relative to that of other people. (11)	○	○	○	○	○	○	○	○	○

Q14 **This question examines your comfort with expressing opinions and how others views may influence your beliefs.** Indicate how much you agree or disagree using the same scale: 1 = Strongly Disagree to 9 = Strongly Agree.

	Strongly Disagree (1)	2	3	4	Neutral (5)	6	7	8	Strongly Agree (9)
People generally consider me to be a very opinionated person. (1)	○	○	○	○	○	○	○	○	○
I don’t really feel comfortable expressing an opinion on an issue until I’ve heard what other people have to say. (2)	○	○	○	○	○	○	○	○	○
I find it difficult to know what to think when people I talk to have different opinions about an issue. (3)	○	○	○	○	○	○	○	○	○
It doesn’t bother me if I’m the only one who believes something when most people I know disagree with me. (4)	○	○	○	○	○	○	○	○	○

I like to know what other people are thinking before I form my own opinion on an issue. (5)	○	○	○	○	○	○	○	○	○
I often worry about what others will think of my opinions. (6)	○	○	○	○	○	○	○	○	○
I usually know where I stand on an issue without having to hear what other people have to say. (7)	○	○	○	○	○	○	○	○	○
I don’t like to tell people how I feel about controversial issues until I’ve heard what they have to say. (8)	○	○	○	○	○	○	○	○	○
If I found that a lot of people disagreed with the stand I took on an issue, I would probably change my position. (9)	○	○	○	○	○	○	○	○	○

I often disagree with other people's opinions and tell them so. (10)	○	○	○	○	○	○	○	○	○
I need to know that other people agree with my opinions before I can express them publicly. (11)	○	○	○	○	○	○	○	○	○
I find it important to express my opinions even if I know that other people don't feel the same way that I do. (12)	○	○	○	○	○	○	○	○	○

Q15 What is your age? (Insert numbers only)

____

Q16 What is your gender?

○ Male (1)

○ Female (2)

○ Non-binary/Other (3)

○ Prefer not to say (4)

Q17 What is your highest level of education?

- ◯ No School Degree Completed (1)
- ◯ High School or equivalent (2)
- ◯ Bachelor degree (3)
- ◯ Master or Postgraduate degree (4)
- ◯ PhD/Doctorate (5)

Q18 What is your Nationality?

- ◯ Portuguese (1)
- ◯ Other (2) ____

Q23 What is your English level?

- ◯ Beginner (1)
- ◯ Intermediate (2)
- ◯ Advanced (3)
- ◯ Native or Fluent (4)

Q20 What is your primary language?

- ◯ Portuguese (1)
- ◯ English (2)
- ◯ Spanish (3)
- ◯ French (4)
- ◯ Other (5) ____

Q19 What is your employment status?

- Employed full-time (1)
- Employed part-time (2)
- Student (3)
- Self-employed (4)
- Unemployed (5)
- Retired (6)
- Other (7)

Q21 What is your monthly income? (Net Salary)

- Less than €500 (1)
- €500–€999 (2)
- €1,000–€1,499 (3)
- €1,500–€1,999 (4)
- €2,000–€2,999 (5)
- €3,000 or more (6)
- No Income (7)

Q4 How often do you use social media?

- Rarely (less than once a week) (1)
- Occasionally (a few times a week) (2)
- Sometimes (once a day) (3)
- Often (2–3 times a day) (4)

- Very Often (4–5 times a day) (5)
- Always (more than 5 times a day) (6)
- Never (7)

Q5 On average, how much time do you spend daily on social media?

- Less than 30 minutes (1)
- 1-2 hours (2)
- 2–3 hours (3)
- 3–4 hours (4)
- More than 4 hours (5)

Q6 Which social media platform(s) do you use most frequently? (Select all that apply)

- Facebook (1)
- Instagram (2)
- TikTok (3)
- X/Twitter (4)
- LinkedIn (5)
- Snapchat (6)
- Others (7)

Q24 Do you like Social Media content powered by Algorithms?

- Yes (1)
- No (2)

○ Prefer not to say (3)

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