

How Algorithmic Awareness Predicts Passive and Active Social Media Content Engagement Behavior

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Abstract

Drawing on theories of social media engagement, privacy calculus, and dual information processing, this study examines the relationship between users' awareness of algorithmic influence on social media content and their behavioral engagement on these platforms. Utilizing a survey of U.S. adult social media users (N = 990), we investigate how self-reported internet literacy and awareness of algorithmically curated media content are associated with social media self-disclosure, as well as passive and active behavioral engagement. Structural equation modeling analysis reveals a positive association between internet literacy and algorithmic media content awareness. Furthermore, both algorithmic media content awareness and self-disclosure significantly predict passive engagement, while self-disclosure and passive engagement, in turn, positively influence active engagement.

Keywords: Algorithmic awareness, internet literacy, social media disclosure, social media engagement

Introduction

Algorithms on social media can be thought of as rules or calculations to rank and associate types of content that lead to the recommended organic and sponsored posts that appear on a person's newsfeed (Figueiredo & Bolaño, 2017). These formulas are used on all major social media platforms, and thus, what users see in their feeds is curated by algorithms (Milan, 2015). Consequently, social media algorithms provide predictions of personalized content that is likely to capture and hold social media users' attention (Bechmann & Bowker, 2019) and increase engagement. As awareness of social media algorithms appears to be increasing (De Groot et al., 2023), it is worth investigating if algorithmic media content awareness influences engagement. In this study, we propose an exploratory model that empirically tests the interrelations between internet literacy as a predictor of algorithmic media content awareness and social media self-disclosure, which in turn predict passive and active social media content engagement behavior.

Engagement is critical for all organizations that have a presence on social media, as stakeholders' perceptions, behavior, and ultimately an organization's income are positively influenced by the level of interactions those organizations have with their stakeholders (Smith & Taylor, 2017). Stakeholders refers to all individuals who have an interest in the organization (e.g., social media followers, customer, employees, investors, suppliers, local communities). Social media algorithms prioritize content that will keep users on the platform via engagement (e.g., liking, sharing, commenting, viewing), which in turn makes the platform more appealing for campaigns, brand building, and other strategic endeavors (Khan, 2024). For example, Newberry (2024) details how eight of the most well-known social media platforms (Instagram, TikTok, YouTube, Facebook, X, LinkedIn, Pinterest, Threads) rely on algorithms to collect user information for the explicit purpose of targeted content recommendations to increase engagement on their platforms.

One engagement typology is either passive, which entails simply consuming social media content, or active, when a user interacts with the content (Dolan et al., 2016, 2019; Gainous et al., 2021). Passive social media engagement may occur through incidental exposure, whereby users encounter content unintentionally while navigating the platform without a specific goal (Yamamoto & Morey, 2019). Alternatively, it can involve intentional consumption, in which users deliberately seek out information or updates yet refrain from any direct interaction, such as liking, commenting, or sharing. Studying passive and active engagement as separate constructs is theoretically relevant as they encompass different psychological processes and impacts on users. Dolan et al. (2016) argued that social media engagement behavior manifests as passive and active, distinct constructs that reflect a low vs. high continuum of intensity of engagement. Comparatively, dual processing theory suggests passive (active) engagement likely results from automatic (conscious) deliberation via system 1 (system 2) processing; and that active and passive engagement behaviors occur simultaneously or immediately after one

another (Dolan et al., 2019).

The present study aims to establish what individual-level factors relate to behavioral engagement with algorithmically curated social media content. Specifically, we propose and investigate how internet literacy, algorithmic media content awareness and social media self-disclosure relate to creating and contributing (active) as well as simply consuming (passive) social media content. We reason that internet literacy may enhance individuals' ability to understand how algorithms influence the content they see, thereby increasing their awareness of how that content is curated and personalized on social media platforms. In turn, this greater algorithmic media content awareness, fostered by high internet literacy, may influence users' decisions about social media self-disclosure as they become more conscious of the potential privacy risks and data usage by algorithms.

Privacy issues with algorithms on social media (e.g., data-based discrimination, data misuse, lack of user control) have been explicated by previous scholars (Huh et al., 2023; Tucker, 2018), and underly the reasoning here that internet literacy and awareness of social media algorithms negatively relate to the amount of information users indicate they self-disclose on social media. The privacy calculus model (Dinev & Hart, 2006) suggests that users are reluctant to self-disclose information when they have privacy concerns and lack knowledge of what purposes their information could be used for. Thus, the present research ponders whether a negative or positive relationship exists between users' awareness of algorithms in the U.S. and their self-disclosure.

Moreover, within the privacy calculus framework it is likely that users evaluate the tradeoffs between the benefits of social media engagement (e.g., social capital, information access) and the perceived risks associated with disclosing personal information (e.g., data exploitation, identity theft). When users perceive the costs to outweigh the gains, they are likely to curtail active engagement behaviors (posting original content or commenting) to minimize potential privacy breach. Instead, they may engage more passively (observing or liking) to minimize personal disclosure because these activities yield informational or social rewards while imposing lower privacy costs.

Conversely, the "privacy paradox" phenomenon (Barth et al., 2019; Norberg et al., 2007; Thon & Jucks, 2014) shows that despite users reporting significant privacy concerns, their actual behavior remains relatively unchanged. It could be that if users believe that the platform's privacy controls and data policies effectively mitigate risks, the perceived benefits of active engagement increase relative to potential harms, thereby incentivizing more frequent self-disclosure and interactive participation. Taking these insights together, this study explored how perceived privacy risks may relate to different expressions of passive vs active social media engagement.

A few contributions of this study are worth noting. First, as empirical research on social media algorithmic awareness and literacy is nascent, this study will explore the extent to which internet literacy is positively

associated with users' awareness of algorithms as distinct but also overlapping constructs. Second, by exploring the theorized relations between social media algorithmic content awareness and users' self-disclosure on social media, theoretical implications for 1) social media engagement theory (Di Gangi & Wasko, 2016) and 2) privacy calculus theory (Chen, 2018; Dinev & Hart, 2006) will be produced. Third, we will differentiate between passive and active engagement as reflections of system 1 and system 2 processing, respectively, suggested by dual processing theory (Dolan, 2019) to understand how awareness of social media algorithmic content awareness influences these interrelated but different types of engagement. As a result, this study contributes to the emerging literature on user perceptions of algorithms by providing preliminary empirical evidence of the theoretical antecedents and consequences of algorithmic media content awareness.

Literature Review

The following review of literature will explain how users tailor their self-disclosure and engagement behavior on social media based on perceived algorithmic influences. We theorize that increased internet literacy facilitates critical thinking about algorithmic processes, which can amplify or diminish social media engagement behaviors, depending on users' perceived control over self-disclosure and content interaction. The review of literature will first define social media engagement behavior and use dual processing theory to ground the distinction and connection between passive and active engagement behaviors. Next, the constructs and theorized interrelations between internet literacy, algorithmic media content awareness, and engagement behaviors will be presented. Lastly, the privacy calculus model is utilized to contextualize how as users' internet literacy and algorithmic awareness increase, they weigh the benefits of social media engagement against the potential risks, which can modulate their self-disclosure of information and subsequent engagement behaviors.

Passive and Active Social Media Engagement Behavior

There exist mixed definitions of social media engagement. Some scholars emphasize the cognitive and emotional dimensions (e.g., Di Gangi & Wasko, 2016), others highlight the behavioral dimension (e.g., Dolan et al., 2016), and additional researchers conclude engagement to be multidimensional and encompass all three dimensions (e.g., Dessart, 2017). Since the scope of this study is to examine engagement behavior, the present study adopts Dolan et al.'s (2016) social media engagement behavior construct that categorizes engagement as either passive (e.g., reading, watching, or viewing) or active (e.g., sharing, commenting, and posting) activities on social media (Escobar-Viera et al., 2018; Khan, 2017). Valkenburg et al. (2022) explain that passive behavioral engagement refers to when a user takes a monitoring approach to view an online exchange (e.g., watching, scrolling, or reading). Meanwhile, situations where a person displays targeted behavior to communicate their thoughts or opinions (e.g., liking, sharing, or commenting) are considered active behavioral engagement.

Dolan et al. (2016) argued that passive engagement can be considered a

low-intensity display of behavior where a person seeks to benefit from the online space without strongly participating. In contrast, active engagement is high-intensity behavior that contributes to shaping the online space. Furthermore, they propose a typology comprising seven distinct types of behavior that flow between a passive (low) or active (high) continuum of intensity (Florenthal, 2019; Shahbaznezhad et al., 2021). Namely, consumption, dormancy, and detachment represent passive engagement behavior that impact only the individual user; while active engagement behaviors encompass co-creation, positive contribution, negative contribution and co-destruction forms of expression that impact other users (Dolan et al., 2016).

Passive engagement can manifest as either incidental exposure or intentional consumption. Incidental exposure can be thought of as unplanned encounters with content while browsing, often shaped by algorithms and social ties (Fletcher & Nielsen, 2018). In contrast, intentional passive engagement involves purposive content consumption without contributing to discussions or visibly interacting (Dreston & Neubaum, 2025). For example, regularly viewing a friend's posts or following news updates without commenting or sharing. Both forms serve important functions, enabling users to stay informed or socially connected while minimizing self-disclosure and interaction. In this study, we do not distinguish between them, as both represent fundamentally passive modes of engagement.

This study logically assumes that before a user actively engages with content (e.g., comment), they must passively engage (e.g., scrolling and reading). To contextualize this reasoning, we consulted literature on dual processing theories on how passive social media engagement results likely from fast intuitive processing and active social media engagement likely results from slower deliberate processing. Dual processing theories of reasoning (Wason & Evans, 1975) propose that people process information through system 1 processing, which is fast and automatic for less mentally involved scenarios, while system 2 processing operates consciously, slower, and takes more effort for higher mentally involving scenarios. Scholarly discourse generally divides dual process theories into two groups consisting of parallel-competitive theories that propose system 1 and 2 operate simultaneously, or default-interventionist theories where system 1 is typically activated by default and then system 2 intervenes after system 1, if needed (Bago & De Neys, 2020; Evans, 2011).

In the social media context, scholars (e.g., Swani et al., 2017) have noted that passive social media engagement behavior results from system 1 processing, and active social media engagement behavior reflects system 2 processing to express higher involvement and expression of opinion. For example, when social media users read and view content (passive engagement) on their feeds, they will likely engage in fast and automatic system 1 processing. Conversely, system 2 processing likely comes into play when a user actively engages with content (e.g., writing their post), as doing so would require them to spend more time and deliberation about the exact words, thoughts, and/or ideas they wish to express. Dolan et al.

(2019), in line with the default-interventionist theories of dual processing (Bago & De Neys, 2020; Evans, 2011), postulate that passive and active engagement may occur simultaneously or active engagement as system 2 processing may occur immediately after the passive engagement as system 1 processing. To test this presumed relationship, we hypothesize:

H1: Passive social media engagement will positively relate to active social media engagement.

Internet Literacy and Algorithmic Literacy

Literacy is broadly understood as a person's ability, skill, and knowledge about a topic (Cope & Kalantzis, 2000). With respect to the nuanced discourse that disagrees on the exact definition and operationalization of internet literacy (the focus of this research), we conceptualize internet literacy as a skills-based ability to access, analyze, create, evaluate, and create content on devices with internet access (Yeşilyurt & Vezne, 2023), such as smartphones, desktop computers, laptops, smart TVs, etc. As explained by Julien (2015), the more skills a person has with internet content could hint at their accumulated knowledge and past behavior regarding internet literacy. Internet literacy likely relates to social media use in terms of frequency of use (Ye et al., 2018) since many of the basic components of navigating most content on the website (access, understanding, creating, etc.) are important for practical usage of social media (Bauer & Mohseni Ahooei, 2018; Reisdorf & Blank, 2021).

Like consumers have literacy in adjacent topics such as computers, websites, data, social media, etc. (Bauer & Mohseni Ahooei, 2018), they can also have algorithmic literacy. There is a presumable overlap between internet literacy and algorithmic literacy; however, they are likely distinct constructs that preliminary research should examine separately. Research finds that tech-savvy individuals vary widely in how much they understand social media algorithms (e.g., Hamilton et al., 2014; Rader & Gray, 2015), suggesting that internet literacy does not guarantee that one will understand algorithms. As an illustration, Reisdorf and Blank (2021) found small to moderate correlations between self-reported internet skills-based literacy and algorithmic literacy (0.2-0.4) and asserted that the constructs are different.

Thus, internet literacy generally refers to the ability to efficiently navigate, evaluate, and use online resources and tools, encompassing basic knowledge of web browsing, online safety, and troubleshooting. In contrast, algorithmic literacy specifically involves understanding how algorithms curate, filter, and recommend content, as well as recognizing the implications of automated decision-making on information exposure and privacy. While internet literacy equips users to function effectively in digital environments, algorithmic literacy empowers them to critically assess and potentially influence the invisible processes that shape their online experiences. Therefore, distinguishing between these literacies is crucial, as someone may be highly proficient in using the internet but lack awareness of how algorithmic systems impact the content they see and interact with (Dogruel et al., 2021).

Algorithm-based decision-making is extensively used in many aspects of human life, and thus, studies on algorithmic literacy are imperative (Ridley & Pawlick-Potts, 2021). However, defining and measuring algorithmic literacy is difficult because the technology behind algorithms is inaccessible to the public, varies between platforms, and is constantly evolving (Oeldorf-Hirsch & Neubaum, 2023; Kitchin, 2017). Moreover, initiatives aiming to educate children and the general population remain challenged in planning and execution, leaving the public with few formal and accessible places to learn and eventually become algorithmically literate (Chiu et al., 2024). As a result, scholars observe that algorithm literacy is low and in its infancy stages (Frau-Meigs, 2024; Shin et al., 2021). Considering this, the present research studies awareness of how social media content is influenced by algorithms rather than algorithmic literacy.

Given that social media algorithms are proprietary and most of the population does not have the technical skills to create an algorithm, other scholars have instead studied algorithmic awareness (Dogruel et al., 2021; Silva et al., 2024). For example, while a person may not be able to edit a social media platform's algorithm, they may be aware of how it generally works and will not like, share, or extensively view content they do not wish to see again. Thus, in line with the suggestions of other scholars (Koenig, 2020), it is necessary to first study users' perceptions of and responses toward algorithmic-curated content in online environments before studies on literacy emerge. Based on these justifications, this study examines algorithmic media content awareness on social media.

Algorithmic media content awareness can be defined as "the extent to which people hold accurate perceptions of what algorithms do in a particular media environment, as well as their impact on how users consume and experience media content" (Zarouali et al., 2021, p. 2). Moreover, algorithmic media content awareness includes awareness of the following dimensions: 1) content filtering, 2) automated decision-making, 3) human-algorithm interplay, and 4) ethical considerations. Additionally, some scholars note that digital literacy (which broadly entails literacy around technologies in the digital realm) may positively influence algorithmic awareness (e.g., Hosman & Pérez Comisso, 2020; Zarouali et al., 2021). Notably, the skills and competencies accumulated with internet literacy may positively associate with algorithmic awareness by contributing to how users understand how algorithms influence their in-feed content, targeted ads, and search engine results (Gran et al., 2020).

Thus, we surmise that algorithmic media content awareness is likely associated with internet literacy. This theoretical relationship between these concepts is rooted in the idea that internet literacy provides the tools necessary for users to decode the often opaque mechanisms of algorithmic content delivery. For instance, users with high internet literacy may question why certain content appears in their feeds and understand how their digital behaviors influence algorithmic recommendations. Moreover, aside from social media, algorithms also influence several other internet-based functions such as search engine results, content suggestions on

streaming services, suggested romantic partners on dating apps, and product recommendations on shopping sites (Dogruel et al., 2022; Reisdorf & Blank, 2021). Consequently, it could be that the more consumers broadly engage with these services via the internet and sharpen their literacy, the more they develop a heightened ability to recognize and understand the role of algorithms in curating and personalizing media content. Therefore, we hypothesize:

H2: Social media users' internet literacy will positively relate to social media algorithmic media content awareness.

Social Media Engagement and Algorithmic Media Content Awareness

Di Gangi and Wasko's (2016) social media engagement theory (SMET) posits that the extent to which a social media platform provides sound technical features and helps facilitate social interactions will positively relate to their engagement and, ultimately, the frequency of use of the platform. Additionally, SMET notes that the evolution of technology has increased the personalized and unique experience users can receive by removing the physical and temporal distances that exist (Bruce et al., 2023).

Di Gangi and Wasko (2016), in their original study of SMET, stated completeness (i.e., perception that the platform meets a desired level of information need) and evolvability (i.e., new functionalities to meet users' needs and/or desires) to be critical components to engage users. Dewnarain et al. (2019) further propose that social media platforms should aim to evolve by building or integrating new technology that provides novel and unique experiences. Consequently, platforms with more advanced technical features (e.g., messaging, following, liking, sharing, private groups) can help better facilitate social interaction (Jiang et al., 2023).

Scholars further note that when users receive content on their newsfeed that is relatable, personal (Arora et al., 2022), and aligns with their interests (Stoica & Hickman, 2024), they display higher levels of engagement on the platform. This is due to the content being viewed as relevant and contributing to one of the goals (e.g., entertainment, information) users seek to fulfill at a given time (Jiang et al., 2023; Stoica & Hickman, 2024). Algorithms, by design, seek to provide users with related and personal content and, thus, should be well-positioned to drive higher engagement. As a result, greater awareness of algorithmic curation could positively predict engagement on social media by empowering individuals to better understand and influence the content they see.

If a user is aware that their interactions shape their feeds, they may feel a sense of agency to thoughtfully and intentionally shape their feeds to purposefully curate their own experiences and seek out content that aligns with their interests. This would be accomplished through their actions, such as liking, sharing, or commenting on specific content, leading to more active and sustained participation (i.e., engagement). With these rationales, it could be speculated that as users are aware of algorithms and

how they contribute to their personalized social media experience, it may lead to greater engagement. Motivated by this assumption, the present study considers algorithms as a technical feature postulated in SMET to drive behavioral engagement.

As users know how algorithms work (as a technical feature) to provide relevant content to improve their social media experience, it may positively relate to their engagement behavior. If users are aware of algorithms, specifically that they use their interests and interactions to deliver content more in line with their preferences, it could lead to stronger connectedness to the platform (Bucher, 2017). Consequently, it is reasonable to speculate that this connectedness could be observed via social media engagement behavior. Thus, our next hypothesis states:

H3: Social media algorithmic media content awareness will positively relate to a) passive and b) active social media engagement.

Privacy Calculus Model and Social Media Self-Disclosure

The privacy calculus model proposes that individuals assess the risk to their privacy against their perceived benefits (i.e., social capital) when deciding to disclose information (Dinev & Hart, 2006). While the model suggests that people have inherent concerns about their privacy, they are willing to ignore those concerns if they perceive the benefits outweigh the costs (Dienlin & Metzger, 2016). Such benefits may include personalization of service, convenience, entertainment, and learning new perceived relevant information (Chen, 2018; Wang et al., 2016). This privacy calculus varies between individuals and contexts. However, factors such as trust in the data collector, perceived benefits of sharing, and sensitivity to sharing can influence a user's calculus (Pentina et al., 2016).

As the social media engagement theory noted, integrating new technology (e.g., algorithms) can help facilitate social interactions that would increase engagement on social media (Di Gangi & Wasko, 2016). However, privacy calculus would suggest that a consequence of integrating new technology, such as algorithms, could be reduced engagement if users decide to self-disclose less information. When users are aware of how algorithms work, it may raise internal alarms about perceived privacy risks if users have high sensitivity toward sharing personal data (Huh et al., 2023; Kim et al., 2023). That may influence individuals to disclose less information online to guard against perceived harm or risk. Thus, a potential decrease in engagement via less self-disclosure is plausible.

Self-disclosure can be defined as the expression of thoughts and/or feelings to at least one other person (Green et al., 2006). Furthermore, Green and colleagues noted that self-disclosure is often studied regarding highly personal information but can include superficial information. In the social media context, research suggests that self-disclosing information online will positively relate to perceived benefits of the social networking site (Ellison et al., 2011), via higher engagement on the platform (Swirsky et al., 2021).

Social media disclosure and active behavioral engagement while interrelated, are viewed to be distinct constructs. Self-disclosure refers to the voluntary sharing of personal information that is otherwise inaccessible to others, serving as a foundation for building online relationships and reducing interpersonal uncertainty (Green et al., 2006). In contrast, active behavioral engagement involves intentional interactions such as liking, commenting, or creating content, which serve as a foundation for socially interacting with a platform's features and other users (Dolan et al., 2016). While disclosure focuses on revealing private details to foster connections, active engagement emphasizes participatory behaviors that influence content distribution and platform algorithms, often driven by social motivations. Thus, the conceptual distinction is that self-disclosure is a relational act to curate a user's online image, whereas active engagement is a behavioral mechanism to foster social community and visibility.

Users can vary the breadth and depth of information they self-disclose as a form of regulation or privacy management to mitigate the perceived concern that the information they disclose could be misused (Walsh et al., 2020). However, research (e.g., Barth et al., 2019; Joinson et al., 2010; Thon & Jucks, 2014) has not found strong evidence that even when consumers have privacy concerns, it will influence their actual behavior (e.g., self-disclosing information). It is argued that this could be due to users having relatively little control over what, when, and how their personal information is shared, even if they adjust their privacy settings (Metzger & Suh, 2017).

The online space and the new advent of artificially intelligent systems built through algorithms are noted to pose privacy threats to users (Tucker, 2018). Ethical issues such as surveillance, algorithmic transparency, and unfair predictions made by AI algorithms that perpetuate social inequalities have been articulated by Huh et al. (2023). Mainly, when consumers believe the personal information they disclose online will be used for commercial purposes, it will likely lead to resistance (Kim et al., 2023). Consequently, as users develop literacy about how the internet functions, they will likely develop some understanding that websites, social media platforms, and the like rely on collecting personal information to sell to advertisers. With this reasoning, it could be that the more literate and/or aware they are of this, the more their disclosure will be reduced, and subsequently, their engagement with the platform will decrease. The following hypotheses are stated below to test these theoretical assumptions.

H4: Users' a) internet literacy and b) algorithmic media content awareness will negatively relate to social media self-disclosure.

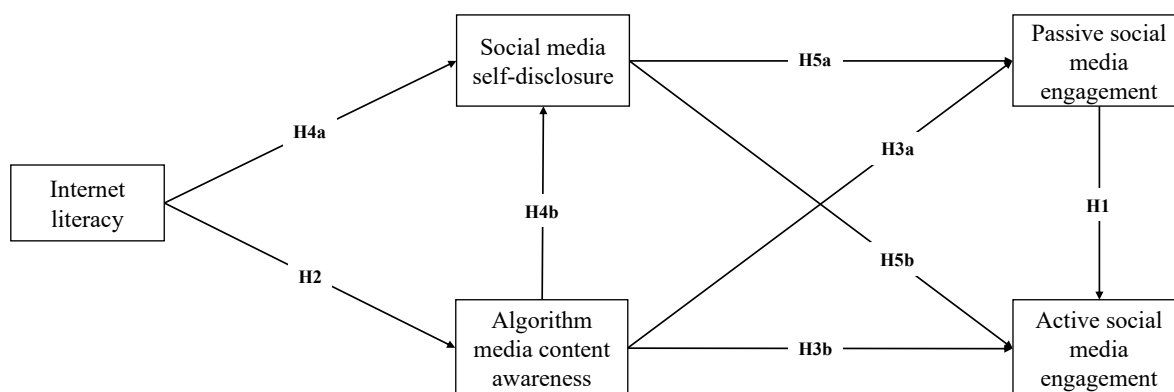
H5: Social media self-disclosure will positively relate to a) passive and b) active social media engagement.

Proposed Conceptual Model

Based on the preceding literature review, we reason that social media users' internet literacy as a skill enables an understanding of algorithmically curated social media content—referred to as algorithmic media content

awareness. This awareness, in turn, shapes decisions about social media self-disclosure and behavioral engagement as individuals weigh the benefits of sharing personal information against potential privacy risks and algorithmic exploitation. A conceptual model is proposed (Figure 1), illustrating that respondents' passive engagement is positively linked to active engagement (H1). Internet literacy is positively associated with algorithmic media content awareness (H2) while negatively associated with self-disclosure (H4a). In turn, social media algorithmic media content awareness is negatively connected to self-disclosure (H4b) and positively connected to passive (H3a) and active engagement (H3b). Lastly, social media self-disclosure is positively related to passive (H5a) and active engagement (H5b).

Figure 1: Proposed Conceptual Relationships



engagement (H5b).

Methods

The data used to test these hypotheses were gathered as part of a larger questionnaire administered via Qualtrics that explored respondents' opinions and experiences with social media algorithms. The present study employed new analyses to test a unique model of variables not tested in previous publications from this dataset. Respondents were paid \$2.50 to complete the larger survey that took approximately 10 minutes. To qualify, respondents needed to be U.S. social media users aged 18 or older. With approval from the university's institutional review board, and following informed participant consent, 1000 respondents from Prolific completed the questionnaire. After removing respondents who did not complete all items on the survey, the final sample consisted of N = 990 valid responses.

Sample and Measurement Instrument

The ethnic composition of respondents (N = 990) was 77% White, 6.9% Asian/Asian American, 5.8% Black/African American, 4.4% multicultural (e.g., selecting more than one ethnicity), 3.3% Hispanic/Latino, 1.6% other, and 0.4% no response. Respondents' average age was 39.10 (SD = 14.66) and their mean value for political leaning/ideology (-10 = Left, Moderate = 0, and 10 = Right) was -3.35 (SD = 5.78). In terms of gender, 57% of participants were female, 40.5% male, and 2.5% non-binary or fluid. Regarding highest education attained, 37% earned a Bachelor's degree, 22.2% some college, 13.1% Master's degree, 12.8% high school diploma,

9.1% Associates degree, 3.7% professional degree (e.g., MD, JD), 1% doctorate degree (PhD), and 1% less than high school. Geographically, the majority of respondents lived in the suburban/small town (56.6%), followed by urban/city (29.1%) and rural (14.3%).

Respondents answered the items gauging the hypotheses constructs and demographic data (age, gender, ethnicity, income, education, and political identity). Relevant studies within the literature were reviewed to inform the operationalization of various survey constructs. Table 1 displays the construct means, standard deviations, zero-order correlations, and reliability statistics. See Table 2 in Appendix A at the end of this manuscript for the exact items included in the analyses.

Table 1: Descriptive Statistics, Correlations, and Square Root of AVEs

Variable	CA	CR	AVE	1	2	4	5	6
1 Internet literacy	.87	.86	.51	0.71				
2 SM algorithmic media content awareness	.94	.94	.58	.28**	0.76			
3 SM algorithmic epistemic curiosity	.96	.94	.77	.29**	.16**			
4 SM self-disclosure	.79	.77	.46	-.03	-.09**	0.68		
5 Passive engagement	.82	.78	.55	.25**	.21**	.11**	0.74	
6 Active engagement	.83	.76	.51	.10**	-.02	.44**	.33**	0.72
<i>M</i>				2.82	4.35	2.32	4.90	2.97
<i>SD</i>				0.68	0.71	0.90	1.16	1.32

Notes. ** p < 0.01 level (2-tailed); CA = Cronbach alpha, CR = composite reliability, SM self-disclosure = social media information disclosure; AVE = average variance explained; Square Root of AVE is shown in bold on the diagonal discriminant validity: highest construct correlation < construct square root of AVE (Fornell & Larcker 1981).

Internet Literacy

Five items were adopted from Livingstone and Helsper (2010) to measure internet literacy. They asked participants to state their proficiency on a four-point scale with performing various activities via the internet ($\alpha = .87$).

Algorithmic Awareness

Thirteen items were adapted from Zarouali et al.'s (2021) scale that examined general understanding of social media algorithms on four dimensions: content filtering, automated decisions, human-algorithm interplay, and ethical considerations. Four additional items were created to capture participants' assessment of how algorithms influence the exposure the content they create receives. Together, these 17 items encompass our measure of algorithmic media content awareness ($\alpha = .94$).

Social Media Self-Disclosure

Seven items from Metzger and Suh (2017) were adapted to explore how much information respondents self-disclose on social media ($\alpha = .79$).

Lastly, seven items were adopted from Escobar-Viera et al. (2018) social media use scale to measure participants passive ($\alpha = .82$) and active ($\alpha = .83$) social media engagement.

Results

Measurement Model and Common Method Bias

Following the recommendations of previous scholars (e.g., Mulaik & Millsap, 2000), we employ a multi-step approach to structural equation modeling (SEM). Specifically, an exploratory factor analysis (EFA) via SPSS with principal axis factoring extraction and varimax rotation preceded a confirmatory factor analysis (CFA) via AMOS before the structural model was tested. From the EFA, six items from algorithmic media content awareness, three items from social media disclosure, one item from internet literacy, and one item from active social media engagement were removed due to low factor loadings ($>.50$) and/or loading on multiple dimensions. After these modifications, the remaining items loaded onto the theorized six latent constructs with eigenvalues greater than 1.00.

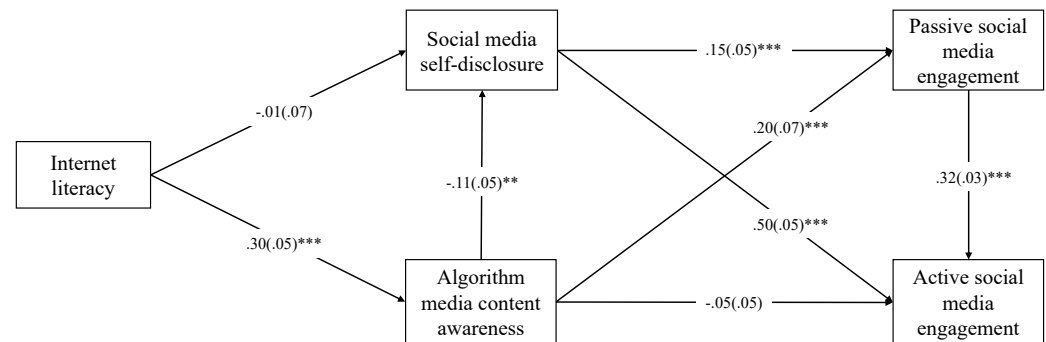
Moreover, since all of the constructs were measured with a single self-report survey, common method bias could have influenced the results. Harman's post hoc single factor test showed that when a single factor was specified in the EFA, it produced $>50\%$ of the total variance (28.56%), and thus suggests that common method bias was unlikely (Arora et al., 2022; Podsakoff & Organ, 1986). See Table 2 in Appendix A for the final items included in the analyses and EFA results.

To assess CFA and SEM model fit, CFI/ TLI/ IFI $>.90$, RMSEA $< .06$, and SRMR $< .08$ were examined as indicators of acceptable fit (Hair et al., 2010; Hu & Bentler, 1999). The initial CFA produced an inadequate fit ($\chi^2 = 17.67.91$, $p < .001$, CMIN/DF = 5.60, CFI = .91, TLI = .90, IFI = .91, RMSEA = .07, SRMR = .04). To improve model fit, following the approach of other researchers (e.g., Ahmed et al., 2016; Shek & Yu, 2014) covariance links were added to eight pairs of error terms within latent constructs with high residual correlations. After these modifications, the measurement model produced a good fit to the data ($\chi^2 = 919.64$, $p < .001$, CMIN/DF = 2.99, CFI = .96, TLI = .96, IFI = .96, RMSEA = .05, SRMR = .04).

Hypotheses Testing

Before conducting the SEM (via AMOS), a zero-order correlation demonstrated that age, gender, education, and political identity significantly related to several of the study variables despite not being the foci of this study (Table 1). Thus, these demographics were controlled in the structural model by allowing each demographic variable to influence each latent construct. The structural model was assessed using the maximum likelihood estimation method and demonstrated acceptable fit ($\chi^2 = 1393.50$, $p < .001$, CMIN/DF = 3.24, CFI = .94, TLI = .93, IFI = .94, RMSEA = .04, SRMR = .05). Figure 2 displays the results of the structural equation model testing.

Figure 2: Results of SEM and Hypotheses Testing



Note: *** $p < 0.001$ level; ** $p < 0.01$ level; * $p < 0.05$ level

H1 was confirmed, as passive social media engagement positively predicted active social media engagement ($\beta = .32, p < 0.001$). Similarly, the assertions of H2 were confirmed as internet literacy positively related to social media algorithmic media content awareness ($\beta = .30, p < 0.001$). Meanwhile, social media algorithmic media content awareness was found to positively relate to passive social media ($\beta = .20, p < 0.001$) but not active engagement ($\beta = -.05, p = 0.17$). This supports H3a, while rejecting H3b. Furthermore, internet literacy did not significantly relate to social media self-disclosure ($\beta = -.01, p = 0.75$), rejecting H4a. However, social media algorithmic media content awareness did negatively relate to social media self-disclosure ($\beta = -.11, p < 0.01$), affirming H4b. Lastly, social media self-disclosure positively related to passive ($\beta = .15, p < 0.001$) and active ($\beta = .50, p < 0.001$) social media engagement, providing support for H5a-b, respectively.

Discussion

As the use of algorithms on social media has accelerated to the point where they are commonplace on major social media platforms, this research used social media engagement theory, dual processing theory, and privacy calculus to substantiate an exploratory conceptual model of the correlates of social media behavioral engagement. Overall, results from a cross-section survey of U.S. adult social media users demonstrated that internet literacy positively related to social media algorithmic media content awareness. Moreover, social media algorithmic media content awareness was negatively associated with self-disclosure. Finally, social media 1) algorithmic media content awareness and 2) self-disclosure positively predicted passive and active social media engagement behavior. Ultimately, these interrelations highlight the critical role of internet literacy and algorithmic awareness in shaping how individuals disclose information and engage with social media.

Theoretical Contributions

A notable undertaking of this research was to integrate theories of social media engagement theory, dual-processing theory, and the privacy calculus model in a conceptual model centered around algorithmic media content awareness. Theoretically, as social media engagement theory (SMET) suggests, features that enhance personalization—such as algorithm-driven feeds—can increase users' perceived benefits (e.g.,

relevant content, social connectivity) and thus motivate further engagement (Di Gangi & Wasko, 2016). However, as users become awareness of how algorithms tailor content can influence perceived privacy risks—which, according to privacy calculus, discourages self-disclosure and active engagement behaviors contributions. Instead, consistent with dual processing theory, algorithmic awareness may manifest as low-effort system 1–driven passive engagement (e.g., scrolling and “liking”), which was found to positively relate to higher-effort system 2–driven active behaviors (e.g., commenting and sharing). Below these general findings are discussed in greater detail.

This study is among the first to provide empirical evidence of the positive association between internet literacy and social media algorithmic media content awareness as distinct constructs. Theoretically, these results support the postulations of scholars like Reisdorf and Blank (2021) that suggest sharpening internet skills and understanding helps users become aware of and eventually literate about new technology. By implication, internet literacy may empower individuals to engage with algorithms and shape their online experiences. Moreover, the role of internet literacy is particularly relevant as algorithmic literacy is hard to achieve since the software underlying algorithms are proprietary and require technical coding skills to fully engage with (Dogruel et al., 2021; Silva et al., 2024).

Furthermore, our theorizing that those who possess skills and experience in one area (e.g., internet literacy) may use those skills to process information in another digital area (e.g., awareness of social media algorithmic media content) is consistent with the suggestion of scholars in the digital inequality literature (e.g., Cotter, 2020; Lutz, 2019). Specifically, a divide in usage, benefit, and reinforcement of social inequalities exists between those with the knowledge and skills about algorithms, and disadvantaged and marginalized communities (based on age, income, etc.) who often do not (Ragnedda, 2020).

Additionally, the positive association of social media algorithmic media content awareness and behavior engagement supports the assertions of social media engagement theory (Di Gangi & Wasko, 2016) that technical features and evolutions in technology (e.g., algorithms) can positively influence engagement. Specifically, in line with the propositions of social media engagement theory and relevant literature (Di Gangi & Wasko, 2016; Dolan et al., 2016, 2019; Shahbaznezhad et al., 2021), it is likely that the algorithms by recommending relevant content that is informational and entertaining contribute to the enjoyment of the social media site that manifests in behavioral engagement. By implication, it could also be that as users are aware that algorithms curate their media content, they may modify and increase their engagement behaviors to exert more control of their content. Future research may consider testing this speculation in a controlled study of causality.

More precisely, awareness of algorithmics predicted passive behavioral engagement but not active behavioral engagement. A possible reason for this could be that as users become aware of algorithms, they develop increased curiosity about algorithms, which in turn contributes to a passive-

based information-gathering process (e.g., reading and watching). As the default-interventionist theoretical perspective of dual processing theories would suggest (Bago & De Neys, 2020; Evans, 2011), when users are seeking out information, they would be more likely to rely on low-effort system 1 processing (reflected in passive social media engagement behavior). Then, simultaneously or immediately after, system 2 processing reflected as active social media behavioral engagement (e.g., sharing, commenting, and posting) may occur to engage in deeper processing and voicing a user's opinion (Dolan et al., 2019). Since this study is cross-sectional, mediation analyses were not suitable. However, future research could investigate the theoretical speculation that algorithm awareness leads to active engagement (a reflection of system 2 processing) by first influencing passive engagement (a reflection of system 1 processing).

Also, this study sought to examine the influence of internet literacy and social media algorithmic media content awareness on self-disclosure. It was observed that algorithmic media content awareness (and not internet literacy) negatively related to respondents' reported self-disclosure on social media. However, despite the negative influence of social media awareness on self-disclosure, respondents' self-disclosure was still positively related to both passive and active engagement.

As artificially intelligent programs built with algorithms pose a threat to users' privacy, researchers have noted that when consumers feel their personal information could be misused, they will take measures to guard their personal information (Huh et al., 2023; Kim et al., 2023). This idea is magnified by the results of algorithmic media content awareness positively predicting passive engagement but not active engagement. By implication, the findings suggest that algorithmic awareness is associated with users adopting a strategic passivity—observing content without disclosing personal information—to navigate privacy risks while maintaining access to platform benefits in lieu of disengaging entirely. This aligns with privacy calculus theory, where passive engagement (as opposed to active engagement) becomes a behavioral compromise, allowing users to mitigate perceived threats without fully withdrawing from socially rewarding digital spaces.

Another theoretical perspective could be that even with social media algorithm privacy concerns, users believe that the reward of participating on social media outweighs the potential harm perceived by algorithms. The privacy calculus theory (Dinev & Hart, 2006; Keith et al., 2013) informs us that users will conduct a risk-benefit ratio to decide if the potential harm of disclosing personal information is outweighed or equal to the potential benefit. Thus, our results support the assertions of scholars (e.g., Chen, 2018; Nguyen, 2021) that the social capital benefit provided by social media by disclosing information and engaging with content is perceived as outweighing privacy risks, particularly if individuals are curious about algorithms (Oeldorf-Hirsch & Neubaum, 2023). Moreover, the results also coincide with the privacy paradox (Norberg et al., 2007), which suggests that despite users expressing concern over online privacy, they will still reveal personal information to satisfy the gratifications they derive from its

use (Hargittai & Marwick, 2016; Taddicken, 2014).

Other potential explanations behind the complex algorithmic awareness-behavioral engagement link could include user apathy, habituation to surveillance, and algorithmic resignation (Draper et al., 2024). Specifically, users may respond to heightened algorithmic awareness with apathy, wherein they recognize the pervasive nature of algorithmic influence yet feel that their individual actions are unlikely to alter their feed or the platform's behavior. Thus they may feel a sense of futility and less motivation for active engagement, while still engaging in low-effort passive consumption (Hargittai & Marwick, 2016). Another possibility could be habituation to surveillance and being profiled by algorithms could desensitize and accustom users to simply scrolling through curated content rather than investing effort in posting or commenting (Soror et al., 2022). Finally, digital resignation—the belief that individual engagement cannot meaningfully disrupt algorithmic curation—could lead users to withdraw from active participation and instead adopt a spectator stance, consuming content without interacting (Draper and Turow, 2019).

Lastly, this cross-sectional study is among the scant body of empirical evidence of this relationship and differentiates between passive and active engagement, which most studies do not. Theoretically, this research supports Dolan et al.'s (2016) theorizing that passive and active social media engagement behavior are distinct dimensions. Furthermore, the observed positive association between passive and active social media engagement behavior empirically align with the passive-active engagement association postulated originally by Dolan et al. (2019). By implication, these correlational findings align with scholars who note that system 1 processing can influence system 2 processing (e.g., Kahneman, 2011; Schley et al., 2020). Importantly, the results here do not dispute that system 1 (passive social media engagement) and system 2 (active social media engagement) occur distinctly as parallel-competitive theories argue, but instead find evidence—in a correlational context—the former can relate to the latter as default-interventionist theories suggest (Bago & De Neys, 2020; Evans, 2011).

Practical Implications

Practically, this research supports suggestions of other scholars (e.g., Voorveld et al., 2023) who note that user knowledge and transparency about algorithmic practice could improve social media user confidence to engage with content. As Cloarec et al. (2024) articulated, explicitly disclosing to users the benefit of providing personal information to receive highly relevant and interesting content can contribute to their belief of the benefit rather than the cost of disclosing. For instance, Spotify's new "AI DJ" informs listeners that the DJ takes their listening habits and behaviors to provide a curated listening experience (Sound Guys, 2023).

However, there is a discrepancy between users who feel they can vs. cannot control what is shown on their timeline and how sincere they believe platforms are regarding their willingness to provide users agency to curate their feeds (Swart, 2021). As a suggestion, practitioners and social media

platforms, when displaying sponsored recommended posts, should consider explicitly informing users that the content is recommended based on their past behavior. Indeed, some platforms have already begun to inform consumers of the role of artificially intelligent programs and algorithms in their online experience.

As an illustration, Google search results provide an “AI overview” that summarizes the key information regarding what a user searches for (Radel, 2024). However, more importantly, in the right-hand corner is a “learn more” button that sends the user to a page where they can learn more about what and how the AI technology works and provide feedback. In a similar vein, platforms should (and practitioners can demand) that a “lean more” option be presented. As the results demonstrate here, user awareness of how social media algorithms influence their content positively relates to their passive behavioral engagement. That passive engagement (e.g., reading and watching) in turn is positively associated with active social media engagement behavior (e.g., reacting and commenting).

Limitations & Future Research

This study has several limitations worth noting that subsequently inform future research directions. First, the concepts measured here are self-reported accounts of internet literacy and algorithm awareness. Concerning the nuanced discourse on these topics, it must be mentioned that it can be challenging to fully measure literacy with self-reports. Future research may consider using more objective test-style questions to gauge literacy. Ambitious attempts could be made to pair self-reported measures with physiological measures (e.g., eye-tracking, electroencephalography) to assess the extent to which these self-reports align with physical reactions.

Second, given the nascent nature of social media algorithmic research, an exploratory survey was deemed most appropriate. However, future research may advance this discourse by examining branding and consumer factors. For instance, an experiment manipulating perceived errors in social media algorithmic content representations could be employed to examine if brand perceptions and/or engagement behavior are negatively influenced. Conversely, qualitative methodology such as in-depth interviewing could be used to gauge if (and why) users’ past knowledge and skills using the internet (i.e., internet literacy) contribute to what they know about social media algorithms and how much they self-disclose online.

Third, it must be emphasized that the results of this research are correlational and not causal. The findings observed from testing the conceptual model of this work reflect an association between constructs in a moment in time. Survey research and structural equation modeling are not inherently predictive; thus, any directionality of relationships should be approached with caution. Future research that explicitly tests the cause-and-effect relationships (via an experiment) between algorithmic media content awareness and social media behavioral engagement would prove to be a valuable advancement of the literature.

Fourth, although this study integrates three theoretical frameworks to enhance its conceptual depth, this broad approach may limit its impact within any single domain. To enable more substantial contributions to specific fields, future research could focus on one or two theories and pursue a more comprehensive examination and extension of those perspectives. By narrowing the theoretical lens, subsequent work can offer richer insights, develop more precise hypotheses, and advance a deeper understanding of the mechanisms at play.

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Appendix A

Table 2: Factor Loadings, AVE, and Eigenvalues of Measured Constructs

Construct & Items	Factor Loadings	AVE (Eigenvalue)
Internet literacy (Livingstone & Helsper, 2010; 1 = Beginner, 4 = Expert)		0.52 (3.93)
Finding information you need on the web	.642	
Setting up an email account	.677	
Downloading and saving an MP3 file	.757	
Setting up a filter for junk mail or pop-up adverts	.724	
Getting rid of a virus on your computer	.756	
Fixing a problem by yourself when something goes wrong	.750	
Algorithmic media content awareness (Zarouali et al., 2021; 1 = Not at all aware, 5 = Completely aware)		0.58 (7.71)
Algorithms are used to recommend content to me on social media	.821	
Algorithms are used to prioritize certain content above others	.847	
Algorithms are used to tailor certain content to me on social media	.852	
Algorithms show someone else different content than I get to see on my social media	.719	
Algorithms are used to show me content on social media based on automated decisions	.776	
Algorithms do not require human judgments in deciding which content to show me on social media	.586	
Algorithms make automated decisions on what content I get to see on social media	.806	
The content that algorithms recommend to me on social media depend on the data that I make available online	.782	
The content that algorithms recommend to me on social media depend on my online behavioral data	.804	
The content that algorithms recommend to me on social media depend on the data that I make available online	.718	
Algorithms use my personal data to recommend certain content on social media, and this has consequences for my online privacy	.633	
SM self-disclosure (Metzger & Suh, 2017; 1 = Strongly disagree, 6 = Strongly agree)		0.46 (3.07)
I have put a lot of information about myself in my social media profile(s).	.770	
I keep my friends updated about what is going on in my life through social media.	.669	
I allow others to provide information about me through things like posts or tags.	.646	

I allow people to find out my location using social media.	.626	
Passive engagement (Escobar-Viera et al., 2018; 1 = Never, 6 = Several times a day)		0.56 (1.84)
Read discussions	.709	
Read comments/reviews	.878	
Watch videos or view pictures	.633	
Active engagement (Escobar-Viera et al., 2018; 1 = Never, 6 = Several times a day)		0.52 (1.20)
Share others' content	.669	
Comment on or respond to someone else's content	.769	
Post your own content	.716	