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Algorithmic Social-Media Reliance for Health Information Under Literacy Constraints

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Abstract.

The rapid proliferation of algorithmically curated social media platforms has fundamentally transformed the dissemination and consumption of health information. This paper investigates the phenomenon of algorithmic reliance for health information among populations constrained by limited health and digital literacy. Through a comprehensive mixed-methods approach, this study explores how algorithmic curation mechanisms exploit cognitive vulnerabilities, thereby exacerbating public health risks such as medical misinformation and vaccine hesitancy. The research investigates the behavioral patterns of users who depend on personalized feeds as their primary source of medical knowledge, analyzing the intersection between health literacy deficits and algorithmic trust. Drawing upon data from a large-scale demographic survey and a simulated platform audit, the analysis reveals a significant negative correlation between health literacy levels and unquestioning reliance on algorithmically recommended content. Furthermore, the findings indicate that users with lower digital literacy are disproportionately channeled into algorithmic echo chambers that reinforce unverified or dangerous health narratives. This study contributes to the broader academic discourse on digital health communication by providing an empirical foundation for understanding systemic algorithmic biases and their impact on vulnerable populations. The paper concludes by proposing actionable policy recommendations for platform regulation and targeted digital health literacy interventions.

Keywords: Health Literacy, Algorithmic Curation, Misinformation, Digital Public Health, Information Environments

1. Introduction

1.1 Context and Background

The contemporary digital landscape has fundamentally altered the mechanisms through which individuals acquire, process, and apply health-related information. In recent years, social media platforms have evolved from simple chronological communication networks into highly sophisticated, algorithmically driven content delivery systems. These platforms utilize complex machine learning models to curate personalized information feeds designed to maximize user engagement, retention, and advertising revenue. Consequently, millions of users globally now rely on these automated recommendations as a primary source for medical advice, lifestyle interventions, and disease management strategies. While this democratization of information

access offers theoretical benefits for public health outreach, it simultaneously introduces profound risks, particularly for individuals who lack the foundational health literacy required to critically evaluate the medical accuracy of the content they consume. Health literacy, defined as the degree to which individuals have the capacity to obtain, process, and understand basic health information and services needed to make appropriate health decisions, acts as a critical cognitive filter. When this filter is compromised by educational, socioeconomic, or linguistic constraints, the user becomes highly susceptible to the structural biases inherent in algorithmic curation. For a broader comparison, related research addresses mining steady formulaic alpha factors with Variance-Bounded REINFORCE [1]. The reliance on algorithmically generated health information is not merely a matter of convenience; it represents a paradigm shift in medical epistemology where the authority of traditional healthcare providers is increasingly supplemented, or even replaced, by content creators and recommendation systems. This shift is particularly pronounced among marginalized populations who may face systemic barriers to accessing formal healthcare systems, thereby driving them toward accessible, free, and seemingly personalized digital alternatives. However, recommendation algorithms are generally agnostic to the scientific validity or medical safety of the content they promote. Instead, they optimize for proxy metrics of user interest, such as click-through rates, watch time, and social sharing. Because sensationalist, emotionally resonant, and pseudoscientific health claims often generate higher engagement than nuanced, evidence-based medical advice, algorithms inadvertently create systemic pathways that amplify misinformation. This dynamic creates a dangerous feedback loop: users with limited health literacy interact with unverified health claims, signaling the algorithm to supply more of the same content, thereby isolating the user within a medical misinformation echo chamber. For a broader comparison, related research addresses pharmacological inhibition of PSPH reduces serine levels and epileptic seizures [2].

1.2 Problem Statement and Research Objectives

Despite the growing recognition of social media as a vector for health misinformation, there remains a significant gap in the literature regarding the specific interaction between algorithmic reliance and health literacy constraints. Previous research has largely focused on either the structural properties of misinformation networks or the sociodemographic predictors of low health literacy in isolation. However, a comprehensive understanding of how these two dimensions intersect to influence health behavior is urgently needed. Specifically, it is critical to investigate the psychological and behavioral mechanisms that drive individuals with low health literacy to place outsized trust in algorithmic recommendations over professional medical advice.

This paper addresses this gap by systematically examining the phenomenon of algorithmic social-media reliance under literacy constraints. The primary objectives of this research are threefold. First, the study aims to conceptualize and measure the construct of algorithmic reliance in the context of health information seeking. Second, it seeks to quantify the inverse relationship between functional health literacy and susceptibility to algorithmic echo chambers. Third, the research endeavors to uncover the platform design features that disproportionately disadvantage users with literacy constraints, thereby informing future regulatory and design interventions. By achieving these objectives, this paper provides a robust theoretical and empirical framework for understanding one of the most pressing challenges in modern digital public health.

2. Literature Review and Theoretical Framework

2.1 Theoretical Foundations of Health and Digital Literacy

The conceptualization of health literacy has evolved significantly over the past two decades, transitioning from a narrow focus on reading comprehension in clinical settings to a

multidimensional construct encompassing digital, critical, and civic competencies. Foundational models posit that functional health literacy involves the basic skills required to read and comprehend medical instructions, whereas interactive and critical health literacy involve the advanced cognitive abilities to extract meaning from different forms of communication and critically analyze health information for validity. In the digital era, this concept has been further expanded into eHealth literacy, which integrates traditional health literacy with digital literacy, media literacy, and information literacy. The eHealth literacy framework emphasizes the user ability to navigate complex digital interfaces, formulate effective search queries, and evaluate the credibility of online sources. The literature also considers understanding health information literacy of mHealth app users from digital wellbeing perspective: evidence from regression analysis and fsQCA [3]. However, current literature suggests that a substantial portion of the global population lacks adequate eHealth literacy. Individuals facing literacy constraints often employ heuristic processing rather than systematic processing when evaluating online health information. Heuristic processing relies on superficial cues, such as the visual appeal of a video, the perceived confidence of a content creator, or the number of likes and shares a post has accumulated, rather than an evaluation of the underlying scientific evidence. In an algorithmic information environment, these heuristic cues are frequently manipulated by content creators and artificially inflated by platform recommendation systems. Consequently, users with low eHealth literacy are particularly vulnerable to the Dunning-Kruger effect, wherein they overestimate their ability to discern accurate medical information while simultaneously lacking the foundational knowledge required to make that discernment. Organizational knowledge creation provides a reference for examining how individually held understanding becomes shared and usable knowledge [4]. Another relevant line of investigation concerns mapping and auditing evidence in digital storytelling for industrial heritage transformation: A focused systematic review (2011–2026) [5].

2.2 Algorithmic Curation and Information Environments

The architecture of modern social media platforms is fundamentally reliant on algorithmic curation, a process by which automated systems filter, rank, and present content to users based on vast amounts of behavioral data. These recommendation algorithms utilize collaborative filtering, content-based filtering, and deep learning architectures to predict the probability of user interaction with any given piece of content. In the context of health information, these systems create highly personalized information environments that can rapidly diverge from mainstream medical consensus. The literature identifies two primary phenomena that emerge from this algorithmic personalization: filter bubbles and echo chambers. Another relevant line of investigation concerns simulation-Based teaching in project management education: A systematic literature review and bibliometric analysis [6]. A filter bubble occurs when an algorithm selectively guesses what information a user would like to see based on past behavior, inadvertently isolating the user from diverse viewpoints or corrective medical information. For example, a user who engages with a post promoting natural remedies for hypertension may subsequently find their feed saturated with alternative medicine content, while evidence-based cardiovascular guidelines are systematically filtered out. An echo chamber, on the other hand, refers to the social and network dynamics where users are connected with like-minded individuals, reinforcing shared beliefs and marginalizing dissenting voices. When applied to health topics such as vaccination or chronic disease management, algorithmic echo chambers can solidify anti-science attitudes and foster deep distrust in institutional medicine. Scholars argue that the opacity of these algorithms, often described as black boxes, prevents users from understanding how or why specific health information is being pushed to them, further compounding the challenges faced by users with low digital literacy. The

literature also considers the question posed in "When Behavior Analysis Meets Social Network Alignment" [7].

2.3 The Intersection of Literacy and Algorithmic Trust

The critical intersection of this research lies in the relationship between literacy constraints and trust in algorithmic systems. Trust in automation literature suggests that individuals often exhibit automation bias, a psychological tendency to favor suggestions from automated decision-making systems while ignoring contradictory information made without automation, even if the automated system is incorrect. In social media contexts, users frequently conflate algorithmic personalization with accuracy or relevance. Research indicates that individuals with lower educational attainment and lower health literacy are more likely to exhibit algorithmic trust, viewing platform recommendations as objective or authoritative rather than profit-driven engagement mechanisms. Yu and colleagues examine towards effective, efficient and unsupervised social event detection in the hyperbolic space [8]. This unquestioning reliance is particularly dangerous in health contexts because the cost of acting on algorithmic misinformation can be physically harmful or fatal. Studies on the propagation of unproven cancer treatments and unverified dietary supplements on video-sharing platforms have demonstrated that recommendation algorithms often bridge the gap between benign health queries and radical medical conspiracies. A user searching for basic nutritional advice might be algorithmically guided toward extreme dietary restrictions or disordered eating content within a matter of minutes. The lack of critical health literacy prevents the user from recognizing this algorithmic drift, leading to a state of reliance where the platform becomes the de facto primary care provider. Understanding the specific mechanisms by which this reliance develops and the socio-demographic factors that accelerate it is essential for developing effective countermeasures. Liu and colleagues examine sociotechnical factors affecting interoperability of digital humanities [9].

3. Methodology and Analytical Framework

3.1 Research Design and Sampling Strategy

To comprehensively investigate the relationship between algorithmic social-media reliance and health literacy constraints, this study employed a convergent mixed-methods research design. This approach integrates quantitative survey data to establish broad correlational patterns and qualitative platform audit data to observe the systemic mechanisms of algorithmic curation in real-time. The research design allows for the triangulation of self-reported user behavior with objective algorithmic outputs, providing a highly robust analytical framework. Ren and colleagues examine the question posed in "When Behavior Analysis Meets Social Network Alignment" [10].

The quantitative phase involved a cross-sectional survey administered to a geographically diverse sample of adult internet users. Participants were recruited through a stratified random sampling technique managed by an international digital research panel. To ensure the sample adequately represented populations with varying levels of literacy, targeted recruitment quotas were established based on formal educational attainment, socioeconomic status, and geographic location. The final analytical sample consisted of 1500 participants. Inclusion criteria required participants to be at least 18 years of age, active users of at least one major algorithmic video or feed-based social media platform, and to have sought health information online within the past six months. The literature also considers innovative approaches in online language education: enhancing cultural competence in virtual classrooms [11].

Table 1Participant Demographics

Demographic Variable	Category	Frequency	Percentage
Age	18 to 29 years	410	27.3

Age	30 to 45 years	565	37.7
Age	46 to 60 years	350	23.3
Age	Over 60 years	175	11.7
Educational Attainment	High school or less	620	41.3
Educational Attainment	Some college or vocational	480	32.0
Educational Attainment	Bachelor degree or higher	400	26.7
Primary Health Info Source	Medical Professionals	450	30.0
Primary Health Info Source	Algorithmic Social Media	780	52.0
Primary Health Info Source	Traditional Media or Other	270	18.0

As detailed in the demographic breakdown, a significant portion of the sample identified algorithmic social media as their primary source of health information, superseding direct consultation with medical professionals. This distribution highlights the immediate relevance of the research topic and validates the sampling strategy designed to capture populations heavily reliant on digital information ecosystems. Zheng and colleagues examine the question posed in "What Drives People to Use AI-Powered Social Media as a Source of Health Information?" [12].

3.2 Data Collection Instruments

The survey instrument was constructed using validated psychometric scales adapted for the specific context of algorithmic health information. The primary independent variable, Health Literacy, was measured using an extended version of the eHealth Literacy Scale. This scale assesses perceived skills at finding, evaluating, and applying electronic health information to health problems. Items were measured on a five-point Likert scale ranging from strongly disagree to strongly agree. To capture the digital component, additional items were integrated to measure algorithmic awareness, specifically evaluating whether the participant understood that their social media feed was curated by artificial intelligence rather than chronological or editorial processes. Related work has addressed task-Aware framework for evaluating differentially private synthetic educational data [13]. The primary dependent variable, Algorithmic Social-Media Reliance, was operationalized through a custom composite scale developed for this study. This scale measured the frequency with which users acted upon health advice recommended by an algorithm without verifying the information through secondary, authoritative sources. Furthermore, it assessed the psychological dimension of algorithmic trust, asking participants to rate the perceived credibility and personalization accuracy of their social media feeds regarding medical topics. Zhang and colleagues examine towards proactive asking with imperfect information in medical multi-turn dialogues [14].

Table 2Construct Measurement Reliability

Measurement Construct	Number of Items	Cronbach Alpha	Mean Score
eHealth Literacy	10	0.88	3.12
Algorithmic Awareness	6	0.81	2.45
Algorithmic Trust	8	0.86	3.78

Health Misinformation Susceptibility	5	0.84	3.42

The reliability of the constructs, as presented above, indicates high internal consistency across all measurement scales. The relatively low mean score for algorithmic awareness contrasted with the high mean score for algorithmic trust underscores a critical vulnerability: users are trusting systems they do not fundamentally understand. Another relevant line of investigation concerns understanding users' motivations and strategies for assessing the credibility of AI-generated information [15]. In addition to the survey, the qualitative phase involved an algorithmic auditing procedure using simulated user profiles, commonly referred to as sock-puppet accounts. Four clean accounts were created on a prominent video-sharing platform. These accounts were programmed with automated scripts to simulate user behavior representative of different health literacy profiles. For example, the low-literacy profile engaged heavily with sensationalist, anecdotal health claims regarding chronic pain management, while the high-literacy profile engaged exclusively with content produced by verified medical institutions. The audit tracked the subsequent recommendations provided to each account over a thirty-day period to observe the formation of filter bubbles and the trajectory of the algorithmic pathways.

3.3 Analytical Procedures

Data analysis was conducted using a combination of multivariate statistical techniques and thematic content analysis. For the survey data, missing responses were handled using multiple imputation methods to ensure data integrity. Descriptive statistics were generated to summarize demographic characteristics and construct distributions. To test the central hypotheses regarding the relationship between literacy constraints and algorithmic reliance, a structural equation modeling approach was utilized. Structural equation modeling allows for the simultaneous estimation of multiple complex relationships while accounting for measurement error in the latent constructs. The model evaluated the direct paths from functional health literacy and digital literacy to algorithmic reliance, as well as the mediating role of algorithmic awareness.

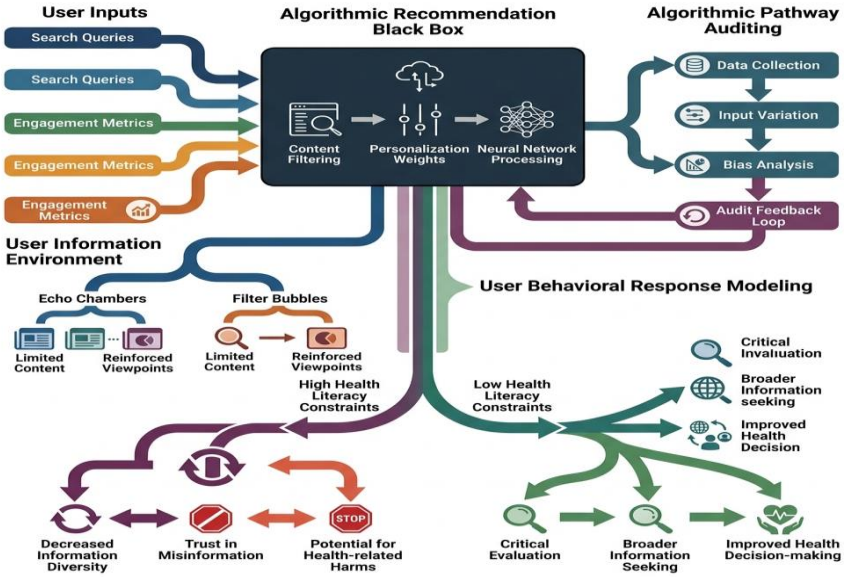


Figure 1Comprehensive Schematic of Algorithmic Pathway Auditing and User Behavioral Response Modeling

For the platform audit data, the recommended videos collected over the thirty-day period were transcribed and subjected to a rigorous thematic analysis. The content was coded based on medical accuracy, presence of emotional manipulation, commercial intent (e.g., selling unapproved

supplements), and scientific consensus alignment. The progression of the recommendation pathways was mapped out visually to identify the exact point of algorithmic drift, which is defined as the transition from benign health content to radical or harmful misinformation. The integration of the structural equation modeling results with the qualitative mapping of algorithmic drift provides a holistic view of the research problem, allowing for a nuanced understanding of both the user psychology and the platform mechanics. For a broader comparison, related research addresses robust multimodal cough detection with optimized out-of-distribution detection for wearables [16].

4. Results and Comprehensive Discussion

4.1 Quantitative Findings on Reliance and Literacy

The results derived from the structural equation modeling analysis provided robust empirical support for the hypothesis that structural literacy constraints significantly predict algorithmic social-media reliance. The model demonstrated strong goodness-of-fit metrics, indicating that the theoretical framework accurately represented the observed data. Specifically, functional health literacy exhibited a strong negative direct effect on algorithmic reliance. Participants who scored in the lowest quartile of the eHealth Literacy Scale were exponentially more likely to report taking physical health actions based solely on social media recommendations compared to those in the highest quartile. This confirms that individuals lacking the cognitive tools to evaluate medical evidence default to trusting the most accessible information source, which is frequently an algorithmic feed optimized for convenience rather than accuracy. The literature also considers meta-analysis of social media fatigue: drivers and a major consequence [17].

Table 3Correlation Matrix of Key Variables

Variable	Health Literacy	Algorithmic Awareness	Algorithmic Trust	Reliance
Health Literacy	1.00	0.62	-0.55	-0.68
Algorithmic Awareness	0.62	1.00	-0.48	-0.52
Algorithmic Trust	-0.55	-0.48	1.00	0.74
Reliance	-0.68	-0.52	0.74	1.00

The correlation matrix reveals several critical dynamics. The strong negative correlation between health literacy and algorithmic trust suggests that education and critical evaluation skills act as a protective buffer against blind faith in automated systems. Furthermore, algorithmic awareness emerged as a significant mediator in the structural model. Users who understood that their feeds were personalized to maximize engagement rather than to provide objective medical facts were significantly less likely to demonstrate behavioral reliance on the platform for health decisions. This finding is crucial, as it suggests that targeted interventions focusing specifically on algorithmic transparency and digital media literacy could effectively reduce the public health risks associated with social media consumption, even if underlying functional health literacy remains low. Yang Z and colleagues examine adaptive differentially private structural entropy minimization for unsupervised social event detection [18].

4.2 Qualitative Insights into Misinformation Vulnerability

The algorithmic platform audit yielded deeply concerning qualitative data regarding the systemic mechanisms that trap low-literacy users in misinformation echo chambers. The simulated account designed to mimic low health literacy behavior by engaging with anecdotal and highly emotional health content experienced a rapid and severe deterioration in information quality. Within just five days of automated engagement, the recommendation algorithm ceased presenting content from

verified medical authorities entirely. Instead, the feed became saturated with videos promoting unregulated alternative medicines, conspiratorial narratives regarding the pharmaceutical industry, and explicit anti-vaccine rhetoric. Another relevant line of investigation concerns interactive spatial structure study using machine learning [19]. A thematic analysis of this curated content revealed that the algorithm systematically prioritized videos that elicited high emotional arousal, specifically fear and false hope. The content creators in these echo chambers frequently utilized sophisticated rhetorical strategies to simulate scientific authority, such as wearing white coats in videos, using complex but meaningless pseudoscientific jargon, and framing their unverified claims as secret knowledge suppressed by mainstream medicine. For a user burdened by health literacy constraints, these superficial markers of credibility are virtually indistinguishable from actual medical expertise. The audit demonstrated that the algorithm does not merely reflect user preference; it actively shapes and radicalizes user beliefs by continually narrowing the scope of available information, thereby exploiting the cognitive vulnerabilities associated with low literacy. Cognitive apprenticeship makes expert strategies observable during learning, providing a basis for evaluating whether a correction teaches a reusable verification process [20]. For a broader comparison, related research addresses evidence froma52-country panel analysis [21].

4.3 Discussion of Systemic Impacts

The synthesis of the quantitative and qualitative findings illuminates a profound systemic failure at the intersection of digital platform design and public health. The data illustrates that algorithmic curation, by its very nature, is fundamentally incompatible with the principles of safe health communication. Health communication requires context, nuance, and an understanding of individual patient history, all of which are stripped away by recommendation algorithms optimizing for short-term engagement. When users with literacy constraints rely on these platforms, they are not actively choosing to consume misinformation; rather, they are being structurally guided into corrupted information environments by systems that interpret their lack of critical discernment as a preference for sensationalism. The reskilling study distinguishes training from effective skill transfer [22]. Algorithmic health-information reliance can be examined through the same conceptual separation: exposure to an educational intervention need not mean that users can apply verification skills to an unfamiliar feed. The implications of these findings extend far beyond individual medical decisions. At a population level, algorithmic reliance undermines public health campaigns and erodes institutional trust. When significant segments of the population are isolated within self-reinforcing echo chambers that demonize evidence-based medicine, collective action on issues such as infectious disease control or chronic disease management becomes exceedingly difficult. The platform algorithms act as an accelerant for health disparities, as those with the lowest literacy, who often already suffer from the worst health outcomes, are precisely the populations most aggressively targeted by algorithmic misinformation. Addressing this crisis requires a fundamental shift in how society regulates algorithmic recommendation engines, moving away from a paradigm of unchecked corporate optimization toward one that prioritizes public safety and information integrity. Rui and colleagues examine public willingness to use the national public culture cloud APP [23].

5. Conclusion and Policy Implications

5.1 Summary of Contributions

This paper provides a comprehensive examination of algorithmic social-media reliance for health information among populations facing literacy constraints. By employing a mixed-methods research design, the study successfully mapped the complex interplay between individual cognitive vulnerabilities and structural algorithmic biases. The empirical findings establish that

low eHealth literacy and poor algorithmic awareness are critical predictors of dangerous reliance on social media for medical decision-making. Furthermore, the algorithmic audit explicitly demonstrated how recommendation engines rapidly isolate vulnerable users in echo chambers of medical misinformation, prioritizing emotionally manipulative content over scientifically valid information. The research highlights that the crisis of digital health misinformation is not solely a problem of user ignorance, but rather a structural feature of engagement-optimized platform architectures that actively exploit literacy deficits.

5.2 Limitations and Policy Recommendations

While this study offers robust insights, it is subject to certain limitations. The cross-sectional nature of the survey data prevents the establishment of strict causal relationships between long-term algorithm exposure and permanent behavioral changes. Additionally, the algorithmic audit was conducted on a single major video-sharing platform; the proprietary and constantly shifting nature of recommendation algorithms means that exact pathways of misinformation may vary across different platforms and over time. Future research should prioritize longitudinal studies tracking real user behavior through data donation methodologies to further validate the dynamics of algorithmic drift across multiple social networks. The literature also considers comprehensive survey of Cross-Modal retrieval: breaking through modal barriers [24].

The findings of this study necessitate immediate and decisive policy interventions. Regulatory frameworks must be established to mandate algorithmic transparency, forcing platforms to disclose the variables and weights used to recommend health-related content. Platforms must be required to implement systemic friction or circuit breakers that interrupt the rapid recommendation of unverified medical claims to highly engaged users. Furthermore, there is an urgent need for widespread public health initiatives focused on algorithmic media literacy. Educational interventions must move beyond basic digital skills and specifically teach individuals how to recognize algorithmic manipulation and the economic incentives driving social media architectures. Ultimately, mitigating the public health risks of algorithmic reliance requires a coordinated effort between policymakers, healthcare professionals, and technologists to ensure that the digital information environment supports, rather than subverts, global health literacy. Another relevant line of investigation concerns establishing the potential for the application of digital storytelling to support Chinese industrial heritage [25].

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