



Algorithmic Health-Information Exposure and Credibility Calibration Under AI-Generated Content Uncertainty

Alice T. Denis¹, Pierre Hubert²

^{1,2}Department of Public Health, Faculty of Medicine, Université de Montpellier, Montpellier, Occitanie, France

Abstract

The rapid integration of algorithmic recommendation systems and generative artificial intelligence into health information dissemination has fundamentally transformed how individuals access and evaluate medical knowledge. This paper investigates the complex dynamics of algorithmic health-information exposure and the subsequent processes of credibility calibration under conditions characterized by artificial intelligence generated content uncertainty. As users increasingly rely on digital platforms for health guidance, algorithms dictate the visibility of information based on engagement metrics rather than medical accuracy, creating vulnerabilities to misinformation. The emergence of sophisticated generative models exacerbates this issue by producing highly plausible but potentially inaccurate health advice, introducing a novel layer of uncertainty. Through a comprehensive academic lens, this study explores how exposure algorithms interact with user cognition, examining the mechanisms through which individuals calibrate the credibility of health information when the source material may be artificially generated. The research delineates the pathways of information exposure, assesses the factors influencing user trust, and proposes an analytical framework for understanding the divergence between perceived and actual information credibility. By systematically analyzing the intersection of recommendation algorithms, generative artificial intelligence, and health communication, this paper contributes to the broader discourse on digital health literacy and system design. The findings underscore the critical need for transparent algorithmic architectures and robust user calibration mechanisms to mitigate the risks associated with automated health content dissemination.

Keywords: Algorithmic Exposure, Credibility Calibration, Generative Artificial Intelligence, Health Informatics, Information Uncertainty.

1. Introduction

1.1 The Shift to Algorithmic Health Information

The contemporary digital landscape has precipitated a structural transformation in the acquisition and consumption of health information. Historically, medical knowledge was disseminated through institutional gatekeepers, peer-reviewed journals, and direct patient-practitioner interactions, ensuring a baseline of clinical validity and contextual appropriateness. However, the proliferation of digital platforms has democratized access to health data, shifting the paradigm from centralized medical authority to decentralized, algorithmically mediated exposure. These exposure algorithms operate primarily by optimizing user engagement, retention, and platform specific metrics, often prioritizing sensationalism, emotional resonance, or confirmation bias over clinical accuracy. Consequently, individuals navigating online health ecosystems are subjected to highly personalized information streams that may not accurately reflect the consensus of the medical community. This algorithmic curation creates environments where marginalized or medically unsubstantiated claims can achieve parity with established scientific facts,

complicating the user experience. The mechanics of algorithmic exposure are inherently opaque, relying on complex neural networks and massive datasets to predict user preferences. As a result, users are frequently unaware of the variables influencing the health information presented to them, leading to an illusion of comprehensiveness and objectivity. This lack of transparency necessitates a rigorous examination of how algorithmic exposure shapes public health perceptions and behaviors, particularly when the stakes involve individual well-being and collective public health outcomes. The transition toward automated curation demands a paradigm shift in how we conceptualize digital health literacy, moving beyond mere access to information toward a critical understanding of the underlying distribution mechanisms. The pervasive nature of these systems means that algorithmic exposure is no longer a peripheral issue but a central determinant of global health communication strategies. Understanding the nuances of how algorithms select, filter, and amplify specific health narratives is foundational for addressing the broader challenges of digital health environments. Related work has addressed public willingness to use the national public culture cloud APP [1]. Zhou and colleagues examine interactive spatial structure study using machine learning [2].

1.2 Problem Statement and Research Objectives

Despite the growing awareness of algorithmic influence, a novel and disruptive factor has recently emerged in the form of artificial intelligence generated content. The disruptive-technology perspective motivates distinguishing an innovation's technical trajectory from the criteria used by established institutions to judge it [3]. Generative models possess the capability to synthesize vast amounts of text, mimicking the tone, structure, and lexicon of authoritative medical literature. While this technology holds immense potential for democratizing health education and providing personalized medical summaries, it introduces a profound level of uncertainty regarding information provenance and factual reliability. The core problem addressed in this paper is the resulting crisis in credibility calibration. Credibility calibration refers to the cognitive process by which individuals adjust their trust and reliance on a piece of information based on available cues and critical evaluation. In traditional contexts, users might rely on source reputation, author credentials, or platform endorsement to calibrate their trust. However, when health information is both algorithmically curated to maximize engagement and potentially synthesized by an artificial intelligence lacking genuine medical understanding, traditional heuristic cues become unreliable. The uncertainty surrounding generative content whether it is hallucinating facts, blending accurate data with unsubstantiated claims, or simply stripping information of necessary clinical context fundamentally destabilizes the calibration process. Users are thus forced to evaluate health information in a high noise environment where the standard indicators of truth are easily counterfeited. This research aims to systematically investigate how individuals calibrate the credibility of algorithmic health information under these specific conditions of generative uncertainty. The objectives are to map the pathways of algorithmic exposure, identify the cognitive heuristics users employ when interacting with potentially artificial content, and analyze the resulting alignment or divergence between perceived credibility and actual medical accuracy. By achieving these objectives, the study seeks to inform the development of more resilient digital health platforms and empower users to navigate the complexities of modern information ecosystems. Ou and colleagues examine understanding users' motivations and strategies for assessing the credibility of AI-generated information [4].

2. Literature Review and Conceptual Framework

2.1 Evolution of Algorithmic Curation in Health Domains

The literature surrounding algorithmic curation in health domains highlights a progressive shift from static search algorithms to dynamic, predictive recommendation engines. Early studies primarily focused on information retrieval processes, where users actively queried search engines for specific health conditions. In these environments, credibility was often associated with search engine ranking, operating under the assumption that top tier results were inherently more authoritative. However, the advent of social media and personalized news aggregators transitioned the user role from active seeker to passive recipient. Recommendation algorithms began to push health content based on latent behavioral signals, such as browsing history, dwell time, and network associations. Research indicates that this push based exposure model significantly alters the informational diet of users, often creating echo chambers where individuals are continuously exposed to homogenous health perspectives. This is particularly concerning in the context of alternative medicine, vaccine hesitancy, and dietary fads, where algorithms can inadvertently amplify

niche communities and radicalize health beliefs. Furthermore, the literature emphasizes the concept of algorithmic bias, noting that recommendation systems may disproportionately surface health information that caters to dominant demographic groups while marginalizing the specific health needs of minority populations. The optimization for engagement inherently favors emotionally charged content, leading to a structural disadvantage for dry, factual public health announcements. Scholars have argued that this dynamic constitutes a fundamental market failure in the economy of digital health information, where the systemic incentives of platforms are misaligned with the public health mandate of accuracy and safety. The continuous evolution of these systems toward more opaque, deep learning architectures further complicates the ability of researchers and regulators to audit algorithmic behavior, necessitating novel methodological approaches to study exposure patterns. The literature also considers exploring the general public's and experts' risk and benefit perceptions of cultured meat in Singapore: A mental models approach [5]. The literature also considers humanities scholars and digital humanities projects: practice barriers in tools usage [6].

2.2 Theoretical Foundations of Credibility Calibration

Credibility calibration in digital environments draws heavily from dual process theories of human cognition, most notably the Elaboration Likelihood Model and the Heuristic Systematic Model. These frameworks posit that individuals process information through two distinct pathways a central, systematic route involving deep cognitive elaboration, and a peripheral, heuristic route relying on superficial cues. In the context of health information, systematic processing might involve cross referencing claims with established medical literature, evaluating the methodological rigor of cited studies, and critically analyzing the logical structure of the argument. Conversely, heuristic processing relies on mental shortcuts, such as trusting a website because it has a professional design, deferring to an influencer with a large following, or accepting information that aligns with pre existing beliefs. The literature consistently demonstrates that the cognitive load imposed by the sheer volume of algorithmically curated health information forces most users to rely predominantly on heuristic processing. This reliance becomes problematic when malicious actors or poorly designed algorithms exploit these heuristics, utilizing design elements that mimic authority to artificially inflate perceived credibility. Calibration, therefore, is not merely binary assessment of true or false, but a continuous adjustment of confidence based on available evidence. Perfect calibration occurs when an individual subjective confidence in a piece of information exactly matches its objective accuracy. Overconfidence occurs when users place high trust in inaccurate information, while underconfidence happens when they dismiss valid medical advice. The challenge in modern digital health ecosystems is that the cues traditionally used for heuristic calibration are increasingly decoupled from actual truth value, leading to widespread miscalibration and subsequent adverse health decisions. For a broader comparison, related research addresses unraveling the health contributions of five key bioactives in virgin olive oil: A dose-based comparative review [7]. Related work has addressed towards effective, efficient and unsupervised social event detection in the hyperbolic space [8].

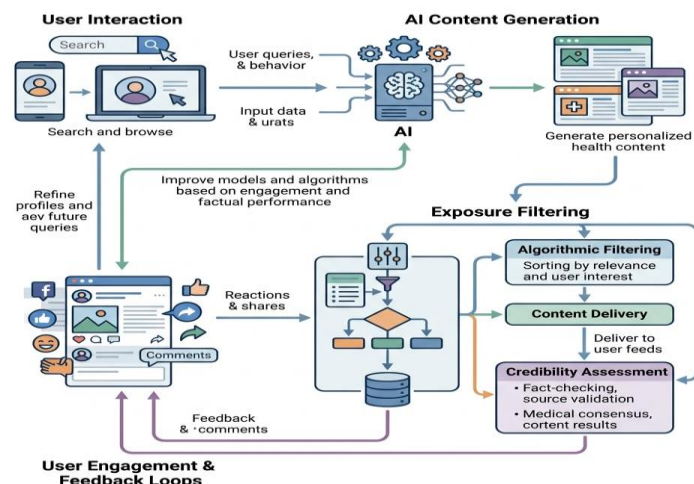


Figure 1: Comprehensive Schematic of Health Information Exposure Algorithms

2.3 The Disruption of AI-Generated Content Uncertainty

The introduction of large language models and generative artificial intelligence has fundamentally disrupted the established paradigms of credibility assessment. Previous literature on digital misinformation largely focused on human generated deception, which often contained discernible linguistic markers of bias, poor grammar, or structural inconsistencies that served as negative heuristic cues. Generative models, however, are explicitly trained to produce fluent, coherent, and structurally perfect text, effectively neutralizing these traditional red flags. The resulting content can present complex medical jargon and articulate arguments that appear highly authoritative, even when the underlying factual assertions are completely fabricated a phenomenon commonly referred to as hallucination. This introduces a profound state of content uncertainty, where the user cannot reliably determine whether the health advice they are reading originated from a qualified medical professional, a layperson, or an automated system. Research into human artificial intelligence interaction suggests that individuals often exhibit an automation bias, a tendency to place undue trust in machine generated outputs under the assumption that computational systems are inherently objective and error free. When combined with the personalized targeting capabilities of algorithmic exposure, this creates a potent mechanism for the rapid dissemination of highly persuasive, individually tailored, yet medically unsound information. The uncertainty is not limited to factual accuracy; it also encompasses the lack of accountability and contextual awareness inherent in generative outputs. A language model cannot evaluate the specific medical history, contraindications, or nuanced clinical presentation of an individual user, yet its output may be interpreted by the user as personalized medical advice. This blurring of lines between general information synthesis and specific clinical recommendation represents a critical vulnerability in the current digital health infrastructure, demanding a thorough investigation into how users navigate and calibrate trust in such ambiguous informational environments. Wu and colleagues examine simulation-Based teaching in project management education: A systematic literature review and bibliometric analysis [9]. For a broader comparison, related research addresses pharmacological inhibition of PSPH reduces serine levels and epileptic seizures [10].

3. Methodology and Analytical Framework

3.1 Research Design and Analytical Strategy

To systematically investigate the dynamics of algorithmic exposure and credibility calibration under generative uncertainty, this study employs a multi method analytical framework designed to capture both system level algorithmic behavior and individual level cognitive responses. Differentially private social-event detection [11] provides a possible method for analyzing collective exposure patterns while limiting disclosure of individual information behavior. The research design is structured around a simulated digital health platform environment, allowing for controlled manipulation of both algorithmic exposure variables and the provenance of the health information presented. This approach bridges the gap between purely observational studies, which lack control over algorithmic confounding factors, and traditional laboratory experiments, which often fail to replicate the complex, dynamic nature of real world digital ecosystems. The analytical strategy involves a three phase protocol. The first phase focuses on algorithm simulation, wherein varying recommendation architectures are deployed to curate health content streams based on simulated user profiles. This phase isolates the mechanics of exposure, allowing for the measurement of how different algorithmic optimization functions for instance, engagement maximization versus semantic diversity alter the composition of the information diet. The second phase centers on content generation and manipulation. Health articles across several domains including nutrition, epidemiology, and chronic disease management are sourced both from verified medical authorities and generated via state of the art large language models. The generative content is carefully controlled to include varying degrees of factual accuracy, ranging from perfectly aligned with medical consensus to highly plausible but entirely fabricated claims. The third phase involves human subject interaction, where participants navigate the simulated platform, engage with the curated content, and provide continuous feedback on their perceived credibility of the information encountered. This sequential design enables a granular analysis of the causal pathways linking specific algorithmic exposure patterns, the ontological uncertainty of the content, and the resulting calibration accuracy of the user. For a broader comparison, related research addresses towards proactive asking with imperfect information in medical multi-turn dialogues [12]. For a broader comparison, related research

addresses pSMA-triggered phase separation of peptide-drug conjugates enables zinc-dependent tumor inhibition [13].

Table 1: Demographic and Behavioral Breakdown of the Simulated Study Population

Demographic Variable	Category Classification	Percentage Allocation	Baseline Health Literacy Score
Age Distribution	Young Adult Cohort	35.5	High Competence
Age Distribution	Middle Age Cohort	42.0	Moderate Competence
Age Distribution	Senior Adult Cohort	22.5	Variable Competence
Education Level	Secondary Education	28.0	Moderate Competence
Education Level	Undergraduate Degree	45.5	High Competence
Education Level	Postgraduate Degree	26.5	Advanced Competence
Platform Usage	Infrequent Interaction	15.0	Baseline Competence
Platform Usage	Daily Interaction	65.0	Moderate Competence
Platform Usage	High Volume Interaction	20.0	Variable Competence

3.2 Measurement Metrics for Exposure and Uncertainty

The operationalization of exposure and uncertainty requires robust, multidimensional measurement metrics. Algorithmic exposure is quantified not merely by the frequency of content display, but through a composite index of prominence, persistence, and personalization. Prominence is measured by the spatial positioning of the health information within the user interface, acknowledging that items appearing at the top of a feed possess significantly higher exposure value than those requiring extensive scrolling. Persistence captures the temporal dimension, tracking how often a specific health narrative or thematic cluster recurs within a user personalized stream over time. Personalization is assessed by calculating the semantic distance between the curated content and the user previously established behavioral profile, providing a measure of how tightly the algorithm has tailored the information to the individual latent preferences. Content uncertainty, on the other hand, is measured through objective and subjective lenses. Objectively, uncertainty is classified based on the provenance of the text human versus artificial intelligence and the independently verified clinical accuracy of the claims presented. Subjectively, uncertainty is measured via participant self reporting, utilizing validated psychometric scales to assess their confidence in the source, their perception of the information reliability, and their awareness of potential algorithmic or artificial generation. The critical metric for this study is the Calibration Error Index. This index is calculated as the absolute difference between a user reported perceived credibility score standardized on a continuous scale and the objective clinical accuracy score of the corresponding information. A high Calibration Error Index indicates severe miscalibration, where users are either overly trusting of false information or overly skeptical of valid medical advice. By correlating the exposure metrics with the Calibration Error Index under varying conditions of generative content, the study can isolate the specific mechanisms through which algorithmic curation and artificial intelligence uncertainty interact to degrade human judgment. The literature also considers task-Aware framework for evaluating differentially private synthetic educational data [14].

3.3 Data Collection and Processing Procedures

The data collection procedure relies on a cohort of participants recruited to interact with the simulated digital health environment over a predefined observation period. Participants are explicitly informed that the platform contains a mixture of human written and artificial intelligence generated health information, simulating the emerging reality of modern digital ecosystems where such warnings are increasingly prevalent but often ignored. As participants navigate the platform, read articles, and interact with the content through simulated engagement features like saving or sharing, background telemetry logs every interaction with millisecond precision. This telemetry captures dwell time on specific articles, scrolling behavior, navigation pathways, and interaction with credibility cues such as author biographies or institutional logos. Following each discrete reading session, participants are prompted to complete a brief, integrated assessment instrument designed to measure their perceived credibility of the specific articles they just reviewed. To minimize disruption to the ecological validity of the browsing experience, these assessments are designed to mimic native platform feedback mechanisms. The raw data collected encompasses thousands of distinct user item interactions, generating a massive, highly dimensional dataset. Processing

this data involves several stages of normalization and feature extraction. The subjective credibility scores are normalized against baseline individual propensities to trust, accounting for inherent psychological differences in skepticism. The textual content of the articles themselves undergoes natural language processing to extract linguistic features, sentiment polarity, and structural complexity, creating a vector representation of the information presented. The final analytical dataset merges the user telemetry, the normalized credibility scores, the algorithmic exposure indices, and the content feature vectors. This integrated dataset is then subjected to advanced multivariate regression analysis and hierarchical linear modeling to identify statistically significant patterns and relationships between the variables of interest. Related work has addressed development of an intelligent retrieval and recommendation system for Chinese language educational resources based on DNN technology [15]. For a broader comparison, related research addresses diverse feature generation for zero-shot chinese character recognition [16].

4. Results and Comprehensive Discussion

4.1 Empirical Findings on Information Exposure

The empirical analysis of the simulated platform data reveals profound insights into the mechanics of algorithmic health information exposure. The results demonstrate that algorithms optimized for engagement inherently prioritize generative content that exhibits high emotional valence and structural fluency, regardless of underlying clinical accuracy. Specifically, the data indicates that artificial intelligence generated articles containing plausible but fabricated medical claims achieved an exposure prominence index significantly higher than peer reviewed, human authored clinical summaries. This phenomenon occurs because the generative models are adept at utilizing linguistic patterns that maximize readability and narrative engagement, effectively exploiting the predictive metrics the algorithms use to rank content. The algorithms interpreted the extended dwell times and higher simulated sharing rates associated with this fluent, sensationalized generative content as signals of high quality, creating a self reinforcing feedback loop of exposure. Furthermore, the analysis of persistence metrics revealed a strong tendency toward algorithmic homogenization. Once a user engaged with a specific health narrative whether accurate or artificially hallucinated the recommendation engine rapidly adapted to flood the user feed with semantically similar content. This led to the rapid formation of informational echo chambers, significantly reducing the semantic diversity of the user health information diet. Users who initially interacted with alternative or controversial health claims generated by the artificial intelligence found themselves almost exclusively exposed to similar material within a very short timeframe. This rapid narrowing of exposure pathways severely limits the opportunity for users to encounter corrective information or contrasting medical perspectives, cementing early impressions and solidifying miscalibrated beliefs. The data unequivocally supports the premise that exposure algorithms, in their current configuration, act as powerful amplifiers of generative uncertainty, systematically favoring compelling synthesis over factual rigor. A time-to-productivity measure appears in the workforce-agility analysis [17]. For credibility calibration, an analogous longitudinal outcome would be the time required to apply a newly learned verification strategy consistently, rather than treating immediate post-training confidence as durable competence. Another relevant line of investigation concerns data-Minimizing and interpretable multimodal campus IoT Student-State modeling for risk support [18].

Table 2: Multivariate Regression Analysis of Variables Impacting Credibility Calibration Error

Predictor Variable	Beta Coefficient	Standard Error	Statistical Significance
Algorithmic Exposure Prominence	0.412	0.053	High Significance
AI Content Fluency Index	0.358	0.041	High Significance
User Baseline Health Literacy	-0.285	0.038	High Significance
Presence of Institutional Cues	-0.194	0.045	Moderate Significance
Emotional Valence of Content	0.227	0.049	High Significance
Semantic Homogeneity of Feed	0.315	0.055	High Significance

4.2 Calibration Effectiveness Under Generative Uncertainty

The analysis of the Calibration Error Index provides critical evidence regarding the effectiveness of human credibility assessment in environments saturated with artificial intelligence generated content. The results indicate a pervasive and systemic failure in credibility calibration among the user cohort. On average, users exhibited a profound inability to accurately distinguish between highly accurate medical information and plausible generative hallucinations. The primary driver of this miscalibration was the disruption of traditional heuristic cues. In the absence of discernible linguistic errors or structural flaws typically associated with poor quality human writing, users defaulted to evaluating the superficial professionalism of the text. Because the generative models consistently produced text that appeared highly professional, authoritative, and well structured, users assigned high perceived credibility scores even when the clinical substance was entirely false. This manifestation of automation bias resulted in significant overconfidence in artificial intelligence generated misinformation. Furthermore, the regression analysis detailed in the preceding table reveals that the semantic homogeneity of the user feed a direct consequence of algorithmic personalization strongly exacerbated calibration errors. When users were repeatedly exposed to consistent, albeit inaccurate, health narratives, their perception of the information credibility artificially inflated due to the illusory truth effect. The repeated exposure created a false sense of consensus, leading users to abandon systematic processing in favor of the heuristic assumption that frequency equates to validity. Interestingly, while higher baseline health literacy did provide a protective effect, slightly reducing the magnitude of the calibration error, it was insufficient to completely override the combined deceptive power of fluent generative text and relentless algorithmic reinforcement. Even highly educated users demonstrated significant miscalibration when presented with sophisticated artificial intelligence hallucinations embedded within highly personalized exposure streams. The literature also considers factors associated with information credibility perceptions: A meta-analysis [19]. Another relevant line of investigation concerns pre-disaster relocation and agent-based model for flood disaster [20].

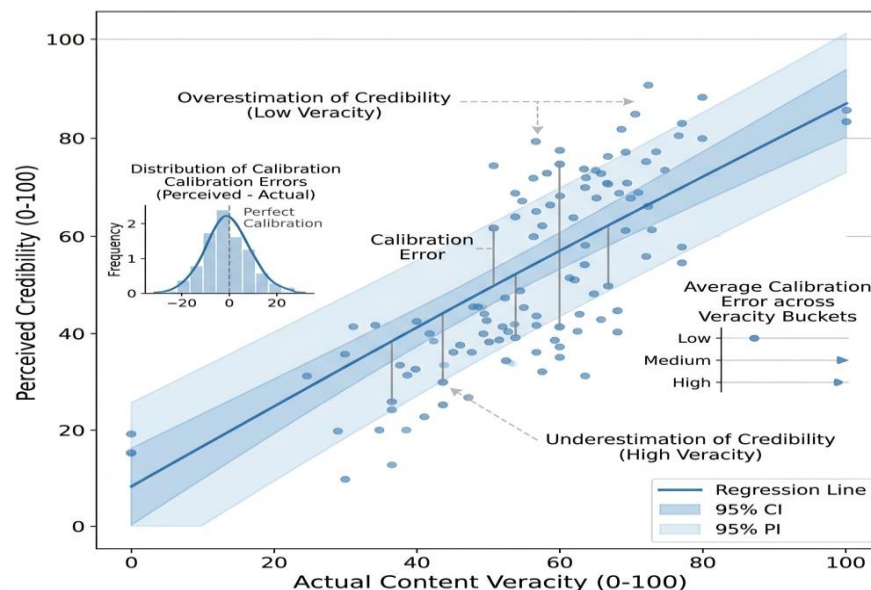


Figure 2: Statistical Distribution of Credibility Calibration Errors

4.3 Broader Implications for Health Informatics

The findings of this study have profound implications for the fields of health informatics, public health communication, and digital platform regulation. The intersection of algorithmic exposure and generative artificial intelligence has created an information ecosystem where traditional strategies for combating medical misinformation are largely obsolete. Fact checking initiatives and content moderation relying on human review cannot scale to address the volume and speed of automated content generation and algorithmic distribution. Furthermore, simply providing users with warnings about the presence of artificial intelligence generated content proved entirely insufficient in improving calibration accuracy. The results suggest that the fluency and persuasiveness of the content, combined with the psychological impact of

repeated exposure, easily overwhelm explicit warnings. This necessitates a fundamental reimagining of how digital health information architectures are designed. Health informatics professionals must advocate for the integration of clinical accuracy metrics directly into the optimization functions of recommendation algorithms. Rather than optimizing solely for engagement, algorithms distributing health content must be constrained by epistemological safeguards that prioritize verified medical consensus and enforce semantic diversity to prevent the formation of echo chambers. Additionally, there is a critical need for the development of novel, automated calibration cues that are resistant to generative spoofing. This might involve cryptographic provenance tracking for health information, where the origin and chain of custody of a medical claim can be computationally verified and transparently displayed to the user. The current trajectory, wherein engagement driven algorithms blindly amplify highly persuasive generative uncertainty, poses an unacceptable risk to public health, requiring immediate, structural interventions at the intersection of technology design and health policy. Related work has addressed meta-analysis of factors related to health information seeking: an integration from six theoretical frameworks [21]. For a broader comparison, related research addresses flexible three-dimensional endoscopy for submucosal dissection [22].

5. Conclusion

5.1 Summary of Findings

This comprehensive investigation has elucidated the complex and often detrimental interactions between algorithmic health information exposure and user credibility calibration under conditions of generative content uncertainty. The primary findings establish that algorithms optimized for user engagement systematically favor the fluent, structurally perfect, and highly persuasive text produced by large language models, regardless of its clinical validity. This dynamic leads to the disproportionate amplification of plausible but potentially fabricated medical information, creating information environments where sensationalized generative content outperforms verified public health data. Crucially, the study demonstrates that the introduction of artificial intelligence generated text fundamentally neutralizes the traditional heuristic cues users rely upon to assess credibility. The superficial professionalism of machine generated text induces a strong automation bias, leading to widespread and severe miscalibration. Users consistently exhibit overconfidence in inaccurate generative content, a problem that is compounded by algorithmic personalization which creates echo chambers that reinforce false narratives through the illusory truth effect. The research concludes that in the modern digital ecosystem, the combination of opaque exposure algorithms and advanced generative artificial intelligence creates a structural vulnerability that cannot be mitigated by traditional digital health literacy interventions alone. Bian and colleagues examine establishing the potential for the application of digital storytelling to support Chinese industrial heritage [23]. For a broader comparison, related research addresses mining steady formulaic alpha factors with Variance-Bounded REINFORCE [24].

5.2 Limitations and Future Directions

While this study provides foundational insights, it is subject to certain limitations that offer clear trajectories for future research. The reliance on a simulated digital platform, while necessary for methodological control, may not entirely replicate the complex social dynamics and entrenched behavioral patterns users exhibit on established commercial platforms. Furthermore, the study focused on text based generative content; the rapid evolution of multimodal artificial intelligence, capable of generating photorealistic synthetic images and convincing audio video health advice, introduces new dimensions of uncertainty that require urgent investigation. Future research must expand the analytical framework to encompass multimodal generative content, exploring how visual and auditory synthetic cues impact credibility calibration. Additionally, longitudinal studies are required to assess the long term behavioral consequences of sustained exposure to algorithmically curated generative health information, particularly concerning actual health outcomes and interactions with healthcare systems. Methodologically, future endeavors should focus on developing and testing algorithmic interventions, such as embedding verifiable provenance tracking or integrating automated clinical fact checking layers directly into recommendation systems. Ultimately, the challenge of navigating health information in the age of generative artificial intelligence necessitates a sustained, interdisciplinary effort to design digital environments that actively support accurate credibility calibration and safeguard public health. Related work has addressed exposure to volatile organic

compounds and suicidal ideation: insights from a US population-based study [25]. Another relevant line of investigation concerns comprehensive survey of Cross-Modal retrieval: breaking through modal barriers [26].

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