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THEME ARTICLE

Artificial Intelligence Bias in Health Communication: Risks and Strategies for Medical Writers

Red Thaddeus D. Miguel, MD, MBA, MSc, RAC, RCC; Manal El Joumaa, MSc; Rami Ali, MScPH / Thera-Business, Inc, Kanata, Canada

ABSTRACT

Artificial intelligence (AI) is rapidly changing the field of health communication. Medical writers, who are central to making complex medical information understandable and usable, now face both new opportunities and new risks. AI can speed up content creation, improve workflow efficiency, and scale production. At the same time, it introduces concerns related to bias, accuracy, and accountability. This paper focuses on 3 core types of bias that affect AI-generated content: data-driven bias, algorithmic bias, and human bias. These biases often arise from unrepresentative training data, flawed system design, or lack of contextual understanding. Left unchecked, they can lead to misinformation and worsen health disparities. Medical writers play a critical role in mitigating these risks by evaluating AI outputs for accuracy, completeness, and fairness. When guided by clear standards, collaborative practices, and sound editorial judgments, medical writers can help ensure that AI supports ethical, equitable, and effective health communication. This paper offers practical strategies to help medical writers integrate AI tools responsibly without compromising the integrity, ethics, or patient equity of health communication.

INTRODUCTION

Health communication shapes how people understand medical information, make care decisions, and engage with the health system. It influences patients, clinicians, and the public, affecting everything from treatment to trust. Medical writers are central to this work, translating complex science into clear, accurate, and audience-specific content.

Effective communication requires more than accuracy. Language, tone, and context must support understanding and reduce confusion. Poor communication can cause harm, whereas strong communication improves outcomes and public health.

Artificial intelligence (AI) is now frequently part of health content creation. Large language models (LLMs) are used to draft patient materials, clinical summaries, and public messages. These tools are fast and consistent, but they do not understand science. They rely on patterns, not reasoning, and may produce fluent but inaccurate or misleading content.

As AI becomes more common, concerns about quality and accountability grow. Medical writers are often reviewing or using AI-generated text. They must check for accuracy, assess relevance, and intervene when needed. This requires a clear grasp of both AI's strengths and limitations.

This paper examines common biases in AI-generated health content and offers practical strategies for responsible use. The aim is not to reject AI but to use it in ways that uphold the core values of health communication: clarity, accuracy, equity, and trust.

BIASES IN AI USE IN HEALTH COMMUNICATION

As AI tools enter health communication, biases become a major concern. These biases can arise from training data, model design, or how systems are used in practice.[1-3] If not addressed, they can distort medical information and reinforce health disparities. To use AI responsibly, we must first understand where these biases come from and how they affect communication.

For example, training data often lacks representation from diverse populations.[3,4] This leads to outputs that ignore or misrepresent certain groups, especially those already underserved. AI may also "hallucinate" facts or apply findings too broadly, further weakening the credibility of the content.[5,6] Another possible issue is a substantial gap between AI developers and health communication experts.[3,7] Without adequate collaboration, AI outputs may fail to meet clinical or ethical standards. When human oversight is limited, flawed content can easily go unnoticed.[8] Table 1 provides detailed information regarding these biases.

STRATEGIES TO MITIGATE AI BIASES

Medical writers play a key role in identifying and correcting AI-related bias. Unchecked, these issues can lead to

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Table 1. Key Biases in AI and Their Implications for Medical Writers

Category	Core Issues	Examples and/or Evidence	Implications for Medical Writers
Data-Driven Bias			
Biased Training Data Sets	- Nonrepresentative training data sets - Lack of data set transparency - Misclassification or omission of demographic subgroups	- A scoping review of 70 studies found that AI training data sets in dermatology often lacked transparency, used unverified labels, and failed to report patient diversity.[1] - A review of 74 studies on image-based diagnostic algorithms revealed a systemic geographic bias, with most US models trained on data from just 3 states, namely California, Massachusetts, and New York.[9] - A scoping review of 7,314 articles published using AI techniques found that US and Chinese data sets and authors were disproportionately overrepresented, amplifying global health inequities by favoring data-rich regions over data-poor ones.[2]	- Risk of reinforcing biased or incomplete narratives - Misrepresentation of underrepresented populations - Risk of content lacking global applicability - Risk of amplifying global health inequities
Algorithmic Bias			
Model Limitations	- Design flaws and poor generalizability - Inability to handle context or nuance - Generation of fabricated or hallucinated content	- Overfitting the model to a training data set leads to poor generalizability to new, unseen cases.[4] - AI can confidently generate plausible but fabricated data or references.[10,11] - A study appraising 2 AI-generated minireviews on hereditary angioedema and eosinophilic esophagitis found that although AI used well-articulated language, the content lacked depth, analytical insight, and contained fabricated references. Despite being instructed to use scientific references, the AI chatbot relied on freely available resources.[12]	- Risk of including false or unverifiable information - Inconsistencies in tone, structure, or depth - Compromised credibility of written outputs, especially on topics with limited resources
Linguistic and Cultural Gaps	- English- and Western-centric training - Exclusion of non-English–speaking populations - Mistranslation and cultural misrepresentation	- The dominance of English in benchmarks and training data for LLMs exacerbates challenges for individuals and organizations in the developing world, predominantly non-English speakers.[13] - Machine translation errors in public-health communication included inconsistent use of terminology, unidiomatic or awkward style, and untranslated text.[14]	- Miscommunication due to inaccurate or culturally inappropriate phrasing - Barriers to multilingual inclusivity - Limited accessibility for global audiences
Human Bias			
Lack of Interdisciplinary Collaboration	- Limited engagement with domain experts - Limited efforts for data exchange - Unstandardized health data systems	- Without standardized terminologies and data formats, integrating AI tools into clinical workflows becomes challenging.[15] - A study assessing health care standards in ophthalmology identified multiple gaps, including limited adoption of imaging standards, lack of use cases for integrating AI-based decision support tools, scarcity in common data models to harmonize large data repositories, and the absence of standardized interfaces and outputs for AI algorithms.[16] - The absence of interdisciplinary collaboration in AI-driven public-health initiatives leads to a lack of standardized classification and summarization of both traditional and AI-based methods. This fragmentation hampers informed decision-making, delays implementation, and deters broader adoption of effective tools.[7]	- Incomplete or contextually flawed content - Lack of alignment with clinical realities or public-health messaging - Inability to critically assess or interpret outputs - Incomplete understanding of AI functionality or context - Undermined reproducibility and generalizability of AI-generated evidence

Table 1 continued on next page.

Human Bias (cont.)			
Infrastructure Inequity	- Disparities in digital infrastructure and funding - Resource disparities in data collection - Underrepresentation of low-income and non-Western regions	- Low-resource or underfunded settings are underrepresented in data sets and model development due to disparities in infrastructure, data access, and resource availability.[17] - Racial, gender, and age disparities are affecting clinical decision-making, quality of treatment, and outcome prognosis.[18]	- Biased messaging rooted in data-rich regions - Exclusion of underrepresented communities - Risk of medical writing failing to address the needs of diverse populations
Lack of Human Oversight	- Overreliance on AI tools (automation bias) - Opaque AI decision-making ("black box") - Inadequate validation and ethical safeguards	- Frequent false alarms can desensitize users, leading to ignored alerts and perpetuation of AI-generated errors (feedback loops).[3] - Many AI models function as "black boxes," making their internal logic opaque and limiting humans' ability to interpret outputs.[19] - Overreliance on AI tools can diminish human critical thinking, leading to uncritical acceptance of AI outputs. This issue is exacerbated by human cognitive fatigue during sustained oversight tasks.[8] - AI systems often depend on large volumes of sensitive personal or biological data, raising ethical and regulatory concerns. Without effective oversight, the balance between data use and individual privacy rights cannot be adequately maintained.[8]	- Overdependence on AI-generated text without verification - Reduced editorial quality and integrity - Risk of ethical or privacy violations in published content

AI, artificial intelligence; LLM, large language model.

misinformation and reduce the quality of health communication. A practical way forward involves combining human oversight, collaboration, and clear editorial standards.

Writers do not need to be programmers to make an impact. They can flag biased language, correct errors, and ensure that outputs match clinical evidence. They can also help ensure that information reflects the needs of diverse audiences.

Working with developers, ethicists, and clinicians strengthens the process. Together, these teams can build AI tools that are more accurate, inclusive, and context aware. Writers can also help create quality control checklists and review protocols specific to different health communication settings.

Bias cannot be eliminated entirely, but it can be reduced. Through careful review and strong editorial judgment, medical writers can guide AI outputs toward accuracy, fairness, and relevance.

Human Oversight

Ensuring Accuracy and Clinical Relevance

Despite their remarkable capabilities, AI systems are not infallible. They lack human qualities such as cognitive reasoning, contextual judgment, and emotional intelligence. These limitations introduce serious risks, especially in high-stakes fields like health communication. In this context, medical writers serve as critical safeguards responsible for validating the consistency, accuracy, and clinical relevance of AI-generated content. This includes checking facts, identifying discrepancies, and correcting biased or misleading content.

A common issue when relying on AI-generated data is the overgeneralization of specific findings beyond the populations studied, especially in summarized medical information.[20] When AI systems generate diagnostic content or treatment suggestions, they may generalize findings toward an irrelevant population, without considering individual patient needs.[21] For example, in a study of chest radiograph classifiers trained on 3 large chest x-ray data sets and 1 multisource data set, AI systems were found to selectively underdiagnose conditions in underserved patient populations.[22] The underdiagnosis rates were even higher for intersectional subgroups, such as Hispanic female patients. These frequent misclassifications increase the risk of delayed or missed treatment. This illustrates how algorithmic generalization can perpetuate or amplify disparities when AI systems are deployed without accounting for specific variations or patient context. Medical writers should remain alert to this dynamic as overgeneralizations produced by AI can distort scientific understanding and undermine the standards of precision and equity required in health communication.

Another issue is hallucinations, in which even the most advanced and well-trained AI tools can generate fabricated data or references. Hallucination in scientific citation was shown to affect approximately 20% to 50% of AI-generated content, depending on task complexity.[6,23] In response to these challenges, medical writers must always scrutinize the sources cited and referenced by AI tools. Their oversight helps uncover potential inaccuracies or hallucinations, which may otherwise go unnoticed.[5] This can be facilitated by the use of citation verification tools that automatically flag fabricated or incorrect references generated by AI.[24] Another effective strategy is applying retrieval-augmented generation, which can constrain AI outputs to trusted, real-time databases, thereby mitigating AI hallucinations.[25,26]

Evidence suggests that AI cannot be solely relied upon to produce complex health communication materials without human oversight. A recent study by McMinn et al highlights the ongoing need for editorial review when using LLMs to generate plain language summary abstracts.[27] The study found that LLMs can introduce persistent errors, such as misrepresenting clinical content, reinforcing inaccurate associations between conditions and demographics, and omitting or misusing sensitive terms. Although AI-assisted approaches improved readability and reduced drafting time, the authors stressed that medical writers remain essential for reviewing and refining content to ensure accuracy, clarity, and appropriateness for lay audiences.

Reviewing Fairness, Equality, and Equity

Medical writers must remain vigilant to detect embedded biases in AI outputs, such as skewed disease associations, exclusion of certain populations, and the use of inequitable language. Although these issues are best addressed at the levels of data collection and algorithm design, human oversight at the postprocessing stage remains critical. By carefully inspecting and revising the generated AI content, medical writers can correct language that may exacerbate existing inequalities, discriminate against marginalized groups, or perpetuate gender stereotypes. Additionally, they can mitigate bias through implementing content filters and transfer learning methods to adapt models to diverse populations. They can also be part of regular audits, continuous monitoring, and feedback loops that are performed to enhance fairness, equality, and equity over time.[28]

A key element in promoting fairness, equality, and equity in health communication is the use of appropriate terminology and word choice. AI content does not consistently use appropriate or inclusive terminology, which highlights the need for supervision by medical writers. For example, medical writers can rely on established terminology standards such as the *International Statistical Classification of Diseases*, Systematized Nomenclature of Medicine—Clinical Terms, and Logical Observation Identifiers Names and Codes.[15] The American Medical Association and the Association of American Medical Colleges have further emphasized the medical writer's role in their guide, *Advancing Health Equity: A Guide to Language, Narrative and Concepts*, which offers comprehensive support for equity-focused, person-first language.[29]

Understanding the characteristics of the targeted audience is essential to effective health communication. However, AI may not be able to implement audience-specific writing in the same way humans do. Medical writers must think about who will read their content and how word choice will influence interpretation. Accordingly, they must tailor their writing tone, structure, and technical depth to suit the target audience. The impact of word choice goes beyond clarity; it shapes perception and can either foster inclusivity or perpetuate exclusion. By being aware of audience needs, both medical writers' expertise and AI can combine to produce content that is accurate, culturally sensitive, and tailored to diverse audiences.

Training and Education

Several studies suggest that training and educating relevant stakeholders can help mitigate AI bias, which can be applied to users such as medical writers. Hasanzadeh et al highlighted the need for training and educating users on how to critically evaluate AI-generated recommendations.[30] They suggested that routine engagement in critical thinking exercises helps teams recognize and overcome AI pitfalls and biases. In addition to improving awareness, these exercises help maintain mindfulness of sensitive attributes such as age, gender, or ethnicity that may be unintentionally amplified in AI outputs. Other studies support this approach, showing that training improves how health care professionals use and assess AI tools.[30-32] One important area for training is explainability, which refers to understanding how AI systems produce their outputs. Many AI models operate as "black boxes," offering little insight into how decisions are made. In health care, in which such outputs can influence care, medical writers must be able to assess whether AI-generated content aligns with clinical standards. This ability to interpret and question AI outputs helps writers ensure ethical, accurate, and safe communication.[31]

Collaboration With Different Stakeholders

Addressing bias in AI requires a coordinated effort across health communication stakeholders, including clinicians, developers, policymakers, and medical writers.[3,17] As digital health tools evolve, medical writers must move beyond content creation and take on more active, collaborative roles.

From the early stages of AI development, writers can help apply clinical terminology appropriately and develop quality control tools, such as standardized review checklists. One example is the model, evaluation, timing, range/randomization, individual factors, count, and specificity of prompts and language checklist, designed to improve consistency in generative AI health care studies by addressing model design, evaluation, timing, and other key factors.[33] These tools can be adapted for use in patient education content, clinical summaries, and public-health messaging.

Interdisciplinary collaboration also helps align AI outputs with current evidence and ethical standards. By working with ethicists, clinicians, and technologists, writers can define limits for appropriate AI use and support policy development for transparent disclosure of AI involvement.[34]

Writers also play a key role in promoting patient-centered communication in AI outputs. AI tools may lack empathy, but writers can help ensure outputs reflect patient needs and values by collaborating with care teams.[35] This improves engagement, supports individualized care, and strengthens trust.

Finally, medical writers can share best practices through conferences and forums. These platforms offer opportunities to refine how AI is used in health communication, promote responsible use, and lead training on reviewing and editing AI-generated content.

Transparency in AI Usage

Transparency is essential to the ethical use of AI in medical writing. Writers must take full responsibility for disclosing when AI tools are used, in line with guidelines from the International Committee of Medical Journal Editors, which state that AI systems do not meet the criteria for authorship.[36] Authors must also ensure that AI-generated content is accurate, free from plagiarism, and properly sourced. Because language models may overlook or exclude alternative viewpoints, writers must actively check for balance and ensure content reflects a full range of perspectives.[37]

Clear disclosure builds trust. When clinicians, policymakers, and the public understand how AI was used to produce medical content, they are more likely to accept it. This includes not only acknowledging AI use but also providing details about model decisions and data sources. Proper citation also gives credit to the creators of the model and its training data.[38]

Public trust is essential for AI adoption in health care. Studies show that lack of transparency leads to skepticism, even when the technology offers real benefits.[39] Medical writers can address this by reviewing AI outputs carefully and ensuring that content remains clear, accurate, and accountable. Rather than resisting new tools, writers can use AI responsibly to strengthen communication and build public confidence in its use.

CONCLUSION

As AI continues to shape health communication, the role of medical writers must adapt. AI tools can support efficiency and help generate various forms of content, but they cannot replace human expertise. The risks of misinformation, hallucination, and bias remain significant. Writers must apply critical thinking and understand the origins of these risks to ensure content remains accurate and responsible.

AI should be used as a tool, not a source. It can assist with early drafting or summarization, but final content must be guided by human input. This approach reflects writing by design, in which writers take intentional control over how content is created, verified, and communicated.

Keeping a human in the loop is essential. Medical writers must stay involved throughout the process to evaluate quality, correct errors, and ensure the message is clear and equitable. Those who learn to work with AI, rather than against it, will help lead the field forward. By using AI responsibly and thoughtfully, writers can maintain high standards and strengthen public trust in digital health communication.

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Author contact: *rmiguel@therabusiness.com*

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