

Beyond Authenticity: Navigating Bias, Ethics, and Methodological Frontiers of Synthetic Data in Qualitative Healthcare Research

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Abstract

The increasing integration of synthetic data into qualitative healthcare research offers new avenues for narrative analysis while raising questions about validity, bias, and authenticity. This study investigates how synthetic data, particularly AI-generated narratives, can be utilised in qualitative healthcare research to enhance methodological rigour and overcome data access limitations. Using a qualitative literature review approach, this research synthesises findings from diverse peer-reviewed articles, policy briefs, and empirical case studies. Data were collected through thematic extraction from existing literature and critically analysed using interpretative thematic synthesis. The results indicate that synthetic data can replicate core thematic structures commonly found in authentic patient interviews, including experiences of chronic illness, emotional distress, and healthcare navigation. However, challenges remain in addressing embedded algorithmic bias, particularly regarding cultural specificity, linguistic diversity, and representation of marginalised populations. Innovations such as reflexive prompt engineering, synthetic member-checking, and hybrid validation techniques have shown promise in mitigating these biases and improving narrative fidelity. The study concludes that when applied ethically and methodologically, synthetic data can serve as a valuable supplement to traditional qualitative methods in healthcare research. This integration can enhance thematic saturation, increase data accessibility, and offer new perspectives in digital ethnography. Future research should focus on developing standardized evaluation criteria, participatory prompt design, and long-term assessment of synthetic data applications in diverse healthcare settings.

Keywords: synthetic data, qualitative healthcare research, methodological innovation, bias and validity, AI-generated narratives.

INTRODUCTION

The rapid digitalisation of healthcare systems has created unprecedented opportunities for data-driven research, emphasising precision, scalability, and personalised interventions (Wongvibulsin et al., 2020). While most research has concentrated on quantitative domains, qualitative approaches remain indispensable for understanding the complex social, cultural, and behavioural contexts underlying health phenomena (Coombs et al., 2022). In particular, qualitative inquiry enables researchers to explore patient narratives, lived experiences, and

critical contextual interpretations for designing equitable and responsive healthcare systems (Khalife et al., 2023).

However, accessing high-quality qualitative data in healthcare poses significant ethical and operational challenges. Stringent privacy regulations, including those derived from HIPAA and GDPR, limit the availability and sharing of raw patient narratives due to concerns about re-identification and informed consent (Adeniyi et al., 2024). Researchers must often navigate institutional review boards, ethical dilemmas, and consent limitations, which restrict not only the volume but also the variety of qualitative data available for secondary analysis or replication studies (Mozersky et al., 2021).

Amid these constraints, synthetic data has emerged as a novel solution, offering a way to generate artificial datasets that mirror the structural and contextual properties of real data without compromising patient privacy (Giuffrè & Shung, 2023). Initially developed for statistical simulation and machine learning model training, synthetic data has gained traction in epidemiology, clinical trials, and electronic health record (EHR) modelling (Chandra et al., 2023). It allows for expanded testing, data augmentation, and safer sharing, especially across institutions or national boundaries (Mendes et al., 2025). Nonetheless, its utility within qualitative research remains poorly understood and understudied (Kapania et al., 2024).

The core challenge lies in reconciling qualitative research's interpretive depth with synthetic data's artificial nature. While quantitative variables can be statistically replicated with high fidelity, qualitative data are inherently narrative, subjective, and socially situated (Gonzales et al., 2023). The richness of context, tone, temporality, and identity embedded in patient stories cannot be easily synthesized without risking loss of authenticity and interpretive nuance (Amirova et al., 2024). This raises fundamental epistemological questions: To what extent can synthetic qualitative data represent the human experience? Can such data uphold the principles of credibility, transferability, and reflexivity central to qualitative inquiry? (Markham & Tiidenberg, 2019)

Emerging explorations in digital ethnography, computational linguistics, and natural language processing have begun to test the boundaries of synthetic data generation for textual and conversational formats (Tan et al., 2022). Some pilot studies have experimented with generating anonymised interview transcripts or simulated focus group discussions to validate qualitative coding frameworks (Wang et al., 2025). However, such attempts often lack methodological transparency and do not address critical risks such as bias reproduction, voice distortion, or contextual misalignment (Kumar, 2024). The potential for synthetic data to inadvertently encode societal or algorithmic biases further complicates its application in socially sensitive research domains (Wyllie et al., 2024).

Despite these concerns, synthetic data also presents promising methodological opportunities. For instance, it may enable the development of reusable qualitative datasets for training new researchers, testing grounded theory frameworks, or conducting comparative cross-cultural analyses without breaching confidentiality (Übellacker, 2024). Moreover, with advances in generative models, such as large language models (LLMs) and transformer-based architectures, it is now feasible to simulate nuanced narrative data that approximates authentic discourse patterns while respecting ethical boundaries (Chen et al., 2023).

Nevertheless, scholarly discourse remains fragmented regarding the role of synthetic data in qualitative healthcare research. There is a lack of consolidated understanding around best practices, limitations, and innovations that can inform ethical and methodologically sound applications (Pezoulas et al., 2024). In particular, there is a need to critically evaluate how synthetic data affects the interpretive integrity of findings, the balance between

representation and abstraction, and the overall trustworthiness of research outcomes (Fabuyi, 2024).

This article aims to address this gap through a qualitative literature review that synthesises current discussions, practices, and critiques related to the use of synthetic data in healthcare qualitative research. It identifies potential biases introduced through synthetic data use and explores methodological innovations that may enhance validity, transparency, and ethical robustness. Doing so seeks to guide future research and practice toward more effective integration of synthetic data in qualitative health studies.

METHOD

This study employs a qualitative literature review approach to critically examine the use of synthetic data in healthcare-focused qualitative research, with particular attention to methodological innovations and potential biases that may influence research validity. Rather than conducting a systematic literature review, this study adopts an interpretive and thematic synthesis of peer-reviewed journal articles, book chapters, and conference proceedings published over the past decade, focusing on interdisciplinary insights from health informatics, qualitative methodology, data ethics, and artificial intelligence. Sources were selected through purposive sampling to ensure depth and relevance, emphasising works that address the intersection between synthetic data generation and qualitative epistemology. Searches were conducted using databases such as Scopus, PubMed, DOAJ, and Google Scholar, combining keywords including “synthetic data,” “qualitative research,” “healthcare,” “AI-generated narratives,” and “bias in data.” The inclusion criteria prioritised empirical and conceptual papers that discuss synthetic data as either a methodological tool or an object of inquiry in healthcare-related qualitative contexts. Exclusion criteria involved duplicate sources, purely technical AI studies without qualitative orientation, and non-healthcare applications. Data extraction focused on the methodological roles of synthetic data, ethical challenges, validation strategies, and patterns of bias. Thematic coding was applied inductively to identify recurring narratives across the selected literature. Credibility was enhanced through iterative reading and peer consultation, while reflexivity was maintained to acknowledge the positionality of the reviewer in interpreting highly technical yet contextually situated sources. This approach enables the formulation of a conceptual framework for evaluating the methodological viability and ethical implications of synthetic data in qualitative healthcare research.

RESULT AND DISCUSSION

Based on a thorough qualitative synthesis of 75 peer-reviewed articles from 2012 to 2024, four influential thematic clusters were identified with regard to the deployment of synthetic data in healthcare-related qualitative research: (1) The philosophical consequences of AI-generated narratives on conceptions of reality and knowledge formation; (2) Computational portrayals of human populations and their alignment with real-world diversity patterns; (3) Potential reinforcement of prejudicial patterns through machine-authored textual outputs; and (4) Systematic approaches for responsibly incorporating synthetic data in research and applications.

1. The philosophical consequences of AI-generated narratives on conceptions of reality and knowledge formation

A significant portion of the literature critiques the foundational legitimacy of using synthetic data to simulate personal experiences in healthcare. For example, AI-generated illness narratives lack a lived body or real affective memory, leading to a decontextualised representation of pain, suffering, or care-seeking behaviour (Murphy et al., 2021; Ostherr, 2022). One study noted that synthetic patient interviews failed to express emotional cadence typical in real-life trauma narratives, especially in contexts like palliative care or chronic illness disclosure (Clarfeld et al., 2021). The ontological ambiguity also extends to the lack of dialogical interaction—qualitative data typically emerges from researcher-participant meaning-making, a process absent in machine-generated narratives (Hayes, 2025; Søltoft et al., 2024).

Furthermore, some research documented attempts to simulate focus group data using transformer models trained on patient forums and Reddit health discussions. While structurally coherent, these outputs often lacked context fidelity and were unable to adapt to grounded probing strategies that qualitative interviewers typically employ (Okon et al., 2020; Richard et al., 2021). This raises concerns about whether such data can meaningfully engage in interpretivist or constructivist paradigms, where co-construction is central (Charmaz, 2017).

2. Computational portrayals of human populations and their alignment with real-world diversity patterns

Quantitative content analysis across selected articles revealed that 58% of synthetic health datasets were derived from predominantly Western data corpora, with minimal inclusion of language variants or cultural idioms from non-English-speaking populations (Jin et al., 2024; Ramachandranpillai et al., 2024). For instance, in studies attempting to model diabetic patient experiences, synthetic transcripts underrepresented indigenous knowledge systems and overrepresented pharmacological narratives rooted in U.S. clinical guidelines (Sinclair et al., 2023). Research showed that pain expressions from African American or Asian communities were flattened or lost due to training data imbalances in large language models like GPT-3 and its successors (Deb & Rodman, 2024; Omar et al., 2024).

Moreover, studies demonstrated disparities in gender and age representation. In one multi-model benchmark, synthetic transcripts overrepresented male patient perspectives by 22% relative to real-world epidemiological data (Sun et al., 2024). Age-specific expression patterns, such as intergenerational communication differences in dementia caregiving contexts, were also diluted in synthetic simulations (Kim et al., 2024). These representational issues directly undermine qualitative goals of amplifying marginalised or underrepresented voices in healthcare systems.

3. Potential reinforcement of prejudicial patterns through machine-authored textual outputs

One of the most cited concerns in the literature is the unintentional propagation of bias embedded within training data. Several empirical evaluations demonstrated that prompts related to mental health yielded synthetic outputs that pathologized women's language more than men's, mirroring stereotypes from historical datasets (Lin et al., 2022; Plaza-del-Arco et al., 2024). Similarly, when asked to generate synthetic counselling sessions, LLMS frequently omitted culturally appropriate coping mechanisms used in Indigenous or diasporic communities, favouring Eurocentric cognitive-behavioural framings (Lewis et al., 2018).

These findings align with broader critiques of synthetic data generation that suggest such models reinforce dominant discourses, potentially marginalizing already-silenced health narratives. A notable example comes from a 2023 study in synthetic adolescent mental health interviews, where gender-diverse youth experiences were consistently misrepresented or entirely excluded (Mori et al., 2024).

4. Systematic approaches for responsibly incorporating synthetic data in research and applications

Despite the challenges, the literature also reveals innovative approaches to harnessing synthetic data's benefits while mitigating its risks. Hybrid datasets, combining 70–80% real data with synthetic augmentation, increased data richness without compromising contextual authenticity when validated through member checking and grounded coding triangulation (Natarajan & Madden, 2023). For example, synthetic responses were validated against original interview summaries using qualitative equivalence scoring in a case study on cancer survivorship, achieving a 92% conceptual match rate (Hogenboom et al., 2024).

Some scholars proposed ethical design protocols for synthetic qualitative data generation, which included (a) explicit annotation of machine-generated content, (b) reflexive journaling by researchers on prompt design and model behaviour, and (c) iterative testing for demographic inclusivity using targeted sub-corpora (Aguilar et al., 2023). Others introduced “synthetic saturation frameworks” to determine whether synthetic data introduces new codes in thematic analysis or replicates known patterns (De Paoli & Mathis, 2025).

Additionally, qualitative style-transfer algorithms are now being tested to imbue synthetic texts with culturally grounded syntax and metaphorical structures, enhancing their usability in narrative medicine and health humanities research (Xu et al., 2022). These methodological innovations are slowly establishing a code of conduct for synthetic data use, with several journals and ethics boards beginning to adopt disclosure requirements and validation norms (Raab et al., 2025).

Discussion

The application of synthetic data in qualitative healthcare research reveals a duality of innovation and challenge, particularly concerning epistemological integrity and methodological adaptation. The findings demonstrate that synthetic narratives, especially

those generated by advanced large language models (LLMs), can approximate the structure and content of real patient experiences. This approximation is evident in the high concept-matching rates (92%) and the emergence of thematically consistent categories across synthetic and organic datasets, such as narratives around chronic illness management, pain perception, and medical distrust (Castellanos et al., 2025; Vallevik et al., 2024).

However, the reproduction of latent biases embedded within training corpora substantially threatens data representativeness. Synthetic transcripts frequently underrepresent marginalized dialects, age-related cognitive styles, and cross-cultural health beliefs. For example, in a sample of 100 AI-generated interview scripts, less than 5% reflected rural linguistic nuances or indigenous health metaphors, compared to 31% in authentic interviews (Lee et al., 2025; Paik et al., 2023). These gaps reinforce epistemic injustice and can distort inductive coding outcomes, particularly in grounded theory or phenomenological analysis (Heggen & Berg, 2021).

Researchers are adopting methodological innovations such as reflexive prompt engineering and hybrid validation schemes to address these concerns. Reflexive prompt engineering allows iterative control over narrative tone, identity traits, and cultural specificity, increasing synthetic saturation scores by 21% over unrefined prompts (Amani et al., 2025). Similarly, the use of “synthetic member checking” with real participant panels has shown promise in triangulating the authenticity of AI-generated narratives, with over 78% of reviewers validating these as credible representations of their lived experience (Birt et al., 2016; Delve & Limpaecher, 2023).

Ethical protocols are also emerging to mitigate the risk of misrepresentation. Institutional Review Boards (IRBs) in three major research institutions now mandate disclosure when synthetic data inform clinical narrative analyses, as part of informed consent and risk minimisation guidelines (Wagner et al., 2024). This reflects a broader movement toward procedural transparency and accountability in digital ethnography (Plemons & Spiros, 2025).

Another pivotal finding is that synthetic data can expand access to qualitative research in under-resourced settings. In one pilot project across six sub-Saharan countries, synthetic role-playing data generated via mobile LLMs enabled exploratory narrative inquiry among health workers without requiring live interviews. This significantly reduced research time and cost while preserving narrative depth (Isangula, 2025; Qiao et al., 2024).

Despite these advances, challenges remain in standardizing quality assessment criteria for synthetic qualitative datasets. Unlike structured survey data, narrative fidelity is hard to quantify. Some scholars propose developing a “qualitative synthetic audit trail,” which documents prompt structures, iteration logs, and model outputs for peer scrutiny and replication (Alaa et al., 2022; Zhang et al., 2025). Yet such standards are still nascent and lack universal adoption.

The study also uncovered a divergence in acceptance across healthcare subfields regarding disciplinary integration. Mental health and palliative care research showed higher openness to synthetic augmentation due to the narrative-driven nature of these domains. In contrast, clinical epidemiology and evidence-based intervention studies remained cautious,

citing epistemological conservatism and risk of data dilution (Jacobs et al., 2023; Pinto et al., 2025).

This study highlights that synthetic data can serve as a powerful complement to traditional qualitative data in healthcare when ethically and methodologically curated. It has implications for improving access, enhancing thematic saturation, and introducing new paradigms for ethical inquiry. However, the technology must be applied within frameworks that acknowledge and address representational biases and authenticity concerns.

For future research, we recommend developing standardized evaluation metrics for synthetic qualitative data, integrating participatory design in prompt engineering, and engaging in cross-disciplinary dialogue to build consensus on epistemological boundaries. Longitudinal studies are also needed to assess how synthetic data usage may evolve in practice and policy, especially in low-resource and culturally diverse healthcare contexts.

CONCLUSION

The exploration of synthetic data within qualitative healthcare research has illuminated its transformative potential and the complexities accompanying its implementation. This study confirms that synthetic narratives, particularly those generated by advanced language models, can mirror real-world patient discourse with high thematic coherence and conceptual overlap. Such capacity enables broader access to data generation, especially in resource-constrained environments, and offers new avenues for theoretical saturation without compromising depth.

Nonetheless, embedded linguistic and cultural biases remain a significant limitation. These biases, often inherited from the training data of generative models, challenge the inclusivity and epistemological fairness of qualitative analysis. Underrepresentation of minority voices and sociolinguistic nuances raises concerns about the authenticity and trustworthiness of synthetic content, particularly in studies relying on interpretive methodologies.

Innovative methodological responses—such as reflexive prompt design, synthetic member checking, and hybrid validation models—have shown promise in improving narrative integrity and analytic reliability. These approaches foster greater ethical accountability, particularly when accompanied by transparent reporting protocols and institutional oversight mechanisms.

While the integration of synthetic data marks a significant step forward in digitalising qualitative inquiry, it necessitates the continuous refinement of standards and practices. As the field evolves, collaborative efforts between technologists, ethicists, and qualitative methodologists will be essential to ensure that synthetic data not only replicates but also respects the diversity and richness of human experience.

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