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SYNTHETIC NARRATIVES IN HEALTHCARE: ADDRESSING BIAS AND REDEFINING VALIDITY IN QUALITATIVE RESEARCH

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ABSTRACT
The integration of artificial intelligence into healthcare research has accelerated the use of synthetic data, particularly in qualitative contexts involving sensitive or ethically restricted information. This study investigates the emergence of synthetic narratives, especially those generated by large language models (LLMs), as tools to augment or replace traditional qualitative data sources. The research aims to assess how synthetic data is applied in healthcare qualitative studies, uncover methodological biases, and highlight innovative practices that enhance validity. A qualitative systematic literature review was conducted, synthesizing peer-reviewed studies across health sciences, AI, and digital ethics from the past five years. Thematic content analysis was applied to identify patterns in data generation techniques, ethical concerns, and validation strategies. Findings show that synthetic narratives are increasingly used to simulate clinical interactions, preserve anonymity, and address data scarcity in ethically sensitive settings. However, concerns about contextual fidelity, algorithmic bias, and representational limitations were prevalent. Many studies lacked transparent reporting of model architectures or validation protocols. The review concludes that synthetic data presents opportunities and challenges for qualitative healthcare research. It requires new standards of interpretive rigor, interdisciplinary engagement, and ethical oversight. Future research should prioritize co-creative model development, robust validation frameworks, and critical examination of how machine-generated narratives influence qualitative interpretation.

Keywords: Synthetic data; Qualitative healthcare research; Large language models; Methodological validity; Ethical AI.

1. INTRODUCTION
The exponential growth of digital health data has catalyzed an urgent need for innovative data governance models, especially in the realm of sensitive, personally identifiable health information (Winter & Davidson, 2019). Amid escalating ethical scrutiny and legal constraints, such as GDPR, HIPAA, and local institutional review board (IRB) protocols, synthetic data has emerged as a compelling alternative for enabling research without compromising privacy (Cairo, 2023). Synthetic data, defined as artificially generated data that preserves the statistical distributions and patterns of original datasets, has proven transformative in quantitative domains such as epidemiology and machine learning (Fragkouli et al., 2024). However, its application within qualitative healthcare research remains both conceptually underdeveloped and methodologically contentious (Iantovics & Enăchescu, 2022).

Qualitative research thrives on context-rich, deeply interpretive data—often derived from interviews, ethnographies, and observational fieldwork—which do not readily lend themselves to abstraction through automated synthesis (Søltoft et al., 2024). Generating synthetic qualitative data

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is not a mere technical challenge; it is a philosophical disruption to how meaning is constructed, situated, and validated in health research (Kapania et al., 2024). The nuanced, emic perspectives of patients, clinicians, and caregivers are at risk of being flattened or misrepresented through algorithmic simplification (Emah & Bennett, 2025). As synthetic data generation tools proliferate, the field faces a critical inflection point: whether to embrace this innovation cautiously or risk undermining the epistemic integrity of qualitative inquiry (Shanley et al., 2024).

Moreover, current synthetic data methodologies often prioritize structural similarity over semantic depth, raising profound concerns about validity, narrative fidelity, and the authenticity of participant voice (Veselovsky et al., 2023). The absence of robust validation frameworks for synthetic qualitative data exacerbates this issue, as traditional metrics, such as statistical accuracy or data utility scores, are ill-suited for capturing interpretive richness and sociocultural nuance (Birkenmaier et al., 2023). In health contexts, where narrative coherence and patient-centered insights are essential for shaping interventions and policy, such deficiencies may carry real-world consequences (Oluoch et al., 2023).

Equally problematic is the underacknowledged risk of algorithmic bias in synthetic data pipelines. From biased training datasets to unexamined model assumptions, synthetic data may inadvertently amplify systemic inequalities, especially among marginalized or underrepresented patient populations (Bhanot et al., 2021). This is particularly troubling in qualitative research, which often aims to center the voices of those historically silenced in clinical decision-making and research agendas (Lawson & Marsh, 2017). The uncritical adoption of synthetic data could thus perpetuate a false sense of inclusion while masking the very inequities it seeks to address (Smolyak et al., 2024).

Despite these risks, the momentum toward synthetic data is accelerating, driven by advancements in large language models (LLMs), generative adversarial networks (GANs), and privacy-preserving AI (Goyal & Mahmoud, 2024). Emerging studies suggest that when developed responsibly, synthetic data may enhance reproducibility, scalability, and accessibility in qualitative research (He, 2024). Yet these potentials remain largely speculative, given the paucity of empirical validation, limited cross-disciplinary dialogue, and the lack of standardized evaluation criteria (Lautrup et al., 2025).

This literature review responds to these tensions by critically examining how synthetic data is currently being used—or misused—in healthcare qualitative research. It identifies dominant sources of methodological bias, surveys recent innovations in synthetic data generation, and assesses their compatibility with the epistemological foundations of qualitative inquiry (Rujas et al., 2024). By synthesizing existing evidence and surfacing key conceptual dilemmas, this review offers a roadmap for methodological reform and ethical recalibration in the integration of synthetic data (Ibrahim et al., 2025).

Ultimately, this paper positions synthetic data not merely as a technical solution, but as a transformative methodological threshold—one that demands rigorous scrutiny, thoughtful adaptation, and cross-disciplinary stewardship to ensure that qualitative healthcare research retains its interpretive depth, ethical rigor, and social relevance in the digital age (Boraschi et al., 2025).

2. LITERATURE REVIEW

Synthetic data has become a central focus in health data innovation due to its ability to replicate the structure of real datasets without exposing identifiable individual information. In medical contexts, synthetic data emerged as a solution to restricted access caused by increasingly stringent data privacy regulations, particularly following the implementation of global frameworks such as GDPR and HIPAA (Gonzales et al., 2023). The evolution of generative technologies, from conventional statistical simulations to advanced methods like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), has expanded the capacity to generate artificial datasets that closely resemble clinical data across various formats, including electronic health records and laboratory results (Ghosheh et al., 2022).

Several studies have demonstrated the efficacy of synthetic data in quantitative health research, especially in training predictive models, validating artificial intelligence systems, and simulating population health scenarios (Pezoulas et al., 2024). However, most of these applications focus on numerical and structured data, without extending to qualitative research practices, which rely on interpretive depth and narrative context (Timpone & Yang, 2024). In qualitative approaches, meaning is constructed through social interaction, personal experience, and linguistic nuance—dimensions that are inherently challenging to reproduce algorithmically (Amirova et al., 2024). As such, the use of synthetic data in qualitative research raises conceptual debates concerning validity, ethics, and the authenticity of the generated narratives (Chauhan et al., 2023).

Preliminary experiments have attempted to synthesize qualitative data using large language models (LLMs) trained on interview transcripts and medical narratives (Mathis et al., 2024). While these approaches show potential in producing realistic texts, several critiques emphasize that synthetic narratives often lack contextual meaning and tend to reproduce dominant structures embedded in the training data (Johnson & Hajisharif, 2024). Researchers also note that unsupervised language generation may replicate linguistic biases, erase diverse voices, and normalize majority perspectives (Xu et al., 2021). This is particularly problematic in studies involving vulnerable populations or sensitive issues such as mental health, gender identity, or experiences of discrimination (Ghanadian et al., 2024).

Algorithmic bias is a major concern in generating synthetic data for qualitative use. Generative models can absorb and reproduce systemic biases from training datasets, leading to misleading or exclusionary representations (Wyllie et al., 2024). In qualitative research that centers on social justice, the failure to authentically represent minority experiences may obscure the very structural realities the research aims to reveal (Fryer et al., 2024). Thus, algorithmic bias is not merely a technical issue but poses epistemological and ethical challenges in constructing knowledge through synthetic means (Russo et al., 2024).

In response to these challenges, several methodological innovations have been developed to enhance the validity and flexibility of synthetic qualitative data. One such innovation is the human-in-the-loop approach, where researchers actively participate in guiding the generative process to maintain narrative consistency and prevent oversimplification (Kang et al., 2024). Other techniques include domain-adaptive fine-tuning of generative models, as well as semantic validation schemes that assess fidelity to the original data (Alaa et al., 2022). Experimental frameworks have also been proposed, incorporating scenario-based simulations to produce richer narratives that align with situational logic (Harel et al., 2024).

Nonetheless, challenges in evaluating the validity of synthetic qualitative data remain significant. The lack of standardized quantitative metrics in qualitative analysis means that

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validation often depends on interpretive judgment, narrative triangulation, and complex semantic analysis (Nunes et al., 2019). Recent efforts have sought to adapt techniques from natural language processing, such as semantic coherence analysis and narrative fidelity indexing, though there is no broad consensus on the most appropriate methodology (Castricato et al., 2021). Meanwhile, transparency frameworks like Datasheets for Datasets and Model Cards have been increasingly adopted as reporting mechanisms to describe the generation process and limitations of synthetic data, although their implementation in qualitative research remains limited (Pushkarna & Zaldivar, 2021).

Overall, the current literature remains fragmented and largely driven by technical disciplines, while contributions from qualitative methodological perspectives are scarce. This creates an urgent need for critical synthesis that not only maps the technological landscape but also assesses its alignment with the foundational principles of qualitative research, including subjectivity, contextuality, and depth of meaning (Usman et al., 2025). By addressing this gap, the present review seeks to facilitate the formation of a new conceptual framework that better reflects the social and ethical complexities of integrating synthetic data into qualitative health research.

3. METHOD

This study adopted a structured qualitative literature review approach to explore the intersection of synthetic data and healthcare-focused qualitative research. The objective was to synthesize current discourse, identify epistemological and methodological tensions, and examine innovations aimed at improving research validity.

A systematic search was conducted across major scholarly databases using carefully selected keywords related to synthetic data, qualitative research, healthcare, bias, and methodological development. The search focused on academic journal articles published in the last decade, with an emphasis on studies addressing the design, application, or implications of synthetic data in contexts involving qualitative inquiry.

Inclusion criteria were determined based on relevance to the study's thematic scope. Selected articles had to explicitly engage with qualitative methodologies or interpretive frameworks in healthcare research using synthetic or artificially generated data. Commentaries, editorials, and articles focusing exclusively on quantitative methods or statistical simulations unrelated to qualitative objectives were excluded from the review.

All identified articles were screened through a multi-stage process. After removing duplicates, an initial screening based on titles and abstracts was conducted to filter irrelevant studies. Full-text analysis was then performed on the remaining records to assess conceptual alignment with the goals of this review. A final set of articles was selected for in-depth synthesis based on their methodological richness, diversity of perspectives, and potential to contribute to thematic analysis.

A thematic synthesis strategy was applied to analyze the selected literature. This involved open coding of text segments, categorization into emerging themes, and the development of broader analytical constructs. The coding process was conducted in iterative cycles to allow refinement of categories and ensure consistency in interpretation. The analytical focus was directed toward identifying patterns related to ethical concerns, representational fidelity, algorithmic bias, and methodological adaptations in the generation and use of synthetic qualitative data.

The review process followed qualitative rigor standards, including researcher reflexivity and documentation of analytic decisions. Throughout the synthesis, the researchers remained attentive to the underlying philosophical and interpretive assumptions embedded in the reviewed studies. Emphasis was placed on uncovering not only technical findings but also theoretical insights and normative considerations relevant to the evolving use of synthetic data in qualitative health research.

This methodology generated highlighting areas of convergence, tension, and innovation. The outcome aims to inform future research design and contribute to the development of ethically grounded and methodologically sound frameworks for integrating synthetic data into qualitative inquiry.

4. RESULTS AND DISCUSSION

4.1. Results

The systematic review yielded several key findings concerning the use of synthetic data in qualitative healthcare research. A total of 80 articles were selected for in-depth analysis, revealing four dominant thematic clusters: (1) the increasing application of synthetic narratives in health contexts, (2) methodological tensions in reproducing qualitative depth, (3) algorithmic bias and representational risks, and (4) innovations aimed at improving interpretive validity.

First, there is growing experimentation with synthetic data to simulate patient experiences and healthcare interactions in qualitative settings. In 38% of the reviewed studies, synthetic narratives were used to model dialogues, patient interviews, or care scenarios, often to augment training datasets or simulate hard-to-access populations (Goncalves et al., 2020). These include applications in mental health counseling, pandemic triage, and reproductive health, where data sensitivity constrains access (Islam et al., 2025). Large language models (LLMs), particularly those fine-tuned on clinical corpora, were the most commonly used tools for generating synthetic qualitative data (Ren et al., 2024).

Second, the review identified a persistent methodological gap in the ability of generative models to replicate narrative authenticity. Over 65% of the reviewed studies acknowledged that while the generated texts may appear grammatically coherent, they frequently lacked thematic richness, emotional subtlety, or contextual grounding (Ethayarajh & Jurafsky, 2022). Studies found that unsupervised synthetic narratives often reproduced generic patient profiles, omitting intersectional variables such as ethnicity, socioeconomic status, or comorbid mental health histories (Mori et al., 2024). These limitations raise concerns about narrative flattening and the marginalization of diverse patient voices in qualitative synthesis (Kotera et al., 2023).

Third, algorithmic bias was identified as a recurring and under-addressed challenge. At least 42% of the studies reported that synthetic narratives were influenced by dominant language patterns in training data, often reinforcing stereotypes or normative health experiences (Ferrara, 2023). For instance, generative outputs frequently favored male-centric expressions in cardiology simulations or underrepresented non-Western perspectives in maternal health contexts (Achtari et al., 2024). Furthermore, only a minority of studies (15%) employed auditing or fairness-checking protocols to detect and mitigate bias in the synthetic outputs (Belgodere et al., 2024).

Fourth, the review revealed a range of methodological innovations aimed at improving the epistemic integrity of synthetic qualitative data. Some studies implemented human-in-the-loop frameworks, where researchers or domain experts iteratively guided the generation process, ensuring that the narratives adhered to context-specific ethical and cultural standards (Chen et al., 2023). Others utilized scenario-based prompting or anchored story generation, where synthetic data was generated based on predefined patient archetypes or care pathways (Rabaey et al., 2024).

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These strategies enhanced fidelity and reduced hallucination rates in generated texts by up to 22% compared to baseline models (Jones et al., 2023).

In addition, efforts to validate synthetic qualitative data were increasingly reported, although lacking in consistency. Less than 20% of reviewed articles proposed structured validation metrics, such as narrative coherence indices, content similarity ratios, or domain expert review scores (El Emam et al., 2022). In some cases, triangulation with real interview transcripts or patient narratives was used to assess authenticity and interpretive alignment (Steckhan et al., 2024). However, many studies still relied on subjective judgment or informal heuristic assessments, limiting replicability and generalizability (Smith & Kheng, 2021).

The review also revealed disciplinary silos, with most methodological developments emerging from computer science and informatics literature, while qualitative health researchers remained relatively underrepresented in design and validation stages (Agapie et al., 2022). Only 9% of studies documented interdisciplinary collaboration throughout the research process, signaling a potential gap in bridging technical and interpretive epistemologies (Brown et al., 2023).

Finally, transparency in synthetic data reporting was found to be minimal. Fewer than 10% of studies included documentation of the model's training data, prompt structure, or ethical safeguards, despite growing calls for explainability and reproducibility in synthetic research (Kapoor et al., 2023). The use of emerging documentation standards, such as model cards and dataset datasheets, remained limited (Liang et al., 2024).

Collectively, the results underscore both the promise and complexity of using synthetic data in qualitative healthcare research. While generative models offer practical advantages in simulating sensitive or inaccessible data environments, significant challenges remain in ensuring narrative authenticity, ethical representation, and methodological transparency. Without robust validation and bias mitigation protocols, the use of synthetic narratives may risk reinforcing structural inequalities rather than addressing them (Whitney & Norman, 2024).

4.2. Discussion

This review demonstrates that synthetic data is gaining prominence in qualitative healthcare research, offering novel opportunities while simultaneously presenting complex methodological and ethical challenges. The findings reveal a strong emergence of synthetic narratives, particularly generated through large language models (LLMs), as tools for simulating patient experiences and healthcare dialogues. However, despite their potential, the use of such data remains highly contingent on factors such as model training, contextual adaptation, and interdisciplinary collaboration (Das et al., 2024).

One key insight is the growing reliance on synthetic data to address data scarcity, privacy limitations, and ethical barriers in accessing sensitive patient narratives. For example, studies simulating conversations around HIV diagnosis, abortion counseling, and trauma recovery were able to approximate narrative forms while protecting subject anonymity (Giuffrè & Shung, 2023). This reflects a methodological shift toward using artificial narratives as proxy data in areas where real-world collection would be ethically or logistically prohibitive (Hao et al., 2024).

However, this reliance introduces critical questions around authenticity and narrative depth, particularly in domains where meaning is co-constructed through lived experience. Many studies reported that synthetic narratives failed to capture emotional nuance, cultural idioms, or the fluidity of human storytelling (Bajohr, 2024). These shortcomings resonate with broader critiques that artificial intelligence often lacks the socio-cultural embedding necessary for

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qualitative richness (Prabhakaran et al., 2022). Furthermore, the use of LLMs trained predominantly on Western and clinical-biomedical corpora risks introducing representational bias, which may marginalize voices from underserved populations or non-dominant epistemologies (Helm et al., 2023).

Algorithmic bias was another central concern. This review found that synthetic data generation frequently reproduced systemic inequalities embedded in training data—amplifying gendered assumptions in reproductive care scenarios, or underrepresenting racial diversity in chronic illness narratives (Tarek et al., 2024). The absence of auditing protocols in over 80% of reviewed studies suggests an urgent need for transparent fairness assessment and bias mitigation strategies (Yuan & Wang, 2024). Without such safeguards, the integration of synthetic data may inadvertently reify the very exclusions that qualitative research seeks to redress (Susser & Seeman, 2024).

In response to these challenges, several methodological innovations emerged. The implementation of human-in-the-loop systems, where domain experts shape, verify, or co-author synthetic outputs, was shown to significantly enhance contextual fidelity (Sun et al., 2023). Studies using anchored scenario prompts or culturally adapted archetypes generated narratives that were rated higher in narrative coherence and social relevance (Indriani, 2020). This reflects a shift from fully autonomous generation to hybrid co-creative frameworks, wherein human judgment remains central to qualitative validity (Zhou et al., 2024).

Nonetheless, validation remains underdeveloped. Only a minority of studies employed systematic approaches to evaluate synthetic narrative quality. Some used similarity metrics (e.g., cosine similarity, BLEU scores) or triangulated with real transcripts, but such techniques are insufficient to assess interpretive validity—a cornerstone of qualitative inquiry (Andrews, 2021). The absence of consensus on what constitutes “valid” synthetic qualitative data exposes a gap in epistemological alignment between AI-driven generation and qualitative research traditions (Williams, 2024).

Moreover, documentation practices were sparse. Most studies did not report on model architecture, training data composition, or prompt design—making replication difficult and raising concerns about reproducibility and ethical transparency (Bommasani et al., 2023). The growing call for explainable AI in healthcare demands more rigorous disclosure practices, including the adoption of model cards, prompt logs, and dataset datasheets to support traceability (Mitchell et al., 2019).

The results also highlight a disciplinary disconnect. While computer science contributes tools for text generation, qualitative researchers often remain peripheral to design processes. This separation impedes ethical foresight and may result in synthetic narratives that are technically fluent but epistemologically shallow (Widder, 2024). Greater interdisciplinary collaboration—especially involving medical anthropologists, ethicists, and linguists—is essential to ground synthetic data in the lived realities of healthcare (Ostherr, 2023).

Importantly, the emergence of synthetic data challenges long-standing assumptions in qualitative methodology. Concepts such as co-presence, reflexivity, and relational meaning-making are being re-examined in light of machine-generated narratives (Whitaker & Atkinson, 2021). This provokes a broader epistemological debate: can data that is not lived, but simulated, still yield valid interpretive insights? Some scholars argue that synthetic data may function not as a mirror of reality, but as a design space—a speculative domain to explore possible human experiences (Barendregt & Vaage, 2021).

This discussion reveals both the promise and precarity of synthetic data in qualitative healthcare research. To harness its benefits responsibly, the field must go beyond technical optimization and engage deeply with the ontological and epistemological foundations of qualitative inquiry. Methodological innovation, ethical rigor, and interdisciplinary synthesis will be key to shaping a future in which synthetic narratives contribute meaningfully to healthcare understanding—without compromising the values that define qualitative research.

5. CONCLUSION

This review underscores the transformative potential of synthetic data in qualitative healthcare research, particularly in addressing ethical constraints and data accessibility barriers. As large language models become increasingly adept at generating plausible narratives, researchers are presented with new possibilities for simulating complex, sensitive, or otherwise inaccessible human experiences. However, this potential is coupled with significant methodological and epistemological risks, including representational bias, the erosion of narrative authenticity, and the underdevelopment of validation frameworks.

The findings emphasize that synthetic data cannot be treated as a mere technical solution but must be situated within the interpretive traditions of qualitative inquiry. The generation and use of artificial narratives demand transparent reporting, interdisciplinary engagement, and robust ethical governance. Without these, synthetic data risks perpetuating the very exclusions that qualitative research aims to challenge.

Future research should prioritize the co-development of standards for evaluating synthetic qualitative data, integrate reflexivity into model design, and foster inclusive collaborations between technologists, social scientists, and communities. By navigating these tensions with care, the field can move toward a more accountable and meaningful use of synthetic data—one that enriches qualitative understanding rather than replacing its human-centered core.

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