Automating Thematic Analysis Using Large Language Models

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Abstract

Thematic analysis is a foundational qualitative research method widely used across social sciences, healthcare, education, and policy studies to identify, analyze, and interpret patterns within textual data. Despite its methodological importance, traditional thematic analysis remains time-intensive, subjective, and difficult to scale, particularly in the era of big data. Recent advances in Large Language Models (LLMs) present a compelling opportunity to automate and augment this process. This paper investigates the feasibility, effectiveness, and limitations of automating thematic analysis using LLMs. We propose an end-to-end framework that leverages transformer-based language models for theme extraction, clustering, and semantic coherence evaluation. Through extensive experimentation on benchmark qualitative datasets, we demonstrate that LLM-driven thematic analysis achieves high alignment with human-coded themes while significantly reducing analysis time. Our results suggest that LLMs can serve as reliable collaborative agents for qualitative research rather than mere automation tools, opening new pathways for scalable, reproducible, and explainable qualitative analysis.

Keywords: Thematic Analysis, Large Language Models, Qualitative Research Automation, Natural Language Processing, Topic Modeling, AI-Assisted Research

I. Introduction

Thematic analysis has long been regarded as a flexible and powerful method for making sense of qualitative data, allowing researchers to identify recurring patterns and interpret meaning within narratives, interviews, and open-ended responses [1]. However, as the volume of unstructured textual data grows rapidly, traditional manual approaches struggle to scale without compromising rigor or consistency. Researchers are often forced to choose between depth and efficiency, a trade-off that limits the practical application of thematic analysis in large-scale studies.

The emergence of Large Language Models, trained on vast corpora of natural language, has fundamentally altered the landscape of text understanding. Unlike earlier statistical or rule-based methods, LLMs demonstrate an ability to capture semantic nuance, contextual dependencies, and latent conceptual relationships within text [2]. These capabilities align closely with the cognitive processes involved in thematic analysis, suggesting that LLMs may be uniquely suited to support or automate this task.

Yet, skepticism remains regarding the use of LLMs in qualitative research. Concerns around interpretability, bias propagation, reproducibility, and epistemological validity have slowed adoption in research communities that prioritize methodological transparency. Automating thematic analysis is not merely a technical challenge but also a conceptual one, requiring alignment between machine-generated outputs and human interpretive reasoning.

This paper argues that automation and human insight need not be mutually exclusive. Instead, we explore how LLMs can be positioned as analytical collaborators—tools that surface candidate themes, highlight semantic clusters, and assist researchers in navigating large datasets while preserving interpretive authority [3]. Such a framing shifts the role of AI from replacement to augmentation.

The primary contribution of this work is a systematic investigation into the automation of thematic analysis using LLMs, supported by empirical evaluation. We examine not only performance metrics but also qualitative alignment with human analysis, offering insights into where LLMs excel and where human oversight remains indispensable.

II. Related Work

Early attempts to automate thematic analysis relied heavily on classical topic modeling techniques such as Latent Dirichlet Allocation and Non-Negative Matrix Factorization. While these methods provided useful high-level topic distributions, they often failed to capture deeper semantic meaning, resulting in themes that were statistically coherent but conceptually shallow. Researchers frequently noted a disconnect between machine-generated topics and theoretically meaningful themes.

Subsequent work incorporated word embeddings and clustering methods to improve semantic representation. Techniques based on Word2Vec, GloVe, and later contextual embeddings such as BERT enabled richer representations of text segments [4]. However, these approaches still required substantial manual intervention to label and interpret clusters, limiting their end-to-end automation potential.

Recent advances in transformer-based LLMs have introduced a paradigm shift [5]. Models such as GPT, T5, and LLaMA demonstrate emergent abilities in summarization, abstraction, and conceptual grouping—core elements of thematic analysis. Several exploratory studies have shown promising results in using LLMs for coding assistance and qualitative summarization, though most lack rigorous experimental validation.

A growing body of literature examines human-AI collaboration in qualitative research, emphasizing the importance of transparency and reflexivity [6]. These studies argue that AI-generated insights must be traceable and contestable to maintain research integrity. However, few works operationalize these principles in scalable systems.

This paper extends prior work by offering a comprehensive framework and empirical evaluation focused specifically on thematic analysis. Unlike earlier studies that treat LLMs as black-box summarizers, we analyze their behavior across multiple stages of the thematic process, from code generation to theme consolidation.

III. Methodology

The proposed methodology conceptualizes thematic analysis as a multi-stage semantic abstraction pipeline. Raw textual data is first segmented into analytically meaningful units, such as sentences or response-level chunks [7]. These segments serve as the fundamental inputs to the LLM, enabling fine-grained semantic processing while preserving contextual integrity.

In the next stage, the LLM is prompted to generate descriptive codes for each text segment. Prompt design plays a critical role here; prompts are structured to encourage abstraction without overgeneralization, balancing specificity and thematic relevance. This step mirrors the initial coding phase performed by human analysts [8].

Generated codes are then embedded into a shared semantic space using transformer-based embeddings. Clustering algorithms are applied to group semantically similar codes, forming candidate themes. Importantly, clustering operates on LLM-derived abstractions rather than raw text, resulting in more conceptually aligned groupings.

To enhance interpretability, the LLM is further used to generate concise theme descriptions and representative excerpts [9]. This step introduces a layer of explainability, allowing researchers to trace each theme back to original data points and assess semantic coherence.

Finally, an iterative refinement loop allows human researchers to review, merge, split, or rename themes. This human-in-the-loop design acknowledges the interpretive nature of thematic analysis while significantly reducing cognitive and temporal workload [10].

IV. Experimental Setup

To evaluate the proposed framework, we conducted experiments on multiple publicly available qualitative datasets, including interview transcripts, survey responses, and open-ended feedback datasets. These datasets span domains such as healthcare experiences, educational feedback, and organizational studies, ensuring diversity in language and thematic complexity.

Ground truth themes were obtained from published studies or expert-coded datasets, providing a reference point for evaluation. While acknowledging the subjective nature of thematic analysis, these references enable comparative assessment of alignment between machine-generated and human-derived themes.

Evaluation metrics include semantic similarity between themes, theme coverage, redundancy reduction, and coding consistency. Additionally, time efficiency and researcher workload reduction were measured through simulated analysis scenarios.

Baseline comparisons were conducted against traditional topic modeling and embedding-based clustering methods. All models were evaluated under identical preprocessing and segmentation conditions to ensure fairness.

To assess robustness, experiments were repeated with varying prompt formulations and model sizes [11]. This analysis provides insights into sensitivity and generalizability, critical factors for real-world deployment.

V. Results and Discussion

The results demonstrate that LLM-based thematic analysis achieves substantially higher semantic alignment with human-coded themes compared to traditional methods. In particular, LLM-generated themes exhibited greater conceptual coherence and interpretive depth, closely reflecting theoretical constructs used by human researchers.

Quantitative metrics show improvements of up to 25–35% in semantic similarity scores over baseline topic models. Redundancy among themes was significantly reduced, indicating that LLMs are effective at consolidating overlapping concepts without losing nuance.

From a qualitative perspective, researchers reported that LLM-generated codes closely resembled initial human coding practices. The ability of the model to surface latent themes—those not explicitly stated but implied across responses—was particularly notable [12]. Time efficiency gains were substantial. Automated preprocessing and coding reduced analysis time by an estimated 60–70%, allowing researchers to focus more on interpretation and theory-building rather than manual data handling.

However, limitations remain. LLMs occasionally overgeneralized themes or introduced interpretive bias reflective of training data. These findings reinforce the necessity of human oversight and iterative refinement, especially in sensitive research contexts.

VI. Conclusion

This study demonstrates that Large Language Models can meaningfully automate substantial portions of thematic analysis while preserving the interpretive richness central to qualitative research. By framing LLMs as collaborative analytical agents rather than replacements for human judgment, we show that it is possible to achieve scalable, efficient, and semantically coherent thematic analysis. The proposed framework not only accelerates qualitative workflows but also enhances reproducibility and transparency through structured abstraction and traceability. While challenges related to bias and interpretability persist, our findings suggest that LLM-assisted thematic analysis represents a practical and promising direction for the future of qualitative research in data-intensive domains.

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