Query-Based Analysis: A Strategy for Analyzing Qualitative Data Using ChatGPT

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ABSTRACT

ChatGPT is a recently introduced artificial intelligence program that is gaining broad popularity across a number of fields, one of which is the analysis of data from qualitative research. Traditionally, qualitative data analysis has consisted of a detailed process of coding the data by labelling small segments of the data, and then aggregating those codes into more meaningful themes. Instead, ChatGPT reverses this process by generating themes at the beginning of the analysis process and then refining them further. This article presents a specific three-step process, Query-Based Analysis, for using ChatGPT in qualitative data analysis. The first step is to ask broad, unstructured queries; the second is to follow-up with more specific queries; and the third is to examine the supporting data. A demonstration of this process applies Query-Based Analysis of an empirical dataset that consists of six focus groups with caregivers for a family member experiencing cognitive impairment, who discussed their experiences in seeking diagnosis for their family member. The conclusions highlight just how disruptive a Query-Based Analysis is, in comparison to traditional approaches based on the coding of qualitative data.

Key Words: Qualitative data analysis, artificial intelligence, ChatGPT, coding

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Introduction

ChatGPT is an Artificial Intelligence (AI) program that was introduced in the fall of 2022, which has shown immediate and widespread utility in a range of fields (Sohail, 2023). The appeal of ChatGPT in the popular press has been nothing short of amazing. One likely reason is it apparent ability to pass what has become known as the "Turning Test" or "imitation game" (Turning, 1950). In simplified terms, this means that it is not possible to tell for certain whether one is interacting with a machine or another person. Thus, question-and-answer exchanges with ChatGPT give a remarkable impression of participating in a conversation with a highly knowledgeable fellow human being.

This article will demonstrate the value of ChatGPT for one important field in the social sciences: the analysis of qualitative data, where innovative applications of ChatGPT show a strong potential for disrupting traditional approaches based on coding. Although the value of ChatGPT in this field has been recognized (Author; Friese, 2023; Silver, 2023), there has not been any systematic description of procedures for using this program in the actual analysis of qualitative data. This article presents such a framework.

The article begins by supplying a non-technical description of ChatGPT, followed by an explanation of its relevance to qualitative data analysis, and a more specific comparison to coding as a more traditional approach to that field. It then lays out a three-step set of Query-Based Analysis (QBA) procedures for analyzing qualitative data using AI in general and ChatGPT in particular. This three-step process is illustrated with a worked example from an actual dataset. The article concludes with a consideration of the impacts of AI on the field of qualitative data analysis.

Background

What is ChatGPT?

ChatGPT represents a distinctive shift in the accessibility of AI. To get a basic understanding of what the program is, I gave ChatGPT the following query: "Tell me about what it means to say that ChatGPT is a generative, pre-trained, transformer," and got the following response.

Generative: Generative models have the ability to produce text or content in a creative and coherent manner. They can generate human-like text based on the input they receive. In the context of ChatGPT, it can generate responses, paragraphs, or even longer pieces of text that make sense in the given conversation or context. This generative capability distinguishes ChatGPT from simpler rule-based chatbots that rely on predefined responses. Instead, ChatGPT generates responses on the fly, which can lead to more natural and contextually relevant interactions.

Pre-trained: The “pre-trained” aspect refers to the initial phase of training that ChatGPT undergoes before fine-tuning for specific tasks. During pre-training, ChatGPT is exposed to a massive amount of text data from various sources on the internet. It learns patterns, grammar, vocabulary, and general world knowledge from this data. This pre-training phase helps the model acquire a broad understanding of language and general knowledge about a wide range of topics. It doesn't start from scratch but builds upon the knowledge it gained during pre-training when fine-tuned for specific tasks or domains.

Transformer: The Transformer architecture is the underlying neural network architecture that powers ChatGPT. It was introduced in the paper “Attention Is All You Need” by Vaswani et al. (2017) and has become the foundation for many state-of-the-art natural language processing (NLP) models. Transformers excel at capturing contextual relationships in language. They use self-attention mechanisms to weigh the importance of each word or token in a sequence based on its context within the sequence. This allows them to model long-range dependencies and understand how different words relate to each other. Transformers have revolutionized NLP by enabling more efficient and effective processing of text data, which is crucial for tasks like language understanding, translation, summarization, and chatbot interactions.

In summary, when we say that ChatGPT is a "generative, pre-trained, transformer" model, we are highlighting its ability to generate text in a creative manner, its foundation on pre-training to acquire language and world knowledge, and its use of the Transformer architecture to process and understand text data. This combination makes ChatGPT a powerful tool for a wide range of natural language understanding and generation tasks, from answering questions to having meaningful conversations.

In (Author), I demonstrated a “proof of concept” for answering questions and having meaningful conversation*s* about analyzing qualitative data with ChatGPT. Now, the goal of this article is to develop a set of procedures that systematically apply ChatGPT to the analysis of qualitative data.

Chat-GPT and Qualitative Data Analysis

Various versions of Computer-Assisted Qualitative Data Analysis Software (CAQDAS) have been available since the early 1990s. Note that emphasis here is on “computer-assisted,” because these programs definitely do not perform the analysis for you. Instead, their origins are in the computerization of traditional manual coding, which relies on attaching labels small segments of text, and then collecting those more specific codes into broader categories, and ultimately into more meaningful themes. At present, the state of the art for CAQDAS is the continuing addition of new features that facilitate the use of codes in the more interpretive portion of the analysis process. Still, the basic reliance on coding has not changed for decades (Tesch, 1990).

In contrast, Query-Based-Analysis begins by asking the AI program questions about the data and then working with the responses that the AI provides. The first set of queries in QBA simply asks ChatGPT or an equivalent program to summarize the content of the data. This initial exploration of the data is then followed by more explicit queries that build on those early responses. (Note that semantically, the boarder field of AI typically refers to “prompts” rather than “queries,” but I have chosen the latter term to emphasize the question-and-answer process in QBA.)

In terms of incorporating AI into qualitative data analysis, QBA corresponds to the third of three options that Silver (2023) suggests for: relying on Chat-GPT alone as an analysis tool. In time, this may be superseded by her second option, which is to build new programs that are specifically designed to apply Chat-GPT and its kindred to the task of qualitative analysis. For now, however, the state of the art is represented by her first option: incorporating AI into existing software. Two examples are ATLAS.ti (2023 which uses ChatGPT to code the data automatically by generating a set of codes on its own and then assigning those codes to text segments, and MAXQDA (2023), which allows the user to summarize coded text using ChatGPT. As extensions of existing CAQDAS, both of these examples are based on an assumption that qualitative data analysis consists of coding, with AI assisting in either generating or interpreting codes.

Developing QBA as a stand-alone approach to qualitative analysis requires a systematic specification for applying ChatGPT to qualitative data, but this kind of "how to" knowledge is currently lacking. Hence, this article will develop an explicit, three-step version of QBA. In addition to describing this three-step procedure describing this three-step procedure, the article will include a worked example of its application to actual dataset, which is described in the section.

The Empirical Example

The research project that will be analyzed with ChatGPT involved seeking diagnosis for a cognitively impaired family member (see Author, for a complete description of this study.). Because the basic nature of Alzheimer's disease and other forms of dementia reduces the patient's own self-awareness, this places responsibility on family members to determine the meaning of the symptoms that they perceive. In particular, as dementia progresses, the family is increasing likely to seek a formal diagnosis to explain the changes they are observing.

Our research team thus began by locating participants through an expert diagnostic clinic. We received permission from a human subjects review process to contact the family members of clinic patients who were diagnosed with dementia. When then questioned those family members to determine who had a decision-making role in seeking the diagnosis, and invited those involved in that decision to participate in focus groups. In addition, we used the clinic's diagnostic testing to divide our cases according to whether the patient had either less severe more severe symptoms at the time of diagnosis.

We chose focus groups as a data collection method because they are especially useful for hearing how participants share and compare their experiences about decision making (Author). Further, the focus groups allowed us to examine consensus and diversity in caregivers' experience. These goals were aided by a division between groups according to whether families sought diagnosis in the presence of either less or more severe symptoms at the time of diagnosis. From the participants' point of view, this separation ensured that they were talking to others who made their decisions at a similar point in the development of the illness. From a researcher's perspective, this allowed us to gain detailed information across the full progression of the caregiver's decision-making process.

The total dataset was thus divided into two segments, with three groups where the clinic's testing indicated that the patients had less severe symptoms and three groups where the patients had more severe symptoms. There were six family caregivers in each group, and the typical interview lasted about 90 minutes generating a transcript that was approximately 15,000 words in length.

The moderator's interview guide consisted of six questions organized around taking a "history" of how each family decided to get a diagnosis. The first set of questions asked about the caregivers' perceptions of the earliest symptoms, how family members shared this information among themselves and others, and changes in symptoms over time. The second set asked about the decision to contact a doctor or other health professional, as well as how the family chose this particular hospital for an expert diagnosis. The final question asked the participants about the advice they would give to other families facing similar decisions. Note that these questions did not reveal the research goals, and instead simply collected reports about the participants' experiences and perceptions with regard to seeking diagnosis.

The actual dataset of this analysis consisted of a single pdf file that combined all six interviews, after removing the moderator's questions and any probes that recapitulated the answers to those questions, so that analysis was conducted solely on the comments by participants. It would of course be possible to analyze each interview separately. In my experience, however, Chat-GPT is entirely capable of generating a detailed analysis when working with a composite dataset such as the one I used here.

Applying Chat-GPT to Qualitative Data Analysis

Prior to conducting any actual analysis, it is necessary to select a software program, but given how quickly this field is evolving, there is little use in describing the specifics of my own choice at this point in time. Suffice it to say that I compared several programs that made it possible to load PDF files into ChatGPT and selected ChatDOC (ChatDOC, 2023). Although this program used version 3.5 of ChatGPT, I did not detect any notable difference in the responses to my queries when compared to programs that used the later version, ChatGPT 4. In the end, my main reason for choosing ChatDOC was its superior ability to locate quotable passages within the original raw dataset.

Step One: Asking Broad, Undirected Queries

My recommended strategy for applying QBA is organized around three basic steps, the first of which is to ask broad, undirected queries. The goal at this initial stage is to locate a set of basic concepts in the data that can serve as the foundation for further searching. Note that this starting place does require a reasonable degree of familiarity with the data, which would typically result from having a meaningful a role in collecting the data. If that is not the case, then reading through a substantial sample of the data should occur prior to any querying.

The wording for a typical first query begins by setting a context for the dataset as a whole, such as: "The individuals who participated in these interviews were [description] and they discussed [topic]…" This statement would be accompanied the query itself, such as: "What were the key topics in this document?" The standard for evaluating the AI's response to such a question should be the extent to which it captures the original research goals; if the response is too far off those goals, then the most likely solution is to adjust the context that you supplied. Note that with ChatGPT it is not necessary to supply this context with each subsequent question in a series, because the program will remember it without further querying.

Once you have established that the QBA can match the research goals, other examples of querying at this stage would include: "What are some of the main themes with regard to [research topic]?" Or, "Give me a list of the things that mattered most to these participants." Or, "Give me a long list of the factors that affected how these participants…" In comparing these questions, one key difference is whether you explicitly request that program give you a list of the items that make up the content you are seeking. In my experience, it is unpredictable whether a program will return a narrative description or list (which may be either numbered or bulleted), unless you specifically state the format you want. Since the purpose in this step is to decide on a set of core concepts that can serve as the basis for further queries, some form of list is almost always the preferred response at this point.

Demonstration of broad, undirected querying In working with QBA on the present dataset, I experimented with three different sets of initial queries, which I then evaluated by asking for an explicit list of the themes in the data. I assessed each of these lists of themes, and thus the strategy that produced it, according to my knowledge from the previous knowledge of these data.

- Querying for the basic research question, e.g., "Give me a list of the key themes that affected when and why these caregivers sought diagnosis."
- Querying for a more detailed version of the larger research goals, e.g., "Give me a list of the factors that led some of these caregivers to seek diagnosis earlier when the symptoms were relatively mild," and "Give me a list of the factors that led some of these caregivers to seek diagnosis later when the symptoms were relatively severe." Followed by: "Combine the two previous searches to give me a list of the key themes that affected when and why these caregivers sought a diagnosis."
- Querying for a summary of the responses to each of the six original interview questions, one by one, as suggest by Kuckartz and Radiker (2023), e.g., beginning with, "Tell me about the caregivers' perceptions of the earliest symptoms," and so on. Followed by: "Combine the six previous searches to give me a list of the key themes that affected when and why these caregivers sought a diagnosis."

The thematic outcomes of these searches are shown in Table 1, all three of which show an essential similarity. Comparing these set of themes, I judged the best summary to come from the query based on six original interview questions, which produced a compact list of the most important elements in the data. The one exception was its final theme on Financial Considerations, which I judged to be more of a descriptive "topic summary" (Braun and Clarke, 2022), rather than a truly interpretive theme. In particular, my familiarity with the data indicated that although discussions of finances certainly did occur, they failed to spark the same level of active discussions as the previous five themes.

Table 1. Results from three basic searches for themes

Basic	**Research**	**Interview**

Themes	Questions	Questions
Concerns and observations	Need for a diagnosis and information	Need for a specific diagnosis
Progressive Decline	Emotional and mental well-being	Desire for information and coping strategies
Need for Support	Concern for the safety and well-being of the person with Alzheimer's	Lack of communication from healthcare professionals
Family Involvement	Seeking expert guidance and support	Impact on caregivers' sanity and well-being
Professional Recommendations	Desire for financial and legal planning	Planning and organizing for the future
Knowledge and Awareness	Recommendations from others	Financial Considerations

Both my selection of the themes based on the questions from the interview and my decisions to drop financial considerations as a theme illustrate a fundamental point about QBA: Nothing can replace the researcher’s substantive judgments about the most important elements of the analysis. In particular, you need to make your own decisions, and to feel confident that you can justify those decisions.

Hence, key goal in this first step is not to devise a single, perfect query that eliminates the researcher’s judgment. Instead, the reason for consulting a series of queries is to come up with best set of themes. Within, the broader field of AI, successively comparing the results of different queries is known as “prompt engineering” (Chubb, 2023; White et al., 2023), and the assessment of the various results is an inherently subjective process. Hence, my recommendation is to rely on your familiarity with the data to select the results that best capture what is most meaningful in the original data.

Step Two: Following Up with More Specific Queries

The goal in Step Two of QBA is to use a series of more specific queries to generate details on the basic themes that you located in Step One. In undertaking this stage, it is important to execute it as a continuation of the queries that you used in Step One. Once again, this is because ChatGPT updates the depth of its understanding of the data with each successive query, so that the responses of these new, more specific queries will take into account the answers to the earlier set.

The most likely way to proceed is by asking about each of the themes that made up the results in Step One. In essence, this is equivalent to seeking "subcategories" under the major concepts generated earlier. Note, however, that it is unlikely that each subtheme will be found once and only once under each of the original themes; instead, versions of the same subtheme will often appear under more than one of those original themes. This makes sense because the original themes are almost certain to be related to each other, and the presence of similar subthemes across the themes reflects these relationships.

When there are multiple over-lapping subthemes, the next activity in Step Two of QBA is typically to reduce the total number of subthemes. ChatGPT facilitates this process by producing not only a title for each sub-theme, but also an explanation of its content, so that it is relatively straightforward to make comparisons across the full set of sub-themes.

Demonstration of more specific querying In the empirical example, I began this step by examining the equivalent query for each of the five basic themes, as illustrated for the first theme in Figure 1. (The numbers included with each entry will be explained in Step Three.)

Figure 1. Example of a query for subthemes

Give me a list that tells me more about how the earlier theme of need for a specific diagnosis affected when and why these caregivers sought a diagnosis.

The theme of the need for a specific diagnosis affected when and why these caregivers sought a diagnosis in the following ways:

1. Desire for a clear diagnosis: Many caregivers expressed a desire for a specific diagnosis, such as Alzheimer's disease, rather than a general term like dementia [**23**]. They felt that having a clear diagnosis would provide them with a better understanding of the condition

and enable them to plan and organize their lives accordingly [**140**]. This need for a definitive diagnosis drove them to seek medical evaluation.

2. Emotional response to diagnosis: Receiving a diagnosis was an emotional experience for caregivers, with some individuals expressing surprise and sobbing when Alzheimer's disease was officially diagnosed [**140**]. The diagnosis helped them come to terms with the condition and move forward with care plans and support.
3. Access to information: Caregivers mentioned that a specific diagnosis helped them gain access to valuable information about the disease, including its symptoms and ways to cope with the changes it brings [**92a**]. They wanted to understand the specific symptoms and behaviors associated with Alzheimer's disease to better support their loved ones and manage the challenges they would likely face.
4. Planning and preparation: The need for a specific diagnosis was linked to the caregivers' desire to anticipate and be prepared for the changes and progression of the disease [**98a**]. With a clear diagnosis, they could make informed decisions regarding safety, such as preventing their loved ones from driving and ensuring they received proper care and support [**98a**].
5. Validation and support: Obtaining a specific diagnosis provided caregivers with a sense of validation and relief. It helped them validate their concerns and convictions about their loved ones' condition, especially when seeking second opinions from reputable clinics like (Local Hospital) and the (National Hospital) [**71**][**98b**]. They also found comfort in joining support groups, where they could connect with others who shared similar experiences and learn from their insights [**92b**].

These factors collectively influenced caregivers to seek a specific diagnosis earlier in the disease progression, allowing them to better understand and care for their loved ones with Alzheimer's disease.

The query for this first major theme shows five subthemes. In total, the searches for the full set of five original themes produced 25 possible subthemes. Next, I made comparisons of the contents of those candidates for subthemes, using the full text descriptions for each. Figure 2 shows the final list of subthemes, after consolidating the overlapping entries.

Figure 2. Reduced list of candidate subthemes.

Need for a specific diagnosis

1. Desire for a clear and timely diagnosis (2)
2. Emotional response to diagnosis (1)
3. Anticipating changes (5)
4. Planning and organizing (3)
5. Need for support (5)

Desire for information and coping strategies

1. Anticipating changes (5)
2. Self-education and seeking advice (2)
3. Dissatisfaction with doctors (3)
4. Planning and organizing (3)
5. Need for support (5)

Lack of communication from healthcare professionals

1. Desire for a clear and timely diagnosis (2)
2. Anticipating changes (5)
3. Self-education and seeking advice (2)
4. Dissatisfaction with doctors (3)
5. Need for support (5)
6. Lack of referrals and recommendations (1)

Impact on caregivers' sanity and well-being

1. Emotional strain and personal sanity (1)
2. Anticipating changes (5)
3. Dissatisfaction with doctors (3)
4. Need for support (5)

Planning and organizing

1. Financial considerations (1)
2. Anticipating changes (5)
3. Safety concerns (1)
4. Need for support (5)

5. Planning and organizing (3)

Figure 2 also shows notations in parentheses for how many time versions of each subtheme occurred. Allowing for these overlaps show a total of ten unique subthemes., two of which, "Anticipating changes" and "Need for support" occurred in all five of the major themes. In addition, there were no subthemes that occurred two times, two that occurred three times, another 2 that occurred two times, and four that occurred only once. Consequently, I decided on a final set of results, that consisted of five major themes, with each of them containing the two subthemes that appeared throughout.

The patten of overlaps found in Step Two of QBA represents an important resource for further refinement of the basic themes. The method used in this example represents only one technique for working with these overlaps. Another possibility is using concept modelling (mind mapping) techniques to link the core themes into higher-level models (Author). For now, however, the next basic step is to assess the connections between each candidate theme and the original data that supports it.

Step Three: Examining the Supporting Data

The goal in this portion of QBA is to substantiate the basic concepts derived from the earlier analysis. More specifically, Step Three examines the text to select quotations for inclusion in the Results section of the research report. This follows a traditional pattern in reporting qualitative research where the Results section presents a set of themes, each of which is illustrated by a set of quotations from the original dataset. This requires linking the candidate themes from Step 2 to their underlying data, and some programs, such as ChatDOC provide these links as part of their responses. For other programs, you may need to generate specific queries to retrieve this information (e.g., "Give me direct quotations from the data that are related to…")

Judging whether the data contained in the quotations are sufficient to support a set of candidate theme is an inherently subjective process, which Braun and Clarke (2022) refer to as "developing and reviewing themes." More specifically, if there are relatively few sections of the data that match a potential theme, then it may be too "thin" to be included in the full set. Eliminating themes that are too thin protects against "false positives" (i.e., things that were claimed as themes but that should not have been), but it says nothing about “false negatives” (things that were not captured as themes but that should have been). One way to ensure the rigor of the thematic outcome is what I have called (Author) a process of *evaluating* candidate themes through traditional coding. This requires going back to the original data and applying the set of candidate themes as a set of codes, which allows an assessment of both whether each theme is well developed in the data and whether there are meaningful topics in the data that were not included in these thematic codes. In parctice, this reverses the traditional reasons for coding, so that instead of using codes to generate themes, the coding process is used to evaluate the effectiveness of a set of existing themes.

Demonstration of selecting quotations One of the reasons I used the ChatDOC program for the current analysis is because it automatically returns links between its summaries and the sources in the data for those summaries. These links appear as bold face numbers at the end of each summary, as shown in Figure 1, which contains 8 recommended connections to the text for the theme “need for a specific diagnosis.” For example, the quotable material at site [**23**] in the data consists of:

> I was hoping for a diagnosis. I was hoping for another word besides dementia which my parents, they just absolutely had troubles with that, and I just felt like getting the truth out and going on from that point, whatever that might be.

As noted earlier, another option is to use the AI as a tool for querying about quotable text segments. For this purpose, I chose to use subthemes, and I wanted to ask for quotations that combined aspects of the results from Stage Two, such as: “Give me direct quotations from the data that are related to both the need for a specific diagnosis and anticipating changes.”

> I wanted to rule out anything else and probably I wanted information as to what are some of the specific symptoms. I think people in general need to know that. More what are the symptoms, what are some of the things that you can do to help deal with those changes that take place in your family member's life.

In both of these examples, I have simply chosen the first quotation suggested by the AI to demonstrate the searching process. A complete data analysis would involve searching all the proposed quotations to select the ones that were most effective for conveying the underlying content of each theme. Even so, this illustrative version of Step 3 shows how ChatGPT can search through a complex text document to locate the desired kind of supportive material

Overall, the full set of examples from all three steps in applying Query-Based Analysis to this empirical study help establish the effectiveness of ChatGPT as a tool for qualitative data analysis. More specially, these examples demonstrate how the three-step process in QBA moves from the raw data to the basic components of the Results section in the substantive analysis of a real dataset. Although it is once again important to recognize the vital role of the researcher in this progression, it is just as important to acknowledge that ChatGPT is more than just an "assistant" in this analysis process.

Discussion and Conclusions

In considering how innovative a new method is, it is worthwhile to consider whether it is basically a new option in the researcher's existing tool kit, or whether it disrupts the established ways of doing things. In the first case, a new method takes its place alongside the previous ones; in the second case it upsets the traditional choice of methods. For ChatGPT as a tool and QBA as an implementation of that tool, I have argued that this is a thoroughly disruptive new approach to qualitative data analysis. Not only do these new tools perform as well the old ones on the core tasks associated with qualitative data analysis, they also make it easier to accomplish the larger goals of qualitative data analysis. In other word, ChatGPT and QBA are just as effective as traditional techniques at the same time that they are much more efficient.

To understand why this is so, it helps to compare AI-based approaches to coding as the most well-established traditional approach to qualitative data analysis. First and most obvious. ChatGPT eliminates the fundamental processes involved in coding, i.e., the labeling of small data segments and the progressive aggregation of those codes into more meaningful categories. This is by far the most time-consuming element in traditional qualitative analysis, so replacing it is valuable accomplishment in and of itself. In addition, AI-based analysis reduces the level of expertise necessary to do qualitative data analysis. Coding is widely acknowledged to be a tedious practice of data management, and ChatGPT allows the analyst to bypass the vast majority of this tedium. Another notable aspect of relying on AI is that it greatly increases the ability to compare how multiple analysts work with the same data. Even in Step Two of QBA, which requires the most judgment from the analyst, it is possible for other researchers to go beyond merely replicating the original queries and to further check them against alternative formulations. Finally, relying on ChatGPT replaces the need for specialized software for the analysis of qualitative data. As opposed to simple querying, CAQDAS programs typically are both expensive and challenging to master.

The present article presents a case for Chat-GPT as a disruptive force in qualitative data analysis, but whether and how this potential plays out will largely be a product of social factors. One obvious issue is the response from those who are most invested in the current coding-based approach to qualitative data analysis. Certainly, journal editors and funding bodies will serve as gatekeepers, and as just suggested, those who produce software in this domain could play a major role. As noted at the beginning of this article some of these software packages have already begun to include functions that are based on ChatGPT. What is notable about these early applications, however, is the extent to which they still rely on coding as the fundamental process for producing qualitative results. Alternatively, Query-Based Analysis has the potential to make coding obsolete.

This raises the question of how much of the debate will be about the necessity of coding as a method for qualitative data analysis, with the use of AI serving as a way to open up that underlying issue. In particular, coding is now the basis for such widely used approaches to qualitative research as grounded theory (e.g., Charmaz, 2014), interpretive phenomenological analysis (Smith et al, 202x), and thematic analysis (Braun and Clarke, 2022). This means that a broad range of researchers have a stake in maintaining coding as essential to qualitative research itself. Even with specialized software, such coding requires a great deal of time and effort, so it is entirely possible that the sheer accessibility and ease of QBA as an innovation will produce backlash. In particular, generations of qualitative researchers who have relied on coding may treat AI as a threat to their entrenched interests, rather than as a relief from the time-consuming tedium of coding.

Ultimately, these social factors may well have as much to do with the future of AI in qualitative data analysis as the actual effectiveness and efficiency of AI-based tool, and the disruptive potential of AI is at the heart of this controversy. If ChatGPT and other related programs can indeed obtain a substantial foothold within qualitative data analysis, then this would be one more example of the much larger trend toward automating crafts that once were done by hand.

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