

# Sage Research Methods: Data and Research Literacy

## How to Use Generative AI to Assist the Analysis of Qualitative Data

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# How to Use Generative AI to Assist the Analysis of Qualitative Data



## Learning Outcomes

Having read this guide, readers should be able to . . .

- Explain the use of Generative AI (GenAI) in qualitative analysis.
- Discuss the ethical and practical implications of AI tools in qualitative workflows.
- Debate the appropriateness of integrating GenAI into qualitative analysis.
- Develop a reflexive protocol for combining GenAI and human analysis in qualitative research.

## Introduction

Following the launch of ChatGPT to the public in November 2022, I noticed many researchers on my Twitter/X feed speculating about whether this marked a new era in qualitative analysis. Within a year, two of the major qualitative analysis software products (MAXQDA and ATLAS.ti) introduced Beta versions that had embedded Generative Artificial Intelligence (GenAI) features to assist with analysis, such as summaries and code suggestions. At the same time, I was working with an organization (SEEd) that had collected data from open-ended survey questions and was wondering how I would analyze this. This survey asked young people about their understandings of and attitudes towards sustainability and included

around 15 open-ended questions, which were all answered (to variable degrees) by over 1,500 respondents. I started to play with GenAI features in MAXQDA, my preferred/usual analysis package, and in preparing this guide I have also experimented with ChatGTP, ATLAS.ti, and NVivo. I have used this technology to assist analysis of qualitative survey data and I believe it offers many opportunities to the qualitative researcher. But we must use GenAI in a human-centered way and be attentive to the possible ethical and practical challenges it presents.

Utilizing technology for qualitative analysis (even without GenAI) has been controversial among some qualitative researchers who feel that computer tools with prescribed functions do not align with the flexible and iterative nature of qualitative inquiry ([Silver & Woolf, 2020](#)). Though there are strategies for harnessing software tools effectively for qualitative analysis, training in CAQDAS (computer assisted qualitative data analysis software) is patchy, with few undergraduates programmes offering guidance ([Silver & Woolf, 2015](#)). Having integrated NVivo training into an undergraduate methods programme, I understand the challenges of convincing both students and staff of its relevance. In the wake of GenAI, we have a strong duty to equip qualitative researchers with appropriate tools for the intentional and reflexive analysis of often messy and complex data. This guide offers an overview of some GenAI tools qualitative researchers are using and considers how these might influence and shape a qualitative analysis workflow. It addresses ethical questions and established understandings of meaning-making within qualitative analysis. It is hoped that after reading this guide, readers should be able to design their own protocols for using GenAI in their qualitative projects.

# What Is Generative AI and How Are Qualitative Researchers Using It?

Let's start with some basics— what is Artificial Intelligence (AI) and what is Generative Artificial Intelligence (GenAI)? IBM offers two relatively simple definitions for these terms:

Artificial intelligence, or AI, is technology that enables computers and machines to simulate human intelligence and problem-solving capabilities. On its own or combined with other technologies (e.g., sensors, geolocation, robotics) AI can perform tasks that would otherwise require human intelligence or intervention. [...]

Generative AI refers to deep-learning models that can take raw data [...] and “learn” to generate statistically probable outputs when prompted. At a high level, generative models encode a simplified representation of their training data and draw from it to create a new work that's similar, but not identical, to the original data. ([IBM, 2024](#))

These definitions highlight AI is about ‘simulating’ human capabilities and through deep learning of multiple data sources, GenAI can create new content based on patterns it has learned from these existing data sources. As [Silver \(2023\)](#) notes, many AI tools currently being discussed, like machine learning and natural language processing (NLP), have an established history within CAQDAS packages, but they have not always been embraced by qualitative researchers. The public release of ChatGTP marked a significant change and has caused quite a “hulla-

baloo” (to quote Silver).

Reviewing available technology is risky because it evolves so quickly so what follows may become outdated. For the latest on CAQDAS AI packages and features, visit the Surrey CAQDAS networking project run by Dr Christina Silver and check her regularly updated blog and podcast series (see Web Resources).

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## Overview of AI Qualitative Analysis Features

As of July 2024, two major CAQDAS packages (MAXQDA and ATLAS.ti) have adopted AI large language models (either partnering with OpenAI, the company behind ChatGPT, or another provider) and are increasingly embedding more GenAI features. As a regular user of MAXQDA, I am aware the software has updated itself about five times already in 2024, and each time some tweak is made to the *AI Assist* feature. The other market leader, NVivo, has not partnered with OpenAI (yet) but has enabled GenAI features to autocode data. There is also a company called CoLoop which specializes in GenAI-driven qualitative analysis. We are starting to see a growing number of published and preprint articles discussing using ChatGPT and ChatPDF to assist qualitative data analysis ([Chubb, 2023](#); [Hamilton et al., 2023](#); [Hitch, 2024](#); [Morgan, 2023](#)). There are also papers which question the appropriateness of using such tools ([Paulus & Marone, 2024](#)), and practical guidance on how to embed them within established workflows ([De Paoli, 2023](#); [Nguyen-Trung, 2024](#); [Paulus & Lester, 2023](#); [Zhang et al., 2023](#)).

The current GenAI tools offered to qualitative researchers (whether via an add-on or bespoke CAQDAS, or via web-based companies and interactive chatbot

providers) are:

**Automatic transcription:** This became common during the pandemic, with data collection on Zoom and Teams, where cloud recordings generated transcripts. There are bespoke automatic transcription companies (like OtterAI), transcription features in Microsoft Word and Dropbox, as well as automatic transcription embedded within CAQDAS programs, MAXQDA and NVivo. Researchers upload their audio files and receive a transcript that will still require some editing, but it is *much* more accurate than those produced even five years ago. From conversations with peers, this is the tool that been most embraced by qualitative researchers, perhaps without them realizing GenAI is involved.

**Summarizing tools:** This feature allows researchers to send parts of their data to a GenAI assistant to receive summaries of the content. These can be applied to short data segments, entire interview transcripts, a code (to provide an overview of already coded data), or a series of open-ended survey questions. Summaries can be customized by length and format. This feature may help researchers familiarize themselves with their data at the start of a project or be harnessed during the analysis stage to generate themes. [Chubb \(2023\)](#) describes using summaries to create vignettes of interview data for analysis and data presentation purposes.

**Coding suggestions:** Closely related to summarizing tools is the pos-

sibility of using GenAI to suggest possible ways to code your data. This can again be performed on a range of ‘chunks’ of data, such as a list of coding ideas for a whole transcript or survey question responses, or on a small segment of data which the researcher has identified as a coding segment. In my survey project, I have found using the coding suggestions on smaller segments of text more useful, as suggestions were more targeted to the unit of meaning. This feature was beneficial in the early stages of coding before my coding list was fixed. However, coding lists for all survey responses mainly reaffirmed summaries, useful for familiarization but not much beyond that.

**GenAI Automatic coding:** While auto-coding based on keyword searches has been established in CAQDAS for years, GenAI auto-coding offers something different. The CAQDAS packages have implemented automatic coding features in different ways, with sentiment analysis, open coding and intentional coding possibilities. All offer sentiment analysis—which uses NLP to detect positive, negative or neutral sentiments within data. MAXQDA auto-codes only survey data with sentiments, while NVivo and ATLAS.ti code all data on request. I have found sentiment analysis unhelpful for my research purposes, not least because the sentiments can be incorrectly labeled and the nuances in the language are not always picked up. For example, “climate change” was detected as “slightly positive” by the feature in MAXQDA.

Researchers (or perhaps companies) are most excited by open and in-

tentional coding features, leading to rumblings that the need to spend hours coding your data are gone (more on this below). Open coding features are available in ATLAS.ti and NVivo and return a list of ‘codes’ and chunked data associated with those labels. For ATLAS.ti what tends to come back is a very long list of codes that will require a lot of sorting, whereas for NVivo the list was shorter but again not terribly useful because codes did not apply to all survey responses. The intentional coding, currently offered by ATLAS.ti, MAXQDA (currently just for single documents) and CoLoop (which I haven’t trialed yet) is the one that promises the end of coding. These systems ask researchers a series of questions about their research projects to train GenAI what to look for, and then code the data based on those answers. The intentional coding feature is the space to watch over coming months.

**Interactive ‘chat’ with your data:** Chatbots like ChatGPT, Copilot, and Bard exemplify the GenAI era, enabling dialogue with your data and intentional coding. Many published/preprint papers have used ChatGPT (or similar) as the GenAI assistant in their projects. Researchers upload their data and ask ChatGPT to analyze it for key ideas or themes, receiving lists of codes and training the GenAI to achieve more relevant results. MAXQDA and ATLAS.ti have a ‘chat’ feature to ask customisable questions of specific documents, with warnings that the resulting content should be carefully checked for accuracy as the chat may make mistakes.

Using GenAI in your qualitative analysis projects is a choice, and it will be a choice that many qualitative researchers will not make. For those who are interested in possible ways to implement these tools, the next section explores how to integrate them into existing qualitative analysis workflows. This is followed by a discussion of the ethics and possible pitfalls of using these features.



## Section Summary

- Breakthroughs in AI technology have opened the possibility of using GenAI tools to assist qualitative data analysis.
- Researchers can use existing CAQDAS packages, new GenAI-Based CAQDAS programmes or free chatbots, like CHATGPT, to assist their analysis.
- The qualitative analysis tasks GenAI can currently assist with are, generating transcripts, summarizing data, suggesting ways of coding data and engaging in dialogues around the content of the data.

## Implementing AI Into Your Qualitative Analysis

### Workflow

Before jumping headfirst into the opportunities these new tools present, consider your methodological position on data construction and interpretation. [Silver and Woolf's \(2015\)](#) five-level QDA emphasizes understanding what your research

goals are and what you want to accomplish through your analysis before turning to technology. For example, [Braun and Clarke's \(2019, 2022\)](#) “reflexive thematic analysis” has been influential and the assumptions behind this approach are that human interpretation and positionality will always shape every stage of the analysis process. Such a position does not sit easily with GenAI-assisted analysis, though there are those who have argued that GenAI can offer a useful second opinion and deepen the researcher’s awareness of their own reflexivity ([Hitch, 2024](#)). For those whose approach to analysis takes a less constructivist stance, such as more realist versions of qualitative content analysis (QCA) ([Schreier, 2013](#)), GenAI-assisted approaches may aid intercoder reliability which an individual researcher can find hard to achieve.

This guide is not the place to outline different types of qualitative data analysis (good overviews are provided by Braun & Clarke, 2021; Gibbs, 2018), but most approaches to qualitative data analysis involve at least four stages in a workflow model, though the importance of each stage may differ and these are often iterative rather than linear. The four stages are familiarization with the collected data, description or categorization of that data, systematic sorting (often called ‘coding,’ but not by all analysts) in search of patterns, interpretation of the preceding stages through writing about the data. The section that follows this discusses the ethical and analytical challenges associated with using GenAI for qualitative analysis tasks. Readers should consider how they might integrate GenAI into their research protocols.

For the rest of this section, I explore how GenAI-tools could be used at each stage, based on my experiences of analyzing open-ended survey data with some GenAI-

assistance ([Wheeler, 2024](#)) and my awareness of analyzing qualitative interviews without it ([Morgan Brett & Wheeler, 2022](#)). Much of the ‘hullabaloo’ surrounding GenAI-tools relates to their time-saving properties, though I’m with [Paulus and Malone \(2024\)](#) when they point out that spending time on analysis is part of the joy and necessity of qualitative research. So, in what follows, timesaving is not my key focus!

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## Familiarization

To move from raw data to interpretation, it is essential you know what your data is about. This involves reading and immersing yourself in the data. With interview data, transcribing helps with familiarization, but GenAI (or a human transcriber) can ease some of the time-burden by providing a transcript. However, you should relisten to the recording alongside the transcript to resituate yourself and judge the accuracy of the transcription. If the transcript contains nonrelevant data (like the consent to tape record for instance), these sections should be removed to avoid skewed AI summaries. GenAI summaries of interviews or survey responses provide useful snapshots of the data, and asking for these in different lengths can aid familiarization. This can be particularly helpful for spotting key features of the data that may have been missed by a single researcher who has a tightly defined focus. For example, when reading thousands of survey responses, it was difficult to hold onto the breadth and diversity of issues in the early stage of analysis, so having a second opinion from GenAI was useful. Researchers should judge the accuracy of GenAI summaries as they become familiar with the raw data.

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## Description or Categorisation of the Data

Initial data summaries can be used as a springboard for developing a list of key concepts or code lists. Entering into dialogue with a transcript or set of survey responses, might help you pinpoint the important features of your data, and relevant quotations to explore further. CAQDAS with embedded GenAI might limit the amount of data processed at once within their ‘free’ features, and ChatGPT also has limits, so results need to be carefully checked for applicability to the whole corpus of responses. I have found the ‘code suggestions’ feature on smaller data chunks useful for sparking ideas about how to categorize data. The GenAI will usually suggest more ways to code data than I would have thought of (perhaps 12 labels for the same piece of text) – which have helped me to think about my data in a range of ways. Here the AI-assistant is acting like a junior researcher who has lots of ideas but needs to be reined in by the more experienced researcher. Those using prompt-based commands in ChatGPT for this categorization stage highlight that getting the right prompt can take time and several iterations, and qualitative researchers will likely have to adapt suggestions made by GenAI-tools ([Hitch, 2024](#); [Nguyen-Trung, 2024](#)).

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## Systematic Sorting to Look for Patterns

Once you have decided how you will categorize your data, you can ask GenAI-tools to code the data for you. I’ll be up-front and say I have not done this—even though trawling through thousands of responses was time-consuming, I needed to be sure that my coding was applied systematically to all answers. Part of my deci-

sion to not use this feature was shaped by the fact that MAXQDA do not (yet) offer intentional AI-Based coding for survey responses (currently limited to single documents) though it can make suggestions for single responses. But experimenting with ChatGPT, I have been impressed with the possibilities, though mindful that getting the prompts right and engaging actively with what GenAI has produced is important. I wanted some of my codes to be mutually exclusive (only one category to apply to each answer) following QCA principles—I had coded survey definitions of sustainability as predominantly environmental, social or economic, more than one of these, or none of these. My attempts to get ChatGPT to do this initially resulted in it miscategorizing over 1,000 responses as ‘none of these,’ and though the broad trends confirmed my manual coding that vague definitions dominated, I coded many responses differently from ChatGPT. I asked ChatGPT for a CSV file to inspect how it had coded the responses and to further train the system to get more relevant answers. The GenAI-coding was an important check on my own coding decisions (much as intercoder reliability might be), forcing me to evaluate why I had coded under some categories rather than others. This is something hard to achieve as a single researcher and for QCA, I see the value of using GenAI to perform this function. For thematic analysis, I need to experiment more – the dialogue feature is helpful for locating key quotations but data length restrictions and GenAI’s forgetfulness are concerns. [Nguyen-Trung \(2024\)](#) describes the process of getting ChatGPT to consolidate and cluster his coding list but found that it was often not up to the task of spotting overlapping codes, so subjective researcher decisions had to be made.

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## Interpretation through writing

Experiments with GenAI show it performs poorly at generating interpretive themes, offering more literal and descriptive summaries instead ([Morgan, 2023](#); [Nguyen-Trung, 2024](#)). While prompts can be adapted to get more relevant results, having the ‘human in the loop’ to intervene and make judgements around interpretation is crucial ([De Paoli, 2023](#)). Already coded data can be summarized by GenAI tools and what I found useful here was the ability to produce code summaries for different groups of responses—such as asking for summaries by gender, age group, and levels of income deprivation (features that were coded as document variables in MAXQDA). Pulling out the nuances between these groups in the summaries helped me to interpret key differences and similarities across survey respondents. Insights are further connected through CAQDAS features like visualization and memo writing. Storing everything in one project file within CAQDAS is a key benefit over ChatGTP, where information can easily be lost if the researcher does not store its outputs systematically.



### Section Summary

- Think carefully about what your key analytic tasks and assumptions are before turning to technology and GenAI tools to assist you.
- GenAI can be embedded at each stage of the qualitative analysis workflow, but its output must be carefully inspected and reflected

upon to ensure its credibility and trustworthiness.

- GenAI could be viewed as a junior assistant whose work is descriptive and sometimes misses the point but who challenges the lead researcher to think about their analysis in different ways.

## Key Considerations for Human Analysis

Though GenAI could be used at each stage of a qualitative analysis workflow, this section asks should it be? The human analyst is central for determining whether AI-generated output is credible and appropriate. Claims that GenAI will save the researcher hours have already been questioned, and many studies using ChatGPT have used data that researchers had analyzed manually meaning they had a good grounding in the data before turning to GenAI. This section considers three major challenges associated with using these tools—ethics, bias, and the construction of meaning through qualitative analysis. Challenges around needing to learn how to use these systems practically and decision trail recording with chatbots have been discussed in the previous section and will not be returned to here.

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### Ethics

A key set of concerns when using GenAI relates to ethical research practice. If interview or sensitive research data is analysed by these systems, questions are raised about the security of this data. Given these systems are trained on data en-

tered, does this mean any data uploaded becomes part of the model, putting the privacy of our participants under threat? OpenAI admits collecting personal data and possibly selling it. Users can choose not to store their chat history with conversations deleted after 30 days—though this does mean saving your chats for your decision trail elsewhere. CAQDAS packages with GenAI assure that user data is secure, not used for training, and deleted within 30 days. The CAQDAS user must opt-in and is in control of what data is sent to AI. At a minimum, data should be deidentified (being mindful that changing names alone is not always sufficient to achieve this) before it is processed. With my survey data (where personal information was not requested) there were still cases where respondents included information like their schoolteacher's name which was removed before using GenAI. Given the widespread use of transcription services for raw data, anonymization is not always happening before processing. Therefore, researchers need to start including statements about GenAI processing on their consent forms, so participants are informed about data use and associated risks. From the participant's perspective, this is similar to giving consent to archive their data for re-use, though researchers can add restrictions about who will access it.

There are also some broader ethical considerations about how GenAI systems have been trained on exploitative data practices, with publishing companies selling content to them without author's consent ([Morreale et al., 2024](#); [Potter, 2024](#)). Sustainability concerns regarding high use of energy and water to power processors might also be a factor to consider before using this technology ([Crawford, 2024](#)).

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## Bias and Research Integrity

Because GenAI systems have been trained on human data which contains biased language and culturally offensive values, there have been cases where its output has reproduced these. Indeed in a study of three GenAI tools, [Zhou et al \(2024\)](#) found these tools exhibited systematic gender and racial bias, under-representing women and ethnic minorities beyond real-world disparities and assigning submissive characteristics to these groups. This, coupled with ‘hallucination’—the production of false though seemingly credible responses by GenAI—raises concerns over its use in research. If inconsistencies and biases in output are not picked up by the researcher, this compromises research integrity. These issues underscore the necessity to engage critically with AI-generated content to ensure accuracy and credibility. This comes down to questions of authorship and researcher responsibility—if we are using results from GenAI, we should declare this in our writing and take full responsibility for anything we publish. GenAI is the assistant/junior researcher who should be acknowledged but ‘the buck stops’ with the lead researcher if what they produce is incorrect or biased. Many academic journals now require authors to disclose GenAI use and explain its contribution.

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## Making Meaning Through Analysis

The final consideration addressed in this guide returns to an earlier point about the epistemology of qualitative research, which values the co-constructed nature of knowledge produced by this collection of methods. Many qualitative researchers make their knowledge claims based on deep relationships with their participants

which have been gathered through spending time in specific research contexts and interpreting these social worlds through the lens of their unique positionality. GenAI is no replacement for human-centered analysis and this guide has stressed throughout that if it is used it must be done actively and reflexively. Claims that GenAI will save the researcher time and that analysis can be a quick process are not compatible with the practices of experienced qualitative researchers who know that iterative cycles of data collection, analysis and reflexivity are central to how meaning is made. The novice researcher may be tempted by quick results, and the danger of GenAI is that it can produce seemingly credible analysis at the touch of a button. [Silver \(2024\)](#) says the “qualitative deepfake”—where technology generates fake data and analysis—is now a reality. Therefore, experienced researchers must train the next generation what it means to produce credible qualitative research which is supported by a clear decision-trail, deep analysis, and reflexive awareness of the impact technology has on practices of research.



## Section Summary

- Using GenAI in your research carries data security and data privacy risks so only anonymized data ought to be uploaded to these systems.
- It is recommended that researchers include a statement on participant consent forms, informing them of the risks of data being processed by GenAI.
- Researchers need to be aware that GenAI can produce biased

and inaccurate outputs and the responsibility for finding and correcting those errors lies with the researcher.

- Good qualitative research prioritizes human analysis and uses GenAI to augment rather than replace this.

## Conclusion

*‘We believe that society and culture influence the construction of technologies and that these technologies also influence society and culture. To accept this view means accepting that our qualitative work is sometimes influenced by NVivo’. ([Jackson & Bazeley, 2019](#), p. 35)*

Writing about CAQDAS more generally, the quotation above capture what I hope readers will take from this guide. Technology is shaped by society and it in turn shapes us. If you choose to use GenAI features in your qualitative analysis, do so mindfully and with careful consideration of how this may affect your research protocols and workflows. The speed of change has taken many researchers by surprise, and as CAQDAS did previously, I feel sure qualitative analysis will be transformed by these technologies—at least for some researchers. Rather than use a technologically determinist lens, I hope this guide has given you some tools to experiment with and imagine how research could be augmented through GenAI. I believe the human analyst must remain in the driving seat of these technologies because not all tasks can be delegated to it. The technology has flaws which could

lead to inaccurate outputs, data privacy breaches, and unethical research practice. Incidentally, these are flaws that a human analyst can also have. It is possible to see how GenAI can become a critical friend that shows the researcher alternative ways of summarizing, categorizing and understanding their data. I do not see GenAI as a threat to qualitative research practices but an opportunity to make our data analysis more robust. But this opportunity can only be realized if researchers are trained in critical, well-documented, and reflexive research practices.



## Multiple Choice Quiz Questions

1. What is a key ethical concern when using GenAI for qualitative analysis?

☐ a. High cost of the technology



### Incorrect Answer

**Feedback:** This is not the correct answer. The correct answer is B.

☐ b. Data security and privacy risks

**Correct Answer**

**Feedback:** Well done, correct answer



**c.** Lack of available software packages

**Incorrect Answer**

**Feedback:** This is not the correct answer. The correct answer is B.

2. What role should GenAI play in the qualitative research process?



**a.** Fully replace human analysis



**Incorrect Answer**

**Feedback:** This is not the correct answer. The correct answer is B.

☐ **b.** Augment and support human analysis

**Correct Answer**

**Feedback:** Well done, correct answer

☐ **c.** Automate the entire research workflow

**Incorrect Answer**

**Feedback:** This is not the correct answer. The correct answer is B.

3. What is a potential benefit of using GenAI tools in qualitative research?

☐ a. Providing alternative ways to summarize and categorize data



**Correct Answer**

**Feedback:** Well done, correct answer

☐ b. Automatically generating research hypotheses



**Incorrect Answer**

**Feedback:** This is not the correct answer. The correct answer is A.

☐ c. Ensuring complete accuracy of research findings

**Incorrect Answer**

**Feedback:** This is not the correct answer. The correct answer is A.

4. Which approach should researchers take to effectively combine GenAI and human analysis in qualitative research?

☐ a. Rely solely on GenAI for all stages of analysis.

**Incorrect Answer**

**Feedback:** This is not the correct answer. The correct answer is C.

☐ b. Use GenAI only for data collection and not for analysis.



**Incorrect Answer**

**Feedback:** This is not the correct answer. The correct answer is C.



**c.** Actively engage with GenAI outputs and critically evaluate them.

**Correct Answer**

**Feedback:** Well done, correct answer

**SUBMIT****CLEAR****START OVER**

## Further Reading

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## Web Resources

CAQDAS chats with Christina, podcast series. <https://open.spotify.com/show/28usVeqag9q7irrrAgJTBh?si=7e44fcf1362c441d>

Computer-assisted qualitative data analysis (CAQDAS) networking project. <https://www.surrey.ac.uk/computer-assisted-qualitative-data-analysis>

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