Integrating Artificial Intelligence (AI) in Qualitative Content Analysis

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The following text examines the role of artificial intelligence (AI), particularly large language models (LLMs), in qualitative content analysis. It explores practical applications and critical considerations of AI integration into the research process. The text outlines how AI can support various stages of qualitative content analysis, from initial data exploration and category development to coding and analysis of coded data. While highlighting AI's potential as both a powerful analytical tool and research assistant, the text addresses important challenges regarding data protection, ethics, and scientific integrity. The authors argue that rather than replacing established analytical methods, AI enhances their implementation and effectiveness when properly integrated into methodological frameworks. The text provides practical guidelines for AI implementation while emphasizing that researchers must maintain responsibility for analysis quality and integrity. It concludes by considering AI's future role in qualitative content analysis, probably evolving toward a 'super-competent colleague'.

The text is a translation of a new chapter that we added to the 6th edition of our German textbook on qualitative content analysis, published by Beltz Juventa in 2024.
(see → www.qualitativeinhaltsanalyse.de for more information on the German edition)

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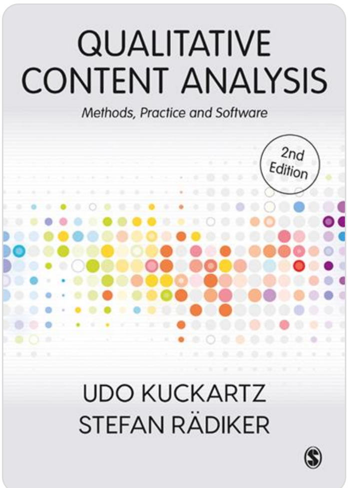


You can find general information on
Qualitative Content Analysis (QCA) in the following book:

Kuckartz, U. & Rädiker, S. (2023, 2nd edition)
Qualitative content analysis: Methods, practice and using software.
published by Sage

For more details, visit → www.qca-method.net

10 Integrating Artificial Intelligence (AI) in Qualitative Content Analysis

In this chapter you will learn about:

- The application of artificial intelligence in qualitative content analysis
- The ongoing debate about LLMs in academia
- The dual role of AI as tool and partner in data analysis
- Practical applications of AI in data exploration and category development
- Further applications in coding and analysis of coded data
- Privacy concerns and ethical challenges
- Potential disruptive effects of generative AI.

10.1 AI and its Role in Qualitative Content Analysis

This tenth chapter is a new addition to the sixth edition of this textbook. It has been written during a period of rapid and significant advances in artificial intelligence, at a time when binding, universal regulations for AI usage were still lacking. The potential role of AI in qualitative content analysis cannot be determined independently from the wider academic discourse on AI and the ongoing debates about its use and limitations. Legal requirements for data protection, ethical standards and principles of good scientific practice ultimately determine how AI can or should be used in the analysis of research data. When the company OpenAI launched the ChatGPT chatbot in November 2022, it initially received little attention from the wider European public. However, with ChatGPT's widespread availability and free access, generative large language models (LLMs) quickly gained attention and sparked an exponential increase in interest in artificial intelligence. The response to ChatGPT extended far beyond media coverage, almost everyone who tried the chatbot was impressed by its capabilities. While this created a 'wow effect', it also raised fears and dystopian concerns.

Universities and scientific organizations, including the German Research Foundation (DFG) and the German Association of University Professors and Lecturers (DHV), were quick to take up the issue of 'artificial intelligence'. In the first issue of 2023 of the DHV journal 'Forschung & Lehre [Research & Teaching]', an article titled 'Milestone in AI Development? The Chatbot ChatGPT' (Weßels, 2023) examined the impact of generative AI models on the future of teaching and learning at universities. The author characterized the development of LLMs as revolutionary:

> 'Since November 30, 2022, my world (...) feels transformed, leading us into a 'new era' that we don't yet know whether to embrace or fear.' (ibid., p. 26)

According to Weßels, AI models offer 'the ability to analyse large data sets more quickly and accurately while gaining new insights and perspectives. They can also improve the quality and validity of research results' (ibid., p. 27). Weßels urged universities and researchers to make a conscious commitment to the responsible and ethical use of LLMs and establish guidelines.

However, this has yet to materialize. The educational and scientific communities are still grappling with uncertainty about how to deal with the new capabilities of generative AI. While the highest educational authorities – ministries and university administrations – remain divided on the permissibility and limits of AI use, empirical studies show that a new generation is emerging within the educational system that naturally incorporates artificial intelligence through LLMs into their work. A study conducted by the Bavarian Institute for Digital Transformation (BIDT) in July and August 2023, which surveyed more than 3,000 internet users, found that 73% of adult students and 78% of university students use generative AI. Nearly half of AI users reported improved grades, and a similar percentage of teachers believed that AI led to improved performance (Schlude et al., 2024). The percentages of users is likely to have increased since then. While LLMs are widely used, guidelines for their use are still lacking. There's often a disconnect between general pro-AI statements and practical implementation: While the DFG states that 'the use of AI models in scientific work should not be excluded as it offers significant opportunities and potential' (DFG, 2023), the Technical University of Munich simultaneously denied admission to an applicant suspected of using ChatGPT for their application essay. The academic community's struggle to establish clear rules of engagement is illustrated by articles published in the German journal 'Research and Teaching'. The journal contains both articles dismissing AI and downplaying its capabilities (e.g., Cap, 2023) and articles advocating the integration of AI in research and teaching (Hoeren, 2023), arguing that AI can improve the quality and validity of research (Weßels, 2023).

The current uncertainty makes it difficult to define the role that generative AI, particularly LLMs, can play in qualitative content analysis. At the time of writing (June 2024), generative language models have developed at a rapid pace, becoming both more numerous and more sophisticated. These models have already found their way into qualitative data analysis software such as MAXQDA and ATLAS.ti. In social science research data analysis, these QDA programs have long incorporated AI-based features such as sentiment analysis and topic modelling without controversy. Using topic modelling in a master's thesis or dissertation would never have risked rejection, and might even have been praised as an innovative methodological approach. However, the situation with generative AI language models is drastically different. Why is this? We attribute this to two factors: the unprecedented power of LLMs and their dual nature as both *tool* and *assistant*.

The most powerful function of AI as a *tool* is its ability to quickly summarize large amounts of data while extracting key points. This ability far exceeds the capabilities of traditional QDA software, which can 'only' extract text passages containing specific words, word combinations or thematically coded segments from large volumes of text.

What's completely new is the role of AI as an *assistant* – a co-analyst in data exploration and evaluation. The chat capability is particularly important here, as it enables direct dialogue with the data being analysed and allows insights to be gained through iterative cycles. However, as with human assistants, this role can be interpreted and implemented in different ways. Support could mean simply delegating basic tasks, or it could extend to handling large parts or even all of the work, including writing analytical reports. In the latter scenario, researchers would become like politicians who merely read speeches written by others.

This dual nature of generative AI – as both a tool and an assistant – makes it difficult for universities and research institutions to establish clear guidelines for the use of AI. Regulating AI as a tool would be relatively straightforward. As suggested by the DFG in its statement, established standards of good scientific practice could serve as a framework. For LLM as a tool, this would require transparency about which methods are used and to what extent. The required level of detail remains to be determined. Looking at current practices for disclosing the use of software in literature review, statistical analysis, qualitative data analysis or text preparation, extensive documentation seems unnecessary. After all, we don't specify tools for every statistical table (such as stating 'created using SPSS version 25'), nor do we specify tools for every qualitative content analysis quote (such as 'selected using MAXQDA's compilation of coded segments for category 'xy'').

Establishing precise guidelines for AI's role as an assistant is much more difficult. Dissertations and undergraduate theses must include a declaration of independent work, stating that the work was written independently and that all external sources are properly cited. However, various forms of assistance have existed long before the advent of generative AI. Constructive doctoral colloquia, critical reading by colleagues, tips and advice from supervisors, as well as proofreading and corrections by competent peers – all of these were by no means forbidden, but rather common and desired practice – and, of course, tools and databases for online literature searches on the state of research, as well as summaries and automatically generated abstracts, were also used. There are no detailed rules, or even regulations, on the nature and extent of such assistance; ultimately, it is a matter of trust: Who could object, for example, to having a master's thesis proofread and linguistically improved by a friend who is a language instructor? Even the further development of the category system on the basis of intensive discussions in the Graduate School is compatible with the declaration of independent work.

What are the implications of all this for the role of generative AI in qualitative content analysis? AI is potentially the most powerful tool currently available for qualitative content analysis, and it's developing at an unprecedented rate. However, generative AI goes beyond the role of a mere tool – it can serve as a competent assistant in qualitative content analysis. It allows us to exchange ideas about category systems and their relevance, engage directly with data, explore connections and summarize large texts at remarkable speed.

Large language models offer even broader capabilities: they can interpret data, compare different perspectives, develop analytical categories, identify unique patterns, and create visual representations of relationships. These capabilities already exist and continue to expand. In Chapter 10.2 we'll explore practical applications and introduce new, integrative analytical approaches. We approach this as active pioneers, exploring how these emerging technologies and capabilities can enhance qualitative content analysis. However, generative AI also presents significant challenges, particularly in terms of ethics and privacy, which we'll address in Chapter 10.3.

10.2 Practical Applications

In this section, we showcase the diverse ways in which artificial intelligence, particularly generative language models, can enrich qualitative content analysis. We want to clarify that, in this process, AI is not a simple automated system that transforms interview inputs into ready-made analysis reports. Rather, we see AI as an assistive tool that provides valuable support at each step of qualitative content analysis. As researchers, we retain full responsibility for the analysis, which requires us to critically evaluate AI-generated outputs and, when needed, adjust them to align with our research goals, ensuring the quality and integrity of our work (Rädiker, 2024a).

AI can enrich to all three variants of qualitative content analysis. Our discussion follows the steps of the general process model (Figure 11, p. 106), beginning with initial work with the text, progressing through category development, coding and analysis of coded data, and ending with the writing of the final report. AI can also be effectively utilized in the preliminary step of transcription, as we have explained in Chapter 8.1.

Various software solutions can be used to implement the applications of AI described in this section:

- **ChatGPT, Microsoft Copilot, and other online tools** that utilize large language models to respond to chat-based queries.
- **QDA software** (see Chapter 8), such as MAXQDA and ATLAS.ti, which now include AI-powered features like automatic summary generation, code suggestions, and integrated chat functionality. Given the rapid pace of feature development, we recommend visiting the vendors' websites for the latest information on available features.
- **Online writing tools** for text refinement, such as DeepL Write.

Using these tools typically involves uploading analysed data to the vendors' servers, which requires anonymizing personal data. Additionally, it must be ensured that these servers comply with data privacy regulations (see Section 10.3 below for more information on data protection).

AI-Assistance in the Initial Work with the Text and Data Exploration

A key objective of initial text work and data exploration is to become familiar with the data, examine it through the lens of research questions, and gain an overview of both individual cases and the dataset as a whole (see Chapter 4.5). This exploratory phase can yield initial insights for the category system, inspire adjustments to the research questions based on the data, provide early assumptions about relationships and differences, and generate other valuable observations. AI support in this phase can assist not only with content and language exploration but also with refining research questions and examining personal biases. The following AI techniques and procedures are available for these purposes:

Creating Summaries for Entire Texts

Automatic text summaries serve as a helpful starting point for exploration. These summaries provide a quick overview of the topics covered in a text and assist in selecting appropriate texts for deeper exploration. Summaries can be created using built-in functions in QDA software, where users can typically define the summary length and opt for bullet point format if desired. Alternatively, the entire text can be copied into an online AI tool.

Figure 36 displays the manually created case summary for a student interview, previously presented in Chapter 4.5, alongside an AI-generated summary of the same interview.

Figure 36: Case Summary for Interview R2 (Manual vs. Automatic)

Interview with Person R2 (Manually Written Summary)
- Rarely went to the lectures but participated in the tutoring sessions more regularly. - Always liked math in school and now likes statistics, too. - Can concentrate better at home, which is why she didn't go to the lectures. - The lectures were useless because she didn't understand anything. - Practice exercises with solutions on the internet were her source for learning materials. - Bought the recommended textbook and worked through it. - Found the tutoring sessions very good. - Also attended another, more practical lecture course on statistics. - Her study methods changed fundamentally in the middle of the course. - She suggests that there be more time to solve practice problems and more material presented in such a way that the students must take their own notes. - Feels like she was well prepared for the final exam.

Interview with Person R2 (Automatically Written Summary)
- The student initially attended the lectures but found it difficult to concentrate and understand the material there. - They found it more effective to review the exercise sheets and solutions at home. - The student regularly attended the tutorials, which they found very helpful. - They did not form study groups with friends, as the focus tended to shift away from studying statistics. - The student purchased the main textbook (Bortz) and worked through it thoroughly, making notes. - The student has a generally positive attitude towards statistics, enjoying the mathematical aspects, but found the lectures too dry and boring. - The student feels well-prepared for the exam, though they expect to achieve a grade in the B/C range rather than an A. - The student suggests improvements like adding more content to the lecture slides to encourage attendance, and allowing more time for the exercise sessions.

The two summaries exhibit substantial content similarities and are largely interchangeable, despite minor variations in phrasing and emphasis – differences one might expect if two individuals were summarizing the same text. Some AI tools allow users to specify themes to structure the summary, which helps ensure consistent comparability across summaries of different texts and should be utilized when available. Additionally, it can be useful to create a manual summary first, then compare it to an AI-generated version. This comparison encourages critical reflection on your own phrasing and any omissions, while also helping to identify potential biases in your perspective.

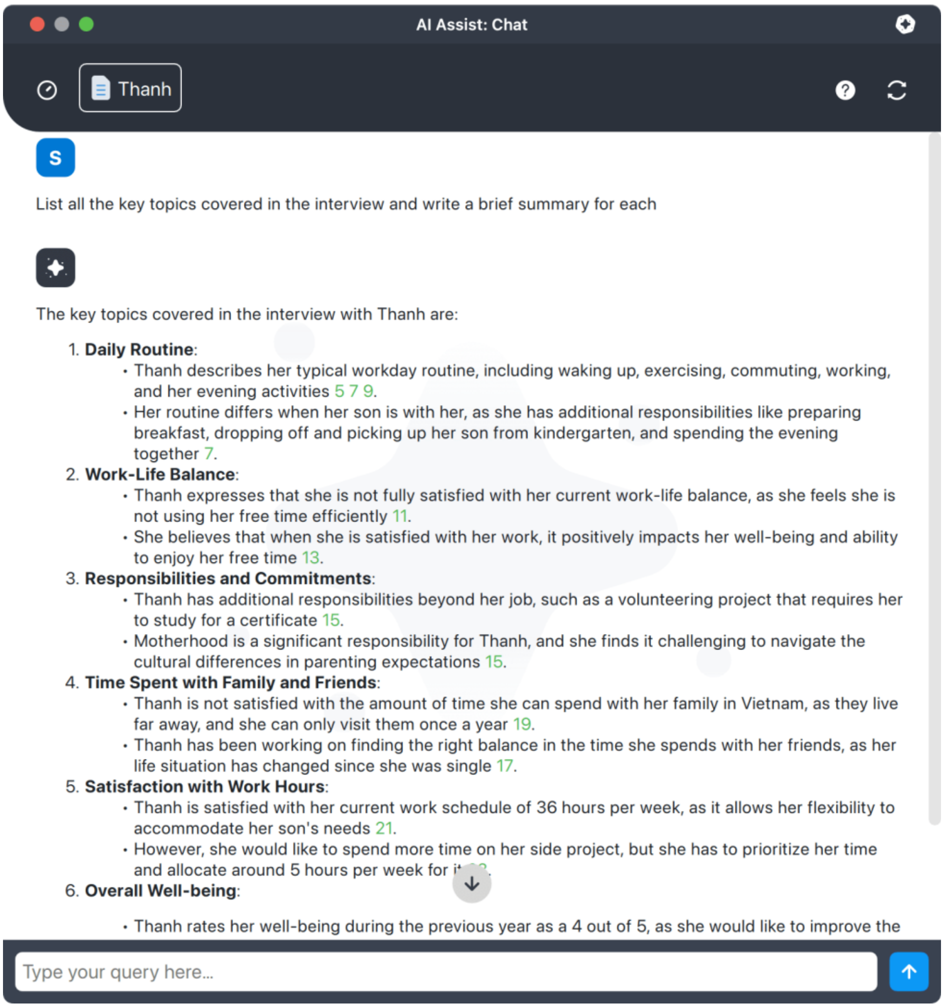
Creating Summaries for Individual Text Passages

Automatic summaries can be generated not only for entire texts but also for individual passages. This approach is particularly valuable when analysing a text section by section. An automatic summary can be created for each section and refined as needed, while the original text's content remains fresh in the mind. This process creates a content overview that later provides quick access to section contents and can serve as a foundation for case summaries and category development.

Chatting About a Text

For in-depth exploration of one or more texts, a chat tool proves valuable, allowing researchers to pose questions about the material and provide analysis instructions (Figure 37). Unlike creating a summary with a simple 'click function', using a chat tool opens up a wide range of possible questions and instructions.

Figure 37: Chat About an Interview in QDA Software (Here: MAXQDA)



Here are some examples for inspiration:

Chat queries for exploring a single text:

- List the key themes of the text and provide a brief summary for each
- Create a summary of the document, organized by these themes: [theme A], [theme B], ...
- Summarize the interviewee's statements regarding [theme]
- Identify potential contradictions in the statements about [theme]
- How might the research question '[question]' be answered using the present text?
- What evidence exists in the text for the relationship between [aspect A] and [aspect B]?
- Which groups of people are mentioned in the text?
- What patterns can be identified in the use of language and metaphors?
- Which adjectives are used to describe [aspect/object]?

Chat queries for exploring multiple texts simultaneously:

- Create a concise summary about [theme] for each interviewee.
- How do the documents differ regarding [aspect/theme]?
- Which respondent demonstrates the highest [aspect]? Provide a detailed justification.

These examples demonstrate that questions can address both manifest and latent content within a text. Particularly when exploring latent content, a chat tool offers the advantage of iterative questioning, as multi-stage conversations enable deeper analysis of selected aspects through follow-up questions such as: 'Are there additional indicators of this relationship in the text?', 'What alternative explanations does the text suggest?', or 'Which adjectives would best characterize this behaviour?'

It can be beneficial to assign a specific role to the chatbot at the beginning of the conversation and communicate the project's objectives or research questions, for example: 'You are an expert in qualitative research. This research project aims to identify causes for the discrepancy between rhetoric and action in climate protection'. Additionally, you can specify the desired output format by requesting a table, bullet points, or a detailed narrative response.

If data exploration reveals that a research question needs adjustment to accommodate unexpected or new aspects, a chat tool can assist by responding to queries such as: 'How can the following research question be refined to incorporate [aspect]?'

Semantic Search

Semantic search enables you to find text passages related to a specific topic without requiring exact keyword matches. Unlike simple text search, which only finds specific terms entered, semantic search can identify both direct and indirect references to a topic. This search can be performed through a chat tool by giving instructions such as: 'List all passages where the interviewee discusses [topic], either directly or indirectly'. Alternatively, some AI tools allow users to run semantic searches for entered search terms.

AI-Assistance in Category Development

AI can support *inductive category development* by generating suggestions for systematizing open codes into higher-level categories. To accomplish this, you can copy developed codes into a chat tool along with a specific instruction, such as: 'Here is a list of open codes from an interview analysis about [topic]. Create more abstract categories for qualitative content analysis to group these codes, including a brief definition for each category'. To evaluate different ways of categorization and to potentially combine them, multiple alternative suggestions should be requested from the chat tool.

If no open codes have been developed from the data, but the texts have already been coded with main categories, AI can suggest appropriate subcategories based on the coded segments. This can be achieved either by engaging in chat interactions about the coded segments of the main category or by using specialized tools within QDA software. Figure 38 demonstrates an AI-generated proposal for subcategories under the main category 'Causes of Discrepancy', which encompasses statements about the gap between rhetoric and action in environmental and climate protection. For each category, explanatory examples from the coded segments have been included.

Figure 38. AI-generated Subcategories for a Main Category

Causes of Discrepancy

1. Social Pressure and Self-Presentation
    - Pressure to appear socially desirable, even when actions don't align with claims
    - Concerns about perception lead to exaggerated or false claims about sustainable behaviours
2. Barriers to Sustainable Behaviour
    - Practical barriers like cost, accessibility, and personal preferences hinder sustainable choices
    - Lack of knowledge about the impact of actions can also prevent sustainable behaviour
3. Responsibility and Agency
    - Practical barriers like cost, accessibility, and personal preferences hinder sustainable choices
    - Lack of knowledge about the impact of actions can also prevent sustainable behaviour
4. Contextual Factors
    - Behaviours are influenced by the situation, relationships, and social dynamics
    - Context shapes how sustainable behaviours are discussed or questioned

As an intermediate step in further differentiating a category into subcategories, generating summaries for each coded segment can be beneficial (see Rädiker, 2024b). This intermediate step can be automated using AI, after which the summaries can be systematically organized by content – either manually or with AI assistance – to develop subcategories. In Figure 39, we compare a manually created summary of a coded segment from a study on autonomously working caregivers with an AI-generated version to demonstrate that the automatic summary provides either a solid foundation for manual refinement or potentially serves as a complete alternative.

Figure 39. Summary of a Coded Segment (Manual vs. Automatic)

Manual	Automatic
More autonomy compared to the traditional approach in shift scheduling; ability to swap shifts; individual coordination with and counselling of clients, and being able to make suggestions for them.	Autonomy in work organization and individual coordination with clients are important aspects that are missing in the classical system.

For *deductive, a-priori category development*, which is conducted independently of the data, a chat tool can support these tasks:

- Developing categories from an interview guide, using instructions such as:

    > You are an expert in qualitative research and category system development. Here is an interview guide from a study [description]. The central research question is: [research question].
    >
    > Interview guide: [interview guide].
    >
    > Create a list of main categories suitable for coding data using qualitative content analysis, encompassing all aspects of the interview guide and research question.

- Optimizing draft category systems. This enables inquiries about potentially beneficial additional categories or possible improvements and standardization of category names and their abstraction levels.
- Developing category definitions. Category definition drafts can be requested for selected or all categories, such as bullet-pointed explanations of each category's substantive meaning.

AI-Assistance in Data Coding

AI can be a valuable tool for data coding. For specific text passages, it can suggest new, inductively developed categories or recommend assignments to existing ones – either directly within QDA software or via a chat tool. Conversely, you can request the software to identify all passages in a text that could be coded under a given category. Including the category definition is essential for this purpose.

Chat tools can assist in developing and refining category definitions by suggesting linguistic improvements, indicator words, and distinctions between categories. Typically, this process involves incorporating coded text segments into the query. Conversation with a chat tool is particularly valuable for evaluative categories, where clear distinction between categories is essential. A chat tool can also help to resolve uncertainties regarding category assignment. For example, one could ask: 'Here is a text segment that needs to be coded with one of two categories in a qualitative content analysis: [text segment]. What arguments support coding with [first category] versus [second category]?'

When coding free-text responses to open-ended survey questions, researchers can not only utilize AI to create suggestions for subcategories as mentioned above but also employ automated sentiment analysis to pre-sort responses from 'very negative' to 'neutral' to 'very positive'. Sorting the responses by sentiment tends to cluster similar content together, significantly streamlining the coding process. Of course, sentiment analysis is only meaningful when responses contain some form of rating by the respondents.

In evaluative content analysis, researchers usually analyse multiple text segments per case on a specific topic to make an informed assessment – such as determining an individual's level of responsibility toward global issues (see Chapter 6). For this scaling, researchers can paste category definitions and relevant case segments into a chat tool to request a reasoned classification, enhancing consistency and depth in the evaluation process.

AI-Assistance in Analysing Coded Data

In qualitative content analysis, coding the data organizes the content into a structured format, as shown in the profile matrix in Table 4 (Chapter 4.2) and presented again in general form for three cases in Table 29.

Table 29. Profile Matrix: Cases and Categories as Structuring Dimensions

	Category A	Category B	Category C	
Case 1	Case 1’s text on Category A	Case 1’s text on Category B	Case 1’s text on Category C	⇨ Case-oriented analysis for Person 1
Case 2	Case 2’s text on Category A	Case 2’s text on Category B	Case 2’s text on Category B	⇨ Case-oriented analysis for Person 2
Case 3	Case 3’s text on Category A	Case 3’s text on Category B	Case 3’s text on Category C	⇨ Case-oriented analysis for Person 3
		Category-oriented analysis for		
	⇩ Category A	⇩ Category B	⇩ Category C	

Building on the profile matrix, where rows represent cases and columns represent themes, several AI-supported approaches can be applied, each leveraging different coded segments:

- Case-Related Thematic Summaries: For each cell, you can use AI to summarize all segments from a specific theme within a single case (we discuss the analytical benefit of these summaries in Chapter 5, beginning on page 111).
- Thematic Summaries: Aggregating coded segments within a column creates category-specific summaries, allowing to prepare all statements on a theme in condensed form for reporting.
- Case-Related Summaries: Summaries can be automatically created for selected categories within each row, providing case-specific insights.
- Case Similarity Analysis: Cases can be compared for similarities and differences in selected categories, which can serve as a valuable first step toward typology development in qualitative content analysis.

If the required AI functions for generating the profile matrix and summarising its components are not available in the QDA software used, relevant coded segments can be transferred to a chat tool for performing the analysis.

AI-Assistance in Formulating and Structuring the Report Text

We have deliberately chosen not to title this section ‘Writing the Report with AI’ because we believe that the final preparation of a report must remain the responsibility of researchers and cannot be delegated to an AI. Nevertheless, the automatically generated summaries described above provide an excellent basis for writing the results report. Today’s AI tools are particularly effective at formulating and editing text, including refining language and style. They can act in a similar way to external editing services, optimising phrasing, improving structure and enhancing readability of the report text.

10.3 Data Protection, Ethics, General Guidelines and Questions

To what extent is it permissible to use artificial intelligence in qualitative content analysis within research projects or academic theses? How should the implementation and use of AI be documented? What specific data protection rules apply to the use of AI? Can the use of generative AI be ethically justified and aligned with principles of good scientific practice, such as those outlined in major research funding guidelines? Will generative AI eventually replace established methods of analysis, in particular qualitative content analysis? These questions of privacy, ethics and the disruptive impact of AI are addressed in the following sections.

Data Protection

A fundamental principle of all research involving humans is the principle of informed consent. This means that all individuals involved – whether participants, interviewees, or focus group members – must be fully informed about the research project, including all aspects that affect them personally, and must give their consent. Necessary information includes the aims and methods of the project, potential risks, and the right to withdraw at any time. The information provided must be clear and understandable, and participants should have the opportunity to ask questions. Participation must be voluntary, and participants' consent should be documented by a written consent form that includes all relevant information. If artificial intelligence is used in the research project, the consent form must be modified accordingly to include a description of how the AI will be implemented.

When using artificial intelligence in the research process, the same legal data protection regulations apply as for non-AI research. In Germany and the EU, data protection is regulated by the General Data Protection Regulation (GDPR). This regulation governs the processing of personal data, which is defined in Article 4 of the GDPR as: 'information relating to an identified or identifiable natural person ('data subject'); an identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier, or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person'. Under this definition, anonymised data is not considered personal data, provided that the anonymization is complete. However, pseudonymised data, where names, places and other identifiers are replaced by pseudonyms, remain classified as personal data. Personal data may only be kept for as long as necessary for its intended purpose. Article 89 of the GDPR contains a 'research privilege', which allows certain provisions to be relaxed for scientific research purposes, such as allowing the use of secondary data for specific research purposes. Otherwise, data that is no longer necessary for its original purpose must be deleted or anonymized.

GDPR regulations apply to all social science data analysis, but the use of AI introduces additional considerations, highlighting issues that predate AI but may have been previously overlooked – such as the transcription of interview recordings by external assistants or transcription services. Although it is standard practice for transcription to be outsourced rather than conducted by researchers, audio and video recordings cannot be fully anonymized or can only be anonymized with significant effort. Anonymizing or pseudonymizing individuals, places, and institutions is feasible only after transcription. Therefore, consent forms must include authorization for the external handling of audio recordings.

The use of AI for automatic transcription and data analysis raises additional considerations:

- Is the data processed using locally installed AI or transferred to a remote server?
- Is the processing/storage server located within GDPR jurisdiction or outside (for example, in the UK or the US)? If outside: Are appropriate measures in place to ensure GDPR compliance?
- Is data deleted immediately after processing and text response generation (for example, after downloading an automatically generated transcript)?
- If data isn't deleted after processing, how long will it be stored?
- Will the data be used for AI training?

These issues need to be addressed before AI is utilized, and appropriate consent needs to be obtained in the informed consent form. Research participants have the right to be fully informed about how their data will be used and stored.

Ethical Aspects

Beyond legal considerations, which primarily relate to data protection and privacy, the use of AI in data analysis raises additional ethical questions about the conduct of researchers – specifically what constitutes right or wrong. Researchers using generative AI face several key challenges:

Privacy. The ability of large AI models to process and cross-reference large amounts of data may render traditional anonymization inadequate. Each case must be carefully considered to ensure real protection for the individuals affected.

Bias. Large Language Models can produce biased results due to selective training data. While these models are programmed to provide neutral, objective answers, their training data may contain prejudices and limited perspectives. When AI is used not only to summarize but also to interpret, this could lead to discrimination against certain groups. Humans also have specific perspectives due to their different socialization, which can manifest as prejudices and biases. Since generative AI is trained on much more material than any human can process, there's no inherent reason to assume that AI is more biased. Nevertheless, it is advisable to critically examine potential biases and to cross-check with other sources. The risk of AI bias is relatively low when analysing data from one's own research project.

Lack of Transparency. Common AI models such as GPT, Mixtral or Claude are trained on trillions of data points. It is virtually impossible to get an overview of this training data. Even if this training data were publicly available, the sheer volume would make it virtually impossible to identify imbalances and biases.

Hallucinations. In the first few months after the release of ChatGPT, AI hallucinations – the generation of false information – were frequently discussed, often with dramatic examples. This was partly due to a misunderstanding of GPT as a knowledge base rather than a language model. These models operate on probabilities of linguistic associations and correlations, not on definitive knowledge bases. Newer language models can access current Internet knowledge, which greatly reduces the risk of hallucination. When analysing one's own research data, hallucinations are almost impossible, as the results are derived solely from the uploaded data corpus. The risk of hallucinations increases if queries extend beyond this data set.

Beyond these specific challenges, scientists are also discussing the broader ethical implications of AI, including increased energy consumption and the potential displacement of jobs, particularly in transcription and translation. There are concerns about the erosion of human skills – the more tasks AI takes over, the greater the risk of the corresponding analytical skills being lost. Similar concerns were raised decades ago about statistical and QDA software, but proved unfounded.

In conclusion, the use of generative AI raises numerous ethical considerations that require careful reflection. Legislation and academic guidelines need to be urgently developed. The EU Artificial Intelligence Act (https://artificialintelligenceact.eu/the-act/), passed by the European Parliament in May 2024, is an important step towards establishing standards and responsible use of AI. We believe the future lies not in bans, but in thoughtful implementation. Until there are binding rules, both generally and within specific institutions, the responsibility lies with individuals. It remains reasonable for institutions to trust individuals, just as they've previously accepted that support from doctoral colloquia, colleagues, friends and family can remain within acceptable limits, while maintaining the validity of the declaration of independence required for qualifying theses.

General Guidelines and Open Questions

This chapter concludes with some general guidelines. It explores the question of the potentially disruptive impact of generative AI.

Dual Function: Inspiration and Quality Control

AI in the analysis process serves both inspiration and verification purposes. If AI is used to generate subcategory suggestions *before* developing one's own suggestions, this preliminary use serves primarily as an inspirational tool, often providing unexpected insights. If used *after* manual development of category systems, AI can suggest improvements, which is primarily a verification function. While this can still be inspirational, quality control becomes the dominant aspect.

The timing of AI implementation in the analysis process requires careful consideration. This applies not only to specific analytical steps such as category development, but to the entire qualitative content analysis process. For example, AI can be used in the ex-post review of analysis and findings to enhance quality assurance. In this case, AI assists in evaluating the category system and coding decisions, assessing the consistency of findings, and identifying potentially conflicting evidence in the data, thus providing a more comprehensive review of the complete analysis process.

Direction-setting by Adding the Project Description

Generative AI results improve with precise questions and rich context. Providing AI with information about the research project and personal background is beneficial. In ChatGPT, for example, custom instructions allow input of project descriptions, researcher roles, and theoretical orientations.

Multilinguality

The multilingual capabilities of Generative AI are remarkable. For example, an English scientific article can be summarized in German. However, AI training data varies significantly between languages. Less common languages, such as Maltese, can be subject to translation distortions, so careful validation of AI responses is required.

The Question of the Disruptive Impact of Generative AI

Will artificial intelligence replace established methods of qualitative data analysis? Do we need to completely rethink data analysis, abandoning core processes such as category development and coding? Will generative AI be disruptive? We think not. Rather than making social science methods of analysis obsolete, AI increases their importance. It requires precise formulation of research questions to produce useful results. Effective implementation of generative AI requires a methodological framework for meaningful integration. The established phases of qualitative content analysis – from exploration to report generation – provide a proven framework for specific AI applications. 'Prompt engineering' won't replace established analytical methods. AI doesn't eliminate the need for categorical thinking, which is characteristic of qualitative content analysis, because categories are not just organizational tools, but socially constructed linguistic expressions that represent systems of thought through which we address, answer, and implement issues of social practice and change.

With generative AI, we have not only gained a very powerful tool, but also an assistant for the entire research process. It aids in verifying category development, differentiating categories, and coding data. Many students have wondered how to implement qualitative content analysis – requiring intersubjective validity – into their dissertations, bachelor's, and master's theses. Since they often work alone, they lack opportunities to compare their categories and coding with others. Generative AI now makes it possible to compare one's own categories and subcategories with those of the AI. The codings can also be compared with those of the AI and, if necessary, inter-coder agreement coefficients can be calculated. The implementation of such workflows is still a bit cumbersome at the moment. However, it is relatively clear, where the development is going: AI capabilities are likely to expand significantly in the coming years. In particular, its role as an assistant opens up entirely new possibilities for integrating AI into the process of qualitative content analysis. In the not-too-distant future, generative AI may evolve from an assistant into what Sam Altman (CEO of OpenAI) calls a 'super-competent colleague' (O'Donnell, 2024).

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