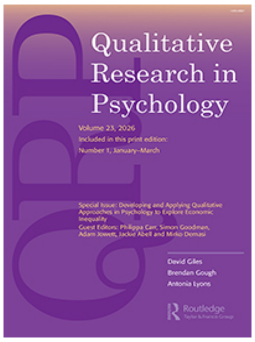

Qualitative Research in Psychology

ISSN: 1478-0887 (Print) 1478-0895 (Online) Journal homepage: www.tandfonline.com/journals/uqrp20

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To cite this article: Kathryn Wheeler (31 Jan 2026): Technological reflexivity in practice: how MAXQDA, NVivo, and ChatGPT shape qualitative survey analysis, Qualitative Research in Psychology, DOI: 10.1080/14780887.2025.2602820

To link to this article: https://doi.org/10.1080/14780887.2025.2602820

Published online: 31 Jan 2026.

QUALITATIVE RESEARCH IN PSYCHOLOGY
https://doi.org/10.1080/14780887.2025.2602820

Technological reflexivity in practice: how MAXQDA, NVivo, and ChatGPT shape qualitative survey analysis

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ABSTRACT

The emergence of Generative Artificial Intelligence (GenAI) into qualitative data analysis software (CAQDAS) intensifies long-standing debates around about how digital tools shape qualitative analysis. This article foregrounds the concept of *technological reflexivity* to examine how analytic practices and claims are co-produced through human-technology relations. Drawing on a reflexive comparison of MAXQDA, NVivo, and ChatGPT, I examine how different software architectures and GenAI features mediate analytic decisions, researcher-participant relationships and interpretive authority. The analysis draws on emotionally-charged data from over 1300 young people (aged 8–25) who responded to a climate-themed qualitative survey imagining the life of a fictional peer in 2050. The article shows how researcher strategies were shaped through distinct software tactics and how GenAI extends existing CAQDAS logics. It conceptualises reflexivity as a distributed practice, unevenly shared across researchers, tools, and infrastructures, and argues for collective responsibility in shaping the ethical and methodological futures of qualitative inquiry.

KEYWORDS

CAQDAS; Generative AI (GenAI); interpretive responsibility; qualitative survey analysis; technological reflexivity

1. Introduction

Since ChatGPT's launch in November 2022, interest in software-assisted qualitative analysis has surged. Yet Generative Artificial Intelligence (GenAI) has earlier roots in Computer Assisted Qualitative Data Analysis Software (CAQDAS) packages (Silver 2023). The uptake of CAQDAS tools – including traditional 'code and retrieve' and more controversial automated features – has been uneven, with persistent concerns raised about issues such as fragmentation, distancing from data, and the erosion of interpretive depth (Jackson, Paulus, and Woolf 2018; Woods, Macklin, and Lewis 2016). There is limited dialogue about the role of digital tools on analytic practice and outcomes. Indeed, in their review of software use in qualitative analysis reporting, Paulus et al. (2017) found that researchers rarely document *how*

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they actually use CAQDAS. This article addresses this gap through a reflexive account of how CAQDAS and GenAI influenced my analysis of qualitative survey data.

Recent scholarship has stressed the need for greater *technological reflexivity* - the critical examination of how digital tools influence methodological choices and meaning-making practices. Lester and Paulus (2025), building on earlier work (Paulus and Lester 2023), argue that researchers must not only acknowledge but actively interrogate how GenAI shapes design decisions within 'qualitative workflows' – that is, the sequence of analytic, interpretive, and digital actions through which qualitative data are prepared, analysed, and reflected upon (a term increasingly borrowed from software development to describe methodological process). They call for scrutiny of 'our technological choices alongside their consequences' (Paulus and Lester 2023, 3). Similarly, Silver and Woolf's (2019) 'Five-Level QDA' emphasises that researcher strategies must drive software tactics. Yet the rapid evolution of GenAI unsettles this principle, as emerging tools may now be reshaping researcher strategies.

Despite some early contributions (e.g. Woods and Wickham 2006), peer-reviewed literature systematically examining how CAQDAS tools (including recent GenAI capabilities) affect qualitative research outcomes remains limited. While studies exploring freely available GenAI systems like ChatGPT are growing (Chubb 2023; Hamilton et al. 2023; Hitch 2024; Morgan 2023; Wachinger et al. 2024), critical analysis of GenAI integration into platforms like MAXQDA and NVivo is still rare. At the time of writing, no systematic comparisons exist between GenAI tools embedded within CAQDAS and public Large Language Models (LLMs). This article documents my use of MAXQDA (Version 24.9.1 and Tailwind [Beta]), NVivo (Version 15.1.2), and ChatGPT (Version 4.5/4o) to aid the analysis of qualitative survey data from a youth sustainability and climate change study involving over 1300 young people (aged 8–25), designed by UK-based charity Sustainability and Environmental Education (SEEd). Participants completed sentence prompts imagining the life of a fictional peer, 'Alex', in 2050, generating over 5000 short responses. I experimented with embedded GenAI tools (MAXQDA's AI Assist, NVivo's AI Assistant) and external LLMs to support coding and interpretation. This article examines how GenAI tools assisted (and hindered) analysis, and how the design assumptions built into different platforms subtly steered the kinds of insights and relationships that were identified and developed.

Before detailing the project, it is important to situate myself in relation to the tools examined. Reflexivity in qualitative research includes attending to the material and technological conditions that shape analysis (Paulus and Lester 2023; Woods, Macklin, and Lewis 2016). I am a white, cis-female researcher working as a sociologist of sustainable consumption in a UK university with a long-standing preference for MAXQDA – my primary CAQDAS since beginning my academic career. I am a Professional Trainer in the software, having run numerous workshops for postgraduate researchers, and was among the first users to trial its AI Assist features. My institution, however, subscribes to NVivo, and I have substantial experience teaching its core features to undergraduate and postgraduate students. I find some of its tools (such as the word-tree function) especially useful, though I had not previously used NVivo in my own empirical work. While my long-standing use of MAXQDA offers detailed insight into its functionalities, I also recognise this familiarity may shape how I perceive its usability relative to other tools. My relationship with ChatGPT is more recent. Over the past year, I have used it for editorial support, but this project (analysis of the 'Alex' dataset) marks my first sustained engagement with an LLM within the context of qualitative research.

My approach to qualitative research is broadly constructionist, but I often adopt pragmatist and mixed-method strategies depending on the research aims – an orientation that presents specific challenges for qualitative survey data (which I will discuss in more detail elsewhere; Wheeler, in preparation). I view CAQDAS and GenAI not as neutral tools but as infrastructures that co-produce meaning. The analysis presented here is not a step-by-step comparison, but as a reflexive exploration of how different analytic environments (MAXQDA, NVivo, and ChatGPT) influenced what was possible and knowable when analysing the 'Alex' dataset. While I draw extensively on Paulus and Lester's (2023) framework of technological reflexivity, I also situate this within a broader, posthumanist understanding of reflexivity as 'intra-active' and distributed. Rather than a purely individual act of introspection – a position widely critiqued (Finlay 2002; Trundle et al. 2025) – I approach reflexivity as co-produced through the entangled relations between researcher, data, tools, and institutional systems (Barad 2003; Jackson and Mazzei 2023; Mazzei 2013). Such a position suggests that interpretive responsibility is shared across human and non-human actors, and highlights how access to digital tools shape the kinds of knowledge that can be produced. Though as my analysis will show this sharing of interpretive responsibility raises important questions about accountability and the continuing need for situated human judgement.

In what follows I explore the concept of technological reflexivity and its relevance for digital qualitative analysis, followed by a brief overview of GenAI developments, evaluation criteria, and methodological debates. The core analysis is structured around Paulus and Lester's (2023) four guiding questions – on methods, knowledge, relationships, and tool design – which I use to frame a comparative account of working with MAXQDA, NVivo, and ChatGPT. Anchored in a Reflexive Thematic Analysis (RTA) approach (Braun and Clarke 2022), I reflect on how interpretations were constructed through my engagements with the data, while also being shaped by the architectures, affordances, and constraints of the tools and political-economic systems

I worked within. As I will show, my analytic decisions were neither entirely autonomous nor wholly determined by the platforms, but unfolded through dynamic entanglements with software design and institutional infrastructures. Recognising these entanglements is not only a methodological concern but also an ethical one, since the access models, labour conditions, and environmental costs underpinning digital infrastructures shape whose analytic practices are enabled and with what socio-material and ecological consequences. This raises broader questions about how qualitative communities can engage with these tools in ways that sustain core interpretive values, while also demanding platforms and systems that prioritise equity and data justice.

2. Technological reflexivity in the use of CAQDAS

Computer-assisted qualitative data analysis has a long history, with bespoke software developed since the 1980s. In her *CAQDASChat with Christina* podcast (2022–2024), Christina Silver – Director of the Surrey CAQDAS networking project (established in 1994 to facilitate knowledge exchange and training) – hosts varied guests who reflect on how software shapes analysis across teaching, research, and commercial contexts. A recurring theme is how technology influences not only what is possible but also how research unfolds (Silver 2025). As co-author of the 'Five-Level QDA method' (Silver and Woolf 2015, 2019), she argues that digital tools should support, not steer, analytic decisions. Her framework outlines five interconnected levels: establishing research objectives, formulating an analytic plan, translating analytic tasks into software actions, selecting appropriate tools, and combining or customising these tools for more sophisticated analysis (Silver and Woolf 2015, 537). Its value lies in providing a flexible, transferable scaffold that can be adapted across approaches (e.g., thematic, content, narrative) and evolving platforms. At a time when GenAI promises speed and scale, it underscores that tools may assist, but cannot replace, the interpretive labour and reflexivity central to qualitative inquiry.

The Five-Level QDA method's distinction between *strategies* and *tactics* has also challenged persistent, yet unsubstantiated, claims that CAQDAS distances researchers from their data (Jackson, Paulus, and Woolf 2018). In tracing the genealogy of such critiques, Jackson and colleagues show that concerns about CAQDAS producing 'separation/distancing, homogenization/standardizing, mechanization/dehumanizing, [and] quantification/decontextualizing' (p. 87) often stem from mis-citations or selective readings. They argue the field would benefit from clearer documentation of actual CAQDAS use. Yet as review papers note (Paulus et al. 2017; Woods, Macklin, and Lewis 2016), there are few detailed accounts. A notable exception is Woods and Wickham's (2006) comparison of the same dataset analysed using QSR International's N6 and NVivo 7. While outcomes were similar, they observed that the process required practical adaptations, highlighting how researcher competencies shape 'the impact of software on methodological integrity' (Woods and Wickham 2006, 169). Woods later showed that CAQDAS use is often tied to 'reflexive moments' when researchers must consciously consider what the software enables or constrains, and how this aligns with their intentions and skills (Woods, Macklin, and Lewis 2016).

While sympathetic to the Five-Level QDA method, Paulus and Lester (2023) note that in digitally mediated contexts and under external constraints (like the COVID-19 pandemic), tactics may sometimes drive strategies. They observe that debates about CAQDAS often oscillate between technological determinism (that technology leads to passive use that undermines qualitative research), and technological instrumentalism (that technology is value neutral, and the researcher can control its use). As an alternative, they propose *technological reflexivity*, emphasising the mutual shaping of humans and technologies. Building on their work, I conceptualise technological reflexivity as a critical, situated interrogation of how digital tools shape (and indeed are shaped by) analytic decisions, interpretive claims, and research relationships. Importantly, this form of reflexivity is not solely individual, but distributed (often unequally) across researchers, tools, and the political-economic and institutional conditions that mediate qualitative analysis. As Paulus and Lester argue 'available digital tools and spaces may actually change the methods we use' (Paulus and Lester 2023, 2). They outline four key consequences of digital tool use that require critical examination; 1) how methods are enacted across disciplines and digital contexts; 2) how evolving tool design enables or constrains analysis; 3) how technology affects researcher-participant relationships; and 4) how technology shapes what counts as legitimate knowledge. This framework offers a valuable lens for tracing the entanglements of tools, methods, and meaning-making. These insights strongly resonate with my own experiences using CAQDAS and GenAI, particularly around how software design and file architecture influence the analytic questions I pose.

Lester and Paulus (2025) extend this framing to GenAI, raising questions about its role as a research assistant, its influence on CAQDAS design, its environmental and labour implications, and the epistemic status of its outputs. Their reflections invite ongoing engagement with GenAI as a 'more-than-human' participant in qualitative research. This aligns with posthumanist approaches that view reflexivity not as the property of an isolated researcher, but as a practice constituted through entangled relations between humans, tools, and infrastructures (Barad 2003; Mazzei 2013). In particular, Barad's (2003) concept of the *apparatus* offers a way of understanding analytic tools not as passive supports but as dynamic configurations that produce knowledge. 'Apparatuses are not mere static arrangements *in* the world,' they write, 'but rather apparatuses are dynamic (re)configurings *of* the world . . . through which specific exclusionary boundaries are enacted' (p. 816). From this perspective, knowledge is part of an ongoing becoming – produced through *intra-actions* within the analytic apparatus composed of researcher, tool, theory, and socio-political context. These insights suggest the need to reconceptualise reflexivity as a distributed practice – one that is materially co-produced and ethically, though unevenly, shared. Drawing on critical feminist data studies (D'Ignazio and Klein 2020), this approach resists locating analytic responsibility solely within the individual and instead considers how accountability is enacted across systems, infrastructures, and collectives. Such a framing must not ignore how power and political economies intra-act as GenAI becomes more embedded in qualitative workflows.

3. GenAI as a 'partner' within qualitative analysis workflows

Before turning to the study at hand, this section reviews how qualitative researchers are using and evaluating GenAI tools – focusing on both their perceived affordances and emerging criteria for their integration into qualitative workflows. Importantly, whilst discussions of CAQDAS have historically been limited, interest in GenAI is growing rapidly (as this special issue attests), with increasing attention to how it shapes qualitative practice through the lens of technological reflexivity.

To begin, it is important to define what GenAI is and why it may appeal to qualitative researchers. GenAI refers to a class of Large Language Models (LLM) – such as ChatGPT, Co-Pilot, Gemini – that generate human-like responses by statistically processing vast datasets. They are language prediction models which process human inputs (like qualitative data and prompts) using 'algorithms to identify information [deemed] . . . relevant from what the platform has learnt to date' (Hitch 2024, 597). As De Paoli (2023) note they do not 'understand' meaning in the way human analysts do; rather, they operate structurally and probabilistically, producing outputs plausible in form but not grounded in interpretation. For qualitative researchers concerned with meaning-making, reflexivity, and positionality, this structural mode of operation presents both opportunities and epistemological challenges.

A growing body of scholarship explores GenAI (mostly ChatGPT) as a support tool in qualitative analysis. Researchers have trialled its use in thematic analysis (De Paoli 2023; Hitch 2024; Morgan 2023; Nguyen-Trung 2024), narrative summarisation (Chubb 2023), and comparisons between GenAI and human coding (Hamilton et al. 2023; Mellon et al. 2024; Morgan 2023; Wachinger et al. 2024). Key insights from these experiments suggest GenAI is a 'supportive friend' rather than a replacement for human interpretation (Chubb 2023; Hitch 2024; Wachinger et al. 2024). In both Chubb (2023) and De Paoli's (2023) accounts, GenAI reduced the labour of initial sorting or summarising, freeing up time for deeper interpretive engagement. Studies comparing human and AI-supported coding suggest that GenAI can replicate surface-level descriptive themes (Hitch 2024; Morgan 2023; Wachinger et al. 2024), though its capacity for generating rich, interpretive codes remains limited (Combrinck 2024). Still, structured prompts enable new interpretive possibilities, particularly for deductive or theory-driven approaches. Wachinger et al. (2024), for example, prompted an LLM with a theoretical model and asked it to fit the data to this. These possibilities have caused some to question whether 'queries from ChatGPT could challenge the dominance of coding as a paradigm for analyzing qualitative data' (Morgan 2023, 9). In a recent preprint, Friese (2025, 1) goes further by proposing 'Conversational Analysis to the Power of AI (CAAI)', which 'replaces coding with structured, dialogic interaction between researchers and language models'. Drawing on insights from this rapidly evolving field (Hayes 2025; Müller and Rädiker 2024), Friese suggests researchers can shift their time and energy away from categorical organisation and toward direct engagement with 'patterns, contradictions, and participant voice' (Friese 2025, 25).

However, caution is warranted given the widely documented limitations of GenAI. Studies highlight its vulnerability to hallucination (generating content not present in the data), bias (stemming from the racial, gendered, and cultural biases embedded in its training data), inconsistency (producing different codes or themes when re-prompted), and forgetfulness (due to token limits impairing coherence across multi-stage tasks) (Ashwin, Chhabra, and Rao 2023; De Paoli 2023; Hamilton et al. 2023; Morgan 2023; Wachinger et al. 2024). A salient concern is GenAI's 'black box' nature, owing to algorithmic complexity and proprietary restrictions that limit transparency (De Paoli 2023, 4). Researchers can prompt GenAI to generate codebooks or themes, but the reasoning behind these outputs is opaque, complicating methodological accountability (Hamilton et al. 2023). Friese (2025) suggests this opacity can be partially mitigated through iterative prompting and deep familiarity with the data. Still, the issue raises important concerns for qualitative traditions that value transparency and reflexivity. As noted earlier, CAQDAS is often under-documented (Paulus et al. 2017); GenAI risks compounding this if researchers cannot explain or justify the processes behind LLM-generated outputs.

Given these opportunities and limitations, a key question emerges: how should GenAI tools be evaluated within qualitative research workflows? Drawing on Paulus and Lester's (2023) framework, one approach focuses on methodological reflexivity, asking how GenAI reshapes analytic practices, tool design, researcher roles, and knowledge production. Montrosse-Moorhead (2023) offers a complementary perspective, stressing criteria such as transparency, interpretive validity, and output effectiveness. More critical voices highlight GenAI's environmental and social costs, including high energy and water consumption, exploitative data extraction, and labour inequities (Crawford 2021; Turner 2024; United Nations Environment Programme 2024). Together, these perspectives suggest a two-tiered evaluation: one focused on research practice, the other on the broader systems enabling GenAI. Methodological criteria (such as transparency, analytic coherence, prompt responsiveness, and reflexivity) can be embedded in qualitative research and aligned with established standards of rigour. In contrast, structural concerns (such as inequitable access, resource intensity, and exploitative labour) raise fundamental questions about responsibility and justice. Following the lead of feminist data studies (D'Ignazio and Klein 2020) and critical analyses of AI's socio-environmental costs (Crawford 2021), I suggest these issues demand collective, rather than individual, responses.

Having explored how GenAI is being used as a partner in qualitative analysis, reflecting on its possibilities, challenges, and emerging frameworks for evaluation, I now return to the study at hand. The analysis presented in this article makes use of GenAI tools, including ChatGPT and AI-assisted features within MAXQDA and NVivo, alongside established CAQDAS functions (text searches, coding frameworks, and visualisation tools). The analysis offers a reflexive comparison of how these platforms shaped the analytic process, informed by the methodological and structural considerations above.

4. Analytic strategy and context

Building on the previous discussion of GenAI's role, affordances, and challenges in qualitative research, this section outlines the analytic context of the study, and the digital tools used. The dataset was drawn from an open-ended sentence completion activity in which over 1300 young people (aged 8–25) imagined the life of a fictional peer, 'Alex', living in the year 2050. Designed by the UK-based charity Sustainability and Environmental Education (SEEd), the four prompts asked participants to describe what Alex likes to do, what Alex worries about, what Alex needs to know how to do, and what Alex thinks of those living today (Wheeler 2023). This generated over 5000 brief qualitative responses, offering insights into young people's views on sustainability, the future, and present-day social challenges. Here I reflect on beginning to analyse a sample of this dataset. Though GenAI poses concerns around data security, this is arguably less acute with anonymous survey data. Nevertheless, data was carefully cleaned to remove all identifying features before it was sent to any samples were sent to LLM tools, and its analysis using GenAI has been approved by my University ethics committee and SEEd.[1]

Working with large-scale open-ended survey data presents both practical and methodological challenges. Responses are often short, vary in conceptual depth, and lack the interactivity of interviews. These features demand flexible analytic strategies that can accommodate both pattern recognition

[1]The 'Analysis of the SEEd Youth Listening Project' was conducted with Ethical Approval from The University of Essex's Ethics Sub Committee 1—–approval number: ETH2324-0210 (02 October 2023), which was updated in August 2025 incorporating a section on GenAI and the use of participant data (ETH2425-1855) (06 August 2025).

and contextual interpretation. I approached the data through Reflexive Thematic Analysis (RTA), which emphasises flexibility, context, and reflexivity throughout the process (Braun and Clarke 2021, 2022). RTA is increasingly recognised as suitable for large-scale qualitative survey datasets (Arnot et al. 2023; Braun et al. 2021; Terry and Braun 2017; Thomas et al. 2024). Unlike content analysis approaches that prioritise frequency or coder reliability (Schreier 2012; Wheeler 2022), RTA encourages flexible codes and themes grounded in the researcher's situated perspective and analytic goals.

My decision to incorporate GenAI and CAQDAS tools was shaped not only by methodological fit, but also by the practical realities of academic labour in the neo-liberal university. As a lone researcher working with over 5000 open-text responses, I sought to balance interpretive depth with the physical and cognitive toll of manually coding each item. The time and labour of such a task sits uneasily alongside a full workload and limited support. Though I do worry (as Braun (2025) recently noted) that turning to GenAI to shortcut these conditions is problematic because it risks further exacerbating the expectation that such data can be analysed quickly. The introduction of LLMs into CAQDAS marks a significant shift, not just in what these platforms can do, but in how qualitative research is marketed, taught, and practiced. As Paulus and Marone (2024) observe, CAQDAS companies now promote GenAI features with promises of speed and efficiency – 'in minutes instead of weeks' – which may appeal to new users but risks encouraging a 'push-button' model of qualitative research. As my discussion will highlight, automation was not a way to bypass interpretation, but part of an intentional, situated adaptation of analytic strategy within constrained conditions – a point I return to in later reflections on tool design and researcher responsibility.

Throughout the analysis, I used three tools: MAXQDA (Version 24.9.1 and Tailwind [Beta]), NVivo (Version 15.1.2), and ChatGPT (Versions 4.5/4.o). These were selected not to run a controlled comparison, but to explore how analytic reasoning is shaped by these tools. While MAXQDA has been my primary platform and offers more user control over GenAI integration, NVivo remains the most widely used CAQDAS globally, and ChatGPT is the most visible and accessible LLM (for which I used a paid subscription). Each brought distinct constraints and affordances: from file structure and document size limits to differences in how prompts and outputs were handled. Drawing loosely on a four-stage RTA-informed framework – familiarisation, description, sorting, and interpretation (Wheeler 2025) – my aim is not to provide a step-by-step walkthrough, but to reflect on how analytic practice was mediated within different digital environments. Consistent with the Five-Level QDA method (Silver and Woolf 2019), I began with a clear analytic strategy and used the tools tactically to uphold the ethos of

RTA. Section 5 examines how these tools participated in and sometimes re-directed the analytic process, raising broader questions about the implications of automation for qualitative research.

5. Findings: tools in practice

Organised around Paulus and Lester's (2023) four key questions, this section explores how CAQDAS and GenAI tools shaped the unfolding analysis. These were not neutral supports because they intervened in decisions about how to organise responses and what interpretive claims felt viable. They functioned, as Barad (2003) would describe, as 'apparatuses' through which meanings, insights, and decisions were produced through intra-actions between the researcher (situated in a distinct socio-political and material context), the data and the digital systems. I differentiate between three kinds of automation in the analysis that follows; rule-based features (e.g., word searches, sentiment analysis), pattern-based tools (e.g., autocoding), and GenAI-powered outputs generated through LLMs. These automatic tools operate with different epistemological assumptions and raise distinct questions about authorship and analytic responsibility.

To ground the reflections that follow, I outline the analytic workflow through which these insights were generated. I began by importing the survey data into both MAXQDA and NVivo, exploring responses through question-based and case/document views. I made initial notes on features of interest before generating preliminary summaries using built-in GenAI tools, and reviewed the automatic sentiment and theme coding applied during import in NVivo. I then moved into active coding. For the first question (what Alex likes to do), I used MAXQDA's 'Categorise Survey Data' window and word-length filters to iteratively develop a manual coding framework. For the second question (what Alex worries about), I coded 10% in NVivo and used its pattern-based autocoding to code the remainder. The third question (what Alex needs to know how to do) was analysed entirely using NVivo's GenAI coding tool. For the fourth (what Alex thinks of all of us living now), I generated codes via ChatGPT and applied them across a small sub-sample of the dataset. Recognising the importance of within-case analysis in RTA (Braun et al. 2021), I also examined responses across questions, using memos, MAXQDA's visualisation and coding co-occurrence tools, and ChatGPT prompts. Finally, I used MAXQDA's 'chat' feature and its new Tailwind add-on, as well as dialogic prompting with ChatGPT to support interpretive insight. These steps highlight how analytic decisions were mediated by my methodological orientation and by the design features of the tools. The following sections explore these entanglements in more detail, beginning with how platform design reshaped the seemingly routine task of familiarisation.

5.1 Tools reshaping familiarisation

The first task was familiarisation, a stage that may appear mundane but is foundational for subsequent and deeper analysis. This section responds to Paulus and Lester's (2023) first evaluative question – 'In what ways might existing methods need to be adapted within digital or GenAI contexts?' (Lester and Paulus 2025; Paulus and Lester 2023, 7) – by examining how platform architectures shaped this process. I reflect on how each tool directed analytic attention differently, opening up certain interpretive possibilities while foreclosing others. These reflections contribute to a view of distributed reflexivity, where the act of 'getting to know' the data is shaped not only by the researcher intentions, but also by technical design and the logics embedded in digital tools.

Platform architectures and import

Each tool invites different ways of encountering qualitative survey data, shaping how patterns of meaning are noticed and pursued. Unlike static formats like SurveyMonkey exports, Excel files, or Word documents, CAQDAS platforms organise the analytic environment through file architecture, interface design, and embedded features. The researcher, the tool, and the data are not separate entities acting upon each other, but are co-constituted phenomena through the 'ontological inseparability of agentially intra-acting "components."' (Barad 2003, 815)

For example, MAXQDA and NVivo take markedly different approaches to importing survey data. In MAXQDA, each participant becomes a standalone document, with each qualitative question coded and linked to document variables. This structure enables movement between question- and case-level views. During familiarisation, I used MAXQDA's '*categorise survey data*' window to filter for longer, richer responses using the word count tool, while grouping shorter responses for comparative review. I could return to the full set of a respondent's answers at any point, supporting early thematic development while keeping the participant's voice in view. In contrast, NVivo retains the spreadsheet structure as its organising logic. Participants are stored as 'cases', but clicking on a coded segment returns the researcher to a single cell within the larger table – not a coherent case – level narrative. Sorting by word length is not possible. While manageable for the Alex dataset's few questions, this fragmented view made it harder to sustain interpretive rhythm and within-case coherence, particularly in larger datasets (e.g. my original dataset had over 150 columns). ChatGPT, on the other hand, is not designed as an analytic environment. The survey spreadsheet could be loaded with project-level organisation alongside conversational history, but it lacked linkages between codes, data, and notes. Outputs were not embedded in a traceable analytic structure, making it harder to sustain interpretive threads over time or to integrate multiple elements of analysis.

These differences are not just functional: they shape how the researcher encounters and comes to know the data. In RTA, immersion depends not only on reading the data but on being able to see it whole – switching between part and whole, and code and case. MAXQDA's document-centric view supported this interpretive rhythm most effectively, facilitating navigation across and within responses. NVivo, while valuable in other respects (discussed later), steered attention toward a more segmented, question-by-question reading. ChatGPT further fragmented the process, with outputs disconnected from the underlying data and limited support for sustained interpretive development. Across platforms, what appears as researcher strategy is also shaped and constrained by the tools through which familiarisation unfolds.

Memoing, GenAI, and reflexive entanglements

A core practice in iterative qualitative analysis (especially in RTA) is writing about the data to record interpretive decisions, raise analytic questions, and reflect on emerging meanings. In CAQDAS environments, this work typically happens through memos. While rooted in Grounded Theory, memos are used across qualitative traditions (Charmaz 2014; Jackson and Bazeley 2019; Paulus and Lester 2023). Braun and Clarke (2022) do not emphasise memos explicitly, but they do recommend note-making during familiarisation. In my practice, memos are central to understanding and engaging with data.

Both MAXQDA and NVivo support memo writing, but in structurally distinct ways. Both also embed GenAI summaries within the memo system, foregrounding them as part of the interpretive workflow. In MAXQDA, memos attach directly to documents, codes, or segments via clickable 'post-it notes', with GenAI summaries displayed alongside researcher text. NVivo, by contrast, stores GenAI output in a separate 'AI Summaries' folder. If a memo already exists, it is relocated and augmented with GenAI content, leaving it to the researcher(s) to differentiate between their own words and the generated text. These subtle design choices reflect differing assumptions about the boundary between interpretation and automation.

As GenAI becomes more embedded in familiarisation practices, memo spaces may increasingly function not just as sites of reflection, but as scenes of negotiation between human and more-than-human perspectives. For example, qualitative survey data is often described as 'thin' (Terry and Braun 2017) and GenAI summaries may appear to compensate. Yet when summaries presort a dataset before deep engagement, they risk constituting rather than merely supporting analysis. What gets summarised, omitted, or framed as a 'pattern' is shaped by algorithmic logics that remain largely invisible. In these digitally mediated contexts, reflexivity is not solely a matter of researcher awareness, but develops through intra-actions with software architecture and

GenAI affordances. Integrating tools into familiarisation demands ongoing scrutiny – of what these tools make possible, but also of what they predispose us to see. Familiarisation becomes a site where methodological intention and technical infrastructure actively co-produce analytic possibilities, with digital and GenAI platforms shaping how established methods are enacted.

5.2 Coding with and without AI: whose interpretive frame counts?

If familiarisation can be shaped by algorithmic summaries, then coding – the interpretive core of RTA – is especially vulnerable to shifts in meaning-making when automated tools intervene. This section responds to Paulus and Lester's question about how digital tools impact the 'kinds of knowledge produced . . . and which types of knowledge are considered worthy of producing' (2023, 11). I compare manual coding in CAQDAS, pattern-based auto-coding, and GenAI-supported coding, reflecting on how each produces different relationships to the data and, in turn, different claims to knowledge. From an RTA perspective, coding is not a neutral act of segmentation but a key site of interpretive labour. It matters *who* codes, *how* they code, and with *what assumptions*.

RTA treats coding as an iterative, subjective process through which researchers engage with the 'diversity and patterning of meaning from the dataset' (Braun and Clarke 2022, 53). Codes are not pre-given labels but are actively generated in dialogue with research questions, as well as the researchers' evolving understandings of the data informed by their positionality and theoretical commitments. Though another researcher may also code the data, the aim is not consensus but to 'collaboratively gain richer and nuanced insights' through multiple perspectives (Braun and Clarke 2022, 55). Codes are the outcome of an analytic process, forming the foundation for subsequent theme development. While RTA centres the researcher's active role in meaning-making, this analysis is also informed by Barad's concept of the 'apparatus'. Coding, when 'plugging in' this perspective (Jackson and Mazzei 2023), is not simply the application of researcher-generated categories, but a practice shaped through intra-actions with software features, data architectures, and theory.

Recent studies have explored whether GenAI can replicate human coding, often using familiar datasets or comparing outputs with human coding (Hamilton et al. 2023; Morgan 2023; Wachinger et al. 2024). They suggest that GenAI can produce initial coding structures, but these often lack interpretive depth. Though Friese (2025) argues that conversational AI may render coding obsolete, this assumes that coding is purely 'mechanical segmentation' that can be outsourced. From an RTA perspective, this reflects a misalignment between 'strategies and tactics' (Silver and Woolf 2019): it confuses the epistemological purpose of coding with its procedural enactment (though

I appreciate that Friese does not claim to use RTA). In my own study, comparing manual, pattern-based, and GenAI-supported coding, differences became apparent through iterative engagement not only in output, but in the analytic and affective relationships I developed with the data. I did not know this data well before using the GenAI – unlike Friese (2025) who used data from her PhD.

Manually sifting through responses, assigning categories, and grappling with both the content and emotional tone was essential to understanding the shared and divergent meanings in the data. As noted in Section 5.1, I began with MAXQDA's 'Categorise Survey Data' window, pre-sorting by word length to prioritise richer responses. This structured view differed markedly from NVivo, where short and long responses were scattered. While I did not code every response (e.g., under the question 'Alex likes'), I made iterative decisions, guided by RTA logic and mediated by the 'apparatus' of tools that intra-actively constituted my evolving understanding. I could use elements like key word searches to explore and visualise frequently used words, make notes about what I thought was important, and begin grouping and developing my themes as the machine and I engaged with the data.

In contrast, automated features such as sentiment analysis, pattern-based autocoding, and GenAI-supported coding rely on lexical and statistical models whose assumptions often remain opaque. For example, NVivo coded just 250 responses to 'Alex worries about' as containing sentiment, compared to 763 flagged by MAXQDA – a discrepancy that highlights the black-box logics behind sentiment libraries and stop-word lists. Pattern-based tools, such as NVivo's autocoding function, can extend researcher codes to similar responses, but again with limited transparency about what is missed or why. While retaining some link to researcher intent, these tools still apply codes mechanically and struggle to capture latent or affective meanings. These concerns are amplified in GenAI-based coding, where LLMs produce categories based on training data and prompt structures that are largely inaccessible to the user. As De Paoli (2023) notes, the relationship between input and output is rarely visible; ChatGPT may surface useful terms, but its suggestions reflect statistical regularities, not theoretical interpretation. Within CAQDAS platforms, these processes are further shaped by file architecture: in MAXQDA, GenAI coding was largely unworkable due to character limits, while NVivo's AI Assistant applied subcodes to only a subset of the dataset without explanation. Across these automated methods, researcher agency is not displaced but reconfigured by the ways tool design and statistical inference pre-structure what can be seen, coded, and known. This is where the tension between interpretive responsibility and the agency of the apparatus becomes most tangible; decisions remain mine, yet what was made visible to me as analytically meaningful had already been filtered by the tools' underlying architectures and logics.

That is not to say pattern-based or GenAI-generated codes were without value – but I remained cautious about what they revealed. They often prompted me to look again, but I rarely trusted their classifications. The tools offered possibilities, but their assumptions were not interpretable in the terms that RTA demands. For example, NVivo's AI Assistant coded responses to 'what Alex needs to know how to do' under categories of 'Energy Management', 'Environmental Awareness', 'Survival Skills', 'Sustainability', and 'Waste Management'. While these reflected content in the data, I felt no interpretive stake in them. Even after reviewing the patchy underlying responses, the categories felt imposed. In contrast, using ChatGPT allowed me to structure prompts that returned both the code label and associated data side-by-side. This worked more effectively for 'what Alex thinks of all of us living now', where it generated groupings that led me to reflect more deeply on the diversity of climate emotions – but the emotional intensity of many responses was flattened (a point I return to in Section 5.3). One-word responses were frequently left un-coded, which might be methodologically appropriate in a survey context, but other responses – such as 'they must have been so bored' (male, aged 12) – were missed entirely. I would have placed this under ChatGPT's suggested code of 'Strangeness/ Underdevelopment', defined as 'marking people in the past as odd, primitive, or outdated'.

Ultimately, these experiences have led me to reflect more deeply on what GenAI and pattern-based tools can and cannot offer in an RTA workflow. They expose a methodological contradiction I had to work within; while meaning-making is co-produced through intra-action, the responsibility for interpretation cannot be shared evenly with technologies whose operations remain opaque. While these tools may support efficiency and can surface familiar lexical patterns, they cannot replace the human interpretive labour that coding demands. And yet, there is something in the patterned outputs – even if partial or mechanised – that can productively interrupt the researcher's expectations and invite further questioning. I remain cautious but curious about this form of computational noticing. I now turn to the emotional and interpretive stakes of this engagement in Section 5.3, where I explore how different tools mediated my proximity to participants' voices.

5.3 Researcher agency and 'chatting' with the data

While the previous section addressed how digital tools shape knowledge production, this section turns to their effects on the researcher-participant relationship – a core concern in RTA and in Paulus and Lester's (2023) framework. I explore how 'chatting with' or prompting GenAI tools can give the illusion of engaging with another human. But these are not 'normal' conversations – they are driven by algorithmic logics that impose interpretive frames, fill in gaps with unseen assumptions, and risk removing the researcher from the affective dimensions of our data.

The data analysed came from a project that prioritises 'youth listening' and many responses to the story completion task were emotionally difficult to engage with. Young people expressed anger at political inaction, fear about the planet's future, grief over potential extinctions, and, at times, hope for collective climate action. Sitting with this data matters. Using ChatGPT or MAXQDA to 'chat' about it raises important questions about how we maintain a relationship with participants when that relationship is mediated by GenAI. I realise as I write this that I am rehearsing a familiar concern (the walking dead analogy) about how software detaches the researcher from the data (Jackson, Paulus, and Woolf 2018). But in the context of GenAI and survey data, the concern feels newly salient. While iterative prompting through dialogic interaction may deepen interpretation (as Friese 2025 suggests), chat-based tools enable a different kind of 'knowing' because they reshape the researcher-data relationship.

There is a real difference between reading a participant's words and reading GenAI's summarised interpretation of those words. This tension became particularly apparent when I asked ChatGPT to generate a typology based on 50 full responses (across all four answers). One of the dominant types it produced was the '*Burdened Fixer*', described as imagining Alex 'as someone who must repair the damage left by previous generations, especially environmental crises.' This category captured a recurring theme of responsibility for the future, but it flattened out the emotional tone and diversity within the grouped responses. Table 1 shows four responses grouped under this typology. While they reflect concerns about repair and inherited responsibility, they also differ sharply in tone, coherence, and affect. Some responses feel sarcastic, others grief-stricken or fearful. The typology misses these differences entirely and imposes coherence where there may be none. I could (and did) use the dialogical interface to better understand the nuances, but this conversational approach to analysis means becoming a 'prompt engineer' for the algorithm (Chubb 2023) rather than feeling or immersing oneself in the data.

I continue to grapple with how difficult it is for both the human analyst and non-human tool to hold a participant together across four questions at scale. It is much easier to read by question than by person and yet that difficulty matters, especially for RTA. In a survey context where the data architecture already slices responses into discrete categories, relationality and emotional threads needs to be foregrounded. To explore whether GenAI could support within-case synthesis, I experimented with Tailwind – an online AI-powered add-on to MAXQDA (Beta version), similar to the one Friese (2025) described. Survey uploads are not supported, so again I was working with four question-level documents. Tailwind could surface thematic overlaps and

Table 1. Four full survey responses grouped under ChatGPT's 'burdened Fixer' typology.

Demographic detail	Alex likes to	Alex has worries about	Alex needs to know how to	What does Alex think of all of us living now?
(1) Male, aged 16	Make music and go for walks	Not ever being able to see rainforests and animals such as tigers in his life	Help protect the natural world and help others to do the same. Overall how we can live sustainably	Immature, self centered and narrow minded
(2) Male, aged 12	fly in his hovering bed	robot demons	fight for his life and repair	they must have been so bored
(3) Female, aged 17	play Hockey	her future	run a household because school still hasn't changed their curriculum to teach student what taxes are	'Woah that was ages ago!'
(4) Female, aged 17	use advanced technologies	climate change and biodiversity loss	help reduce the amount of waste being produced and how to help increase the levels of biodiversity in his area	that we should be doing more to help the planet while we can

contrasts, but these were emotionally subdued and lacked awareness of respondent identity or demographic context.

These analytic encounters reveal the limits of current GenAI tools in supporting relational forms of qualitative interpretation. While chat interfaces may feel interactive, they often reconstruct participant responses in ways that fragment voice and erode coherence. Rather than deepening researcher proximity to participants, they risk flattening complexity – particularly when responses are brief, emotionally charged, or span multiple questions. This is not an argument to reject such tools, but to engage them critically, recognising how they shape the conditions under which meaning is made. Researcher agency, here, involves working within and around the affordances of available tools, and recognising when they fall short. The platforms I used did not fully support the interpretive demands of large-scale qualitative survey work. RTA requires sustained, within-case immersion, but the structure of survey data, and the logics embedded in CAQDAS and GenAI systems, often make this difficult to achieve. My response was to step away from automation and instead draw on MAXQDA's architecture to identify smaller samples for deeper interpretive work (Rädiker and Kuckartz 2020). This workaround is imperfect so highlights the need for more intentional design (either with or without GenAI) to support qualitative interpretation at scale. Importantly, these technical and design challenges in the software expose a deeper epistemological tension at the centre of this study. RTA assumes that meaning is produced through the researcher's interpretive engagement with data, whereas posthumanist approaches understand analysis as co-constituted through intra-actions among humans, technologies, and material conditions. My experience across platforms brought this friction into view; I interpreted the data and made decisions, yet those decisions were continually mediated by software design. In these instances, accountability for my analytic choices cannot be outsourced to the apparatus, but neither can it be imagined as fully individual. These moments of digital negotiation between my analytic strategies and the tactics available to me exemplify what I mean by distributed reflexivity. Reflexivity operates simultaneously as a shared, more-than-human practice *and* as an individual act of interpretive decision-making. To work reflexively is to inhabit this tension – to recognise that meaning is co-constituted, yet responsibility must still be exercised through the researcher's situated judgment.

5.4 Structural blind spots: designing for access, transparency, and ethics

Having considered how distributed reflexivity operates within the analytic encounter, I now turn to the wider infrastructures that sustain and constrain those encounters. While entanglements between the researcher and their tools shape interpretation at the micro level, attention must also be directed to the meso- and macro-level systems within which our research unfolds This final section addresses Paulus and Lester's (2023, 7) fourth guiding question: 'In what ways might existing digital tools and spaces need to be re-designed and/or adapted for an "ideal" digital research workflow?' As GenAI evaluation frameworks evolve, it is important to distinguish between issues manageable through individual researcher practice and those requiring collective action. Earlier, I proposed a distinction between methodologically actionable criteria (such as transparency, analytic coherence, and prompt responsiveness) and structural concerns (such as access inequities, environmental costs, and exploitative labour practices). This section revisits those structural dimensions, focusing on three key areas that warrant closer scrutiny: access, transparency, and ethical sourcing. While some tools show promising signs of aligning with qualitative research values, questions remain about who can use CAQDAS and GenAI, under what conditions, and with what consequences.

First, access to CAQDAS and embedded GenAI remains a key barrier for many qualitative researchers. I experienced this first-hand while preparing this article. Although my institution subscribes to NVivo, it had not purchased the AI Assistant add-on. A free trial request via my institutional account went unanswered, and I had to activate a 14-day trial using a personal email – only for it to be cut short by what appeared to be a licensing conflict with a previous install. To avoid losing access, I left the programme open for nearly a week until a university-mandated restart closed it. With ChatGPT, despite a paid plan, my access to GPT-4.5 kept reverting to GPT-4o, often mid-session and without warning. Realising that switching models risked inconsistent category application, I restarted the project using the more stable version. Even with

MAXQDA, where I have trainer-level access, I encountered delays due to institutional software management. Each new GenAI release required a version upgrade, which meant IT intervention or applying for local admin rights.

While these experiences may seem mundane, they are shaped by privilege: I'm a UK-based academic with institutional support, the personal means to pay for ChatGPT, and the time to navigate glitches and workarounds. For researchers in precarious roles, or in institutions with limited digital infrastructure, these barriers are far more acute. Though ChatGPT is technically free, the unpaid version restricts usage and limits functionality, particularly for tasks requiring multiple prompts or advanced models. In contrast, NVivo and MAXQDA charge substantial fees, often placing them out of reach entirely for many scholars worldwide. This uneven terrain raises difficult questions about whose research is supported and whose is not. Such inequalities intersect with the temporal economies of the neoliberal university, where privilege can provide access but not necessarily time. Even for well-resourced academics, the accelerating demands of productivity compress the space for deep, interpretive engagement. As Braun (2025) notes, GenAI enters a system already shaped by 'fast academia', where expectations for speed and productivity rarely align with the time and depth qualitative interpretation demands. Against this backdrop, there's a growing risk that GenAI tools will be used uncritically – not because it fits methodologically but because its integration into CAQDAS and promotional discourses (Paulus and Marone 2024) presents it as the default way to 'do' qualitative analysis.

Second, transparency is a key evaluation criterion (Montrosse-Moorhead 2023) and valued in qualitative traditions, yet it remains uneven across platforms. NVivo, for instance, produces GenAI summaries and code suggestions without explaining how these outputs are derived. Users must infer what criteria were applied, which parts of the dataset were prioritised, and how meaning was abstracted. This opacity limits the researcher's ability to evaluate or contest the model's interpretations. MAXQDA has introduced some features that move toward greater transparency – such as deterministic models that only use uploaded data, agreements with LLM providers not to train on the data, auto-generated comments explaining GenAI code assignment, and hyperlinked GenAI outputs linking to source text. These features support auditability and allow for iterative comparison of AI output with original material. In a co-constitutive ontology where meaning is negotiated through intra-action, responsibility for interpretation becomes diffuse. Nevertheless, qualitative researchers remain accountable for their claims, albeit in ways mediated by the extent to which platforms disclose their operations. Therefore, reflexivity must be built into tools so that they support transparency, data security, and scrutiny, enabling researchers to acknowledge their own position and critically assess what GenAI brings into view.

Third, as qualitative researchers adopt GenAI tools, questions about ethical sourcing and sustainability must come to the fore given the energy demands of these systems and the extractive way LLMs were trained. As a scholar of sustainable consumption with an interest in how markets are moralised (Wheeler 2012, 2019), there are insights I can bring to the case of GenAI. Placing responsibility onto individual researchers to resist exploitative systems is insufficient, especially when GenAI is embedded in infrastructures governed by a small number of corporate actors whose commercial imperatives shape which forms of research become more possible or desirable. These asymmetries of control and access remind us that distributed reflexivity operates within, rather than outside, unequal relations of power. Though posthumanist approaches help us see entanglements, they can flatten questions of power and accountability. Here, a political economy perspective is vital – it highlights how systems of public and private provision shape access, expectations and use, as well as how resource environments constrain sustainable futures (Harvey 2021; Jasanoff and Kim 2013) While individual objections (voiced by researchers, journalists, and NGOs) matter because moral voices become entwined with market solutions, systemic change requires coordinated action from academic institutions, research communities, and software providers. As I have argued elsewhere (Wheeler 2019), market structures are not moralised from a single location; rather change happens when multiple actors, including users, businesses, and governments exert pressure on supply chains, provisioning, and platform architectures. We are already seeing qualitative software shift to subscription-based models, with GenAI integration accelerating their reconfiguration. This opens space to intervene. If scholars see GenAI as valuable, we must collectively demand tools that reflect our methodological and ethical commitments. Providers like MAXQDA and NVivo could be encouraged to explore partnerships with LLM providers that prioritise fair data practices (such as the Fairly Trained initiative), or design for local use with lower energy demands. *If* GenAI is to play a role in the future of our craft then that future must not only be technically robust, but ethically and environmentally sustainable.

6. Discussion and conclusion

This article has advanced the concept of *technological reflexivity* as a way to critically engage with how digital tools – from long-standing CAQDAS platforms to newer GenAI integrations/offerings – shape the conditions under which qualitative research is conducted. Responding to the four guiding questions posed by Paulus and Lester (2023) concerning methods, the legitimacy of knowledge claims, researcher-participant relationships and tool design, I presented a situated, interpretive account of analysing the 'Alex' dataset using RTA and specific digital platforms. I have shown how the different analytic environments structure what becomes knowable in qualitative survey analysis and how digital infrastructures intervene in meaning-making processes. Through a posthumanist lens, I have argued that reflexivity is best understood as a distributed practice involving entanglements of human and non-human actors within distinct socio-political contexts, while RTA reminds us that interpretation is a matter of human judgment. Working reflexively with digital tools therefore involves negotiating this tension – analysis may be distributed, and meaning may take shape through many relations, but interpretive responsibility ultimately remains with the researcher. In this final section, I draw together these insights and highlight implications of digital tool integration into qualitative research.

Throughout the article, I traced how platform architectures and GenAI features shape and constrain interpretive possibilities. CAQDAS platforms embed assumptions that influence how data is structured and viewed. For example, they can fragment survey data into question-level views rather than case coherent ones, mediating what kinds of interpretation feel possible. I showed how automated features and GenAI outputs risk masking the interpretive labour central to RTA. Coding is not merely segmentation; it is a process of meaning-making that cannot be easily outsourced to digital tools. Yet automation does have a place in the workflow – it can generate moments of 'noticing' in large datasets when it surfaces patterns which researchers and other digital tools (like word searches) can then explore further. The danger lies in leaving these outputs uninterrogated. Chat tools simulate this dialogue and critical interrogation, but lack the relational sensitivity needed to interpret the emotionally charged, nuanced data about climate fears, frustrations, and hopes shared by the young people in this study.

One key issue with such outputs is that researchers cannot always detect why patterns surface, due to the 'black-box' nature of underlying models. I find the auditability features in MAXQDA an important step in the right direction here, but key aspects remain opaque – including the role of the training data, prompt logics, and the criteria for topic selection in chat-based interfaces. This raises important questions about research transparency and accountability. As demonstrated throughout Section 5, interpretive responsibility becomes distributed across researchers, tools, and infrastructures. When meaning is produced through 'intra-action', responsibility is necessarily shared – but it must still be exercised through the situated judgment of the researcher. Accountability is therefore mediated but not displaced. Researchers remain answerable for their analytic claims, even when these are shaped by partially opaque tools. Reflexivity must therefore be designed into tools as well as practised by researchers. This aligns with critical feminist data scholars (D'Ignazio and Klein 2020), who frame reflexivity as a shared practice oriented toward data justice. Such a view resists locating 'bias' or 'transparency' problems solely in 'flawed' individuals or systems. Instead, it recognises that reflexivity is enacted across socio-cultural, techno-political, and historical structures that connect tools, researchers, institutions, and infrastructures. It implicates us as researchers, teachers and members of qualitative communities to collectively discuss and shape the future of qualitative research with or without GenAI.

This is about designing tools that better fit qualitative research practices, but it is not *only* this. It is about acknowledging that research takes place in contexts where there are unequal levels of power and influence between evolving systems and everyday practices of researchers. A political- or moral-economy lens (Wheeler 2019) enables reflection on these broader forces shaping the possibilities for qualitative analysis. GenAI is 'out of the bag' and is already embedded in infrastructures governed by large corporations who are keen to sustain markets for their products. At the same time, researchers in underfunded institutions may turn to these tools as necessary supports. Though posthumanist approaches help us see entanglements, they can obscure how power and accountability are unevenly distributed. Reflexivity may be shared, but the ability to exercise it is not equally available. This is not the time to polarise debates into those 'for' or 'against' qualitative analysis with technology/GenAI. Rather, it is the time for collective discussion (to which this special issue contributes) about what it means to work with non-human tools, how they affect analytic processes and how our methodological choices are situated within larger political and economic systems. As a teacher and practitioner, I feel strongly that we need these conversations with students and colleagues so we can credibly engage with research outputs that will inevitably be co-produced with these tools.

I close with an insight from ethical consumption and global responsibility. Iris Marion Young's (2006) 'social connection model of responsibility' argues that many individuals are implicated in global systems of inequality through everyday actions deemed 'normal' in particular contexts. Responsibility here cannot be isolated or blamed on individuals; it is shared amongst all whose actions contribute to unjust systems. Crucially, this is a forward-looking model that argues that responsibility can only be meaningfully discharged through collective action to create better systems. Whilst Young applied this to sweatshop activists, the principles have some parallels here. Our analytic decisions are made within systems we cannot fully control, but can still influence. As expectations around how to 'do' qualitative research evolve through dynamic intra-actions between humans and non-humans in materially situated contexts, we must come together as a community to shape that future. This is not the task of individual researchers alone. It is a collective challenge requiring coordinated efforts from research communities, software developers, institutions, and funders to ensure digital technologies strengthen rather than erode qualitative research values, and align with ethical commitments to data justice.

Author note

As noted throughout, I have engaged with GenAI tools in the analysis of the survey data. In revising this article, I also used ChatGPT-4.0 and later ChatGPT-5 (OpenAI) at two points. First, ahead of peer review, I worked through the manuscript paragraph by paragraph, using it to help condense sections and improve readability while retaining my own voice. Second, after receiving reviewer feedback, I drew on ChatGPT more explicitly as a thinking partner – using it to explore alternative phrasings, strengthen transitions, and reflect on how best to address the reviewers' comments. At all stages, I remained responsible for the content and direction of the article. ChatGPT supported the craft of writing, but the conceptual and analytic work remained mine.

Acknowledgments

I would like to thank the anonymous reviewers and the editors of this Special Issue for their generous and constructive feedback, which encouraged me to develop this article further. I also acknowledge SEEd as the custodian of the 'Alex' dataset and appreciate their support in enabling its use for this research.

Disclosure statement

The author is a Professional Trainer for MAXQDA, a role which provides free access to the software but no financial remuneration. The author also served as a trustee of the charity Sustainability and Environmental Education (SEEd) from 2019–2024. During this time, the author advised on survey design and analysed the resulting data for a report commissioned by SEEd. A consultancy fee (£2000) was awarded to the University of Essex for this work. SEEd were not involved in the analysis or interpretation presented in this manuscript.

Funding

The initial analysis of the SEEd Youth Listening Survey (Wheeler 2023) was funded by a small consultancy fee from SEEd, awarded to the University of Essex. The research and analysis presented in this paper received no external funding.

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Data Availability Statement

The data underpinning this article are owned by a third party and were accessed under a Data Use Agreement. The author does not have permission to share the raw data. Requests for access should be directed to SEEd (admin@se-ed.org.uk) and will be considered subject to their data governance procedures and restrictions on use.

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References

Arnot, G., S. Thomas, H. Pitt, and E. Warner. 2023. "It shows we are serious": Young people in Australia discuss climate justice protests as a mechanism for climate change advocacy and action. *Australian and New Zealand Journal of Public Health* 47 (3):100048. doi: 10.1016/j.anzjph.2023.100048

Ashwin, J., A. Chhabra, and V. Rao. 2023. *Using large language models for qualitative analysis can introduce serious bias*. Policy research working paper no. 10597. World Bank. https://documents1.worldbank.org/curated/en/099433311072326082/pdf/IDU0995939330948404166 0b85d0ab10e497bd1f.pdf.

Barad, K. 2003. Posthumanist performativity: Toward an understanding of how matter comes to matter. *Signs: Journal of Women in Culture and Society* 28 (3):801–31. doi: 10.1086/345321

Braun, V. 2025. Dr Braun(love) - or: How I learned to stop worrying and love GenAI (yeah nah). *YouTube video*, July 31. https://youtu.be/3zFQC3c-eQk?si=JM2EqZgvX3eycXbC. (date accessed 08/09/2025.

Braun, V., and V. Clarke. 2021. Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling and Psychotherapy Research* 21 (1):37–47. doi: 10.1002/capr.12360

Braun, V., and V. Clarke. 2022. *Thematic analysis: a practical guide*. London: SAGE.

Braun, V., V. Clarke, E. Boulton, L. Davey, and C. McEvoy. 2021. The online survey as a qualitative research tool. *International Journal of Social Research Methodology* 24 (6):641–54. doi: 10.1080/13645579.2020.1805550

Charmaz, K. 2014. *Constructing grounded theory*. London: SAGE Publications.

Chubb, L. A. 2023. Me and the machines: Possibilities and pitfalls of using artificial intelligence for qualitative data analysis. *International Journal of Qualitative Methods* 22 (1–16):16094069231193593. doi: 10.1177/16094069231193593

Combrinck, C. 2024. A tutorial for integrating generative AI in mixed methods data analysis. *Discover Education* 3 (1):116. doi: 10.1007/s44217-024-00214-7

Crawford, K. 2021. *The atlas of AI: power, politics, and the planetary costs of artificial intelligence*. New Haven and London: Yale University Press. doi: 10.2307/j.ctv1ghv45t

De Paoli, S. 2023. Performing an inductive thematic analysis of semi-structured interviews with a large language model: An exploration and provocation on the limits of the approach. *Social Science Computer Review* 42 (4):997–1019. doi: 10.1177/08944393231220483

D'Ignazio, C., and L. F. Klein. 2020. *Data feminism*. The MIT Press. doi: 10.7551/mitpress/11805.001.0001

Finlay, L. 2002. Negotiating the swamp: The opportunity and challenge of reflexivity in research practice. *Qualitative Research* 2 (2):209–30. doi: 10.1177/146879410200200205

Friese, S. 2025. Conversational analysis with AI (CA to the power of AI): Rethinking coding in qualitative analysis. *SSRN*. doi: 10.2139/ssrn.5232579

Hamilton, L., D. Elliott, A. Quick, S. Smith, and V. Choplin. 2023. Exploring the use of AI in qualitative analysis: A comparative study of guaranteed income data. *International Journal of Qualitative Methods* 22:16094069231201504. doi: 10.1177/16094069231201504

Harvey, M. 2021. *Climate emergency: how societies create the crisis*. Bingley, UK: Emerald Publishing Limited. doi: 10.1108/9781800433304

Hayes, A. S. 2025. "Conversing" with qualitative data: Enhancing qualitative research through large language models (LLMs). *International Journal of Qualitative Methods* 24:16094069251322346. doi: 10.1177/16094069251322346

Hitch, D. 2024. Artificial intelligence augmented qualitative analysis: The way of the future? *Qualitative Health Research* 34 (7):595–606. doi: 10.1177/10497323231217392

Jackson, A. Y., and L. A. Mazzei. 2023. *Thinking with theory in qualitative research*, Second ed. Routledge, Taylor & Francis Group. doi: 10.4324/9781315667768

Jackson, K., and P. Bazeley. 2019. *Qualitative data analysis with NVivo*, 3. ed. London: Sage.

Jackson, K., T. Paulus, and N. Woolf. 2018. The walking dead genealogy: unsubstantiated criticisms of qualitative data analysis software (QDAS) and the failure to put them to rest. *The Qualitative Report* 23 (13):74–91. doi: 10.46743/2160-3715/2018.3096

Jasanoff, S., and S.-H. Kim. 2013. Sociotechnical imaginaries and national energy policies. *Science as Culture* 22 (2):189–96. doi: 10.1080/09505431.2013.786990

Lester, J., and T. Paulus. 2025. The AI Dilemma in Qualitative Research: Progress, Pitfalls, and the Price of Innovation. *Computer assisted qualitative data analysis: A University of Surrey Blog* (Accessed 24/02/25). https://blogs.surrey.ac.uk/caqdas/2025/03/25/the-ai-dilemma-in-qualitative-research-progress-pitfalls-and-the-price-of-innovation/.
(date accessed 24/02/25)

Mazzei, L. A. 2013. Materialist mappings of knowing in being: Researchers constituted in the production of knowledge. *Gender and Education* 25 (6):776–85. doi: 10.1080/09540253.2013.824072

Mellon, J., J. Bailey, R. Scott, J. Breckwoldt, M. Miori, and P. Schmedeman. 2024. Do AIs know what the most important issue is? Using language models to code open-text social survey responses at scale. *Research & Politics* 11 (1):20531680241231468. doi: 10.1177/20531680241231468

Montrosse-Moorhead, B. 2023. Evaluation criteria for artificial intelligence. *New Directions for Evaluation* 2023 (178–179):123–34. doi: 10.1002/ev.20566

Morgan, D. L. 2023. Exploring the use of artificial intelligence for qualitative data analysis: The case of ChatGPT. *International Journal of Qualitative Methods* 22:1–10. doi: 10.1177/16094069231211248

Müller, A., and S. Rädiker. 2024. "Chatting" with your data: 10 prompts for analyzing interviews with MAXQDA's AI assist. *Maxqda research blog*, August 12. https://www.maxqda.com/blogpost/chatting-with-your-data-10-prompts-for-analyzing-interviews-with-maxqda-ai-assist. (date accessed 24/02/25.

Nguyen-Trung, K. 2024. *ChatGPT in thematic analysis: can AI become a research assistant in qualitative research?* OSF PrePrint. https://files.osf.io/v1/resources/vefwc/providers/osfstorage/65b59ddd99d0100905626737?action=download&direct&version=3.

Paulus, T., and J. N. Lester. 2023. Digital qualitative research workflows: A reflexivity framework for technological consequences. *International Journal of Social Research Methodology* 1–14. doi: 10.1080/13645579.2023.2237359

Paulus, T., and V. Marone. 2024. "In minutes instead of weeks": Discursive constructions of Generative AI and Qualitative data analysis. *Qualitative Inquiry* 31 (5):395–402. doi: 10.1177/10778004241250065

Paulus, T., M. Woods, D. P. Atkins, and R. Macklin. 2017. The discourse of QDAS: Reporting practices of ATLAS.ti and NVivo users with implications for best practices. *International Journal of Social Research Methodology* 20 (1):35–47. doi: 10.1080/13645579.2015.1102454

Rädiker, S., and U. Kuckartz. 2020. *Analyzing open-ended survey questions with MAXQDA*. Berlin: MAXQDA Press. doi: 10.36192/978-3-948768027

Schreier, M. 2012. *Qualitative content analysis in practice*. London: Sage.

Silver, C. 2023. What's a foot in the qualitative AI space? *qualitative data analysis services*, May 5. https://www.qdas.co.uk/post/what-s-a-foot-in-the-qualitative-ai-space. (date accessed 23/07/24.

Silver, C. 2025. Moments that have changed the course of computer-assisted qualitative analysis. *Computer assisted qualitative data analysis: A University of Surrey Blog* (Accessed 06/05/25). https://blogs.surrey.ac.uk/caqdas/2025/01/07/moments-that-have-changed-the-course-of-computer-assisted-qualitative-analysis/

Silver, C., and N. Woolf. 2015. From guided-instruction to facilitation of learning: The development of *Five-level QDA* as a CAQDAS pedagogy that explicates the practices of expert users. *International Journal of Social Research Methodology* 18 (5):527–43. doi: 10.1080/13645579.2015.1062626

Silver, C., and N. Woolf. 2019. Five-level QDA method. In P. Atkinson, S. Delamont, A. Cernat, J.W. Sakshaug, & R.A. Williams (Eds.), *Sage research methods foundations*. SAGE Publications Ltd. doi: 10.4135/9781526421036818833

Terry, G., and V. Braun. 2017. Short but often sweet: The surprising potential of qualitative survey methods. In *Collecting qualitative data: a practical guide to textual, media and virtual techniques*, ed. V. Braun, V. Clarke, and D. Gray (pp. 15–44). Cambridge: Cambridge University Press.

Thomas, S. L., H. Pitt, S. McCarthy, G. Arnot, and M. Hennessy. 2024. Methodological and practical guidance for designing and conducting online qualitative surveys in public health. *Health Promotion International* 39 (3):daae061. doi: 10.1093/heapro/daae061

Trundle, C., N. Araújo, S. Khan, and T. Phillips. 2025. Beyond the mirror: Challenging the common assumptions of reflexivity in qualitative research. *International Journal of Qualitative Methods* 24:16094069251369311. doi: 10.1177/16094069251369311

Turner, D. 2024. Outsourcing decision making: AI, ethics, and qualitative research. *Quirkos blog*, February 1. https://www.quirkos.com/blog/post/outsourcing-decision-making-ai-ethics-and-qualitative-research/. (date accessed 24/02/25.

United Nations Environment Programme. 2024. *Artificial intelligence (AI) end-to-end: The environmental impact of the full AI lifecycle needs to be comprehensively assessed [issue note]*. https://wedocs.unep.org/20.500.11822/46288. (accessed 23/05/2025).

Wachinger, J., K. Bärnighausen, L. N. Schäfer, K. Scott, and S. A. McMahon. 2024. Prompts, pearls, imperfections: Comparing ChatGPT and a human researcher in qualitative data analysis. *Qualitative Health Research* 35 (9):951–66. doi: 10.1177/10497323241244669

Wheeler, K. in preparation. *To count or not to count: Analysing qualitative survey data.*

Wheeler, K. 2012. *Fair trade and the citizen-consumer: shopping for justice?* Hampshire: Palgrave Macmillan. doi: 10.1057/9781137283672

Wheeler, K. 2019. Moral economies of consumption. *Journal of Consumer Culture* 19 (2):271–88. doi: 10.1177/1469540517729007

Wheeler, K. 2022. Differences between thematic analysis and content analysis: Exploring environmental and sustainability education resources. *Sage Research Methods Cases*. doi: 10.4135/9781529798227

Wheeler, K. 2023. *Seed youth listening project report 2021-23: Attitudes to sustainability*. SEEd (Sustainability and Environmental Education). https://se-ed.org.uk/how-to-get-started/attitudes-to-sustainability-survey/.

Wheeler, K. 2025. How to use generative AI to assist the analysis of qualitative data. *Sage Research Methods: Data and Research Literacy*. doi: 10.4135/9781036217471

Woods, M., R. Macklin, and G. K. Lewis. 2016. Researcher reflexivity: Exploring the impacts of CAQDAS use. *International Journal of Social Research Methodology* 19 (4):385–403. doi: 10.1080/13645579.2015.1023964

Woods, M., and M. Wickham. 2006. Methodological implications of software use: An empirical investigation of the impact of software programs on literature analysis using N6 and NVivo 7. Quality and Impact of Qualitative Research, in Ruth, A. (Ed) Quality and Impact of Qualitative Research. 3rd annual QualIT Conference, Brisbane: Institute for Integrated and Intelligent Systems, Griffith University (pp 163-172).

Young, I. M. 2006. Responsibility and global justice: A social connection model. *Justice and Global Politics* 4 (4):102–30. doi: 10.1017/CBO9780511550744.005