

Human–Ai Collaboration in Qualitative Sustainability and Supply Chain Research: Cognitive Engagement, Interpretative Depth, and Ethical Implications

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Abstract

The integration of Artificial Intelligence (AI) is transforming qualitative research in sustainability and supply chain studies, particularly in areas requiring context-sensitive interpretation and decision-making. This study examines how AI tools influence researcher cognition, interpretative depth, and analytical rigor through semi-structured interviews with researchers actively using AI in qualitative workflows.

Findings indicate that AI enhances efficiency, supports idea generation, and reduces analytical workload. However, it also introduces risks, including surface-level interpretations, loss of contextual nuance, and potential algorithmic bias—critical concerns in sustainable supply chain contexts involving complex socio-environmental dynamics.

The study highlights prompt engineering and AI literacy as key competencies shaping research quality. It proposes a hybrid human–AI analytical approach that emphasizes critical oversight, iterative validation, and ethical reflexivity. The findings suggest that AI can strengthen qualitative research when used as a complement to, rather than a substitute for, human judgment.

Keywords: Artificial Intelligence, Qualitative Research, Sustainable Supply Chain, ESG; Supply Chain Governance, Cognitive Engagement, Data Interpretation, AI Ethics

Introduction

The rising integration of Artificial Intelligence (AI) tools into research workflows is casting a significant influence, some would say an incalculable one, over how qualitative inquiries are conducted, interpreted, and shared with the world. For as long as anyone can remember, qualitative research has relied chiefly on human

intelligence to delve into the intricacies of social life, what we might call the "low-level, parallel-processing" operations of the human brain (Creswell & Poth, 2018). Much has been made of the commitments associated with the qualitative paradigm: valuing narrative form, for instance, or the sorts of in-depth analysis that yield insightful themes and categories. To be sure, some paradigmatic commitments have also translated into valuing the whole range of emergent and canny coding practices that good qualitative researchers know and use. But is AI going to change all that?

AI tools like ChatGPT and other large language models (LLMs) are being used more and more to help with literature reviews, coding interviews, theme identification, and even narrative generation. The speedy processes and fresh takes these tools provide us with bring up some crucial issues tied to the insight's depth, reliability, and authenticity. Who wouldn't want a tool to do all that for them? But what happens if our reliance on tools like this grows? What happens if the process of using them too much leads us down a mental path where we stop thinking as critically, detecting bias as well as we used to, and being as contextually sensitive as we need to be for rigorous qualitative analysis? (Stanford HAI, 2024), Regardless of the increasing use of AI in educational environments, there is little to no literature about how it affects interpretive depth and cognitive engagement of qualitative researchers. The majority of available literature focuses on AI's functions in quantitative research or deals with changes in technology rather than looking into the methodological and epistemological consequences for qualitative inquiry. This gap requires an examination of the impacts of AI on the structure and the thought process of researchers doing qualitative studies (Noble, 2018).

From a supply chain and sustainability perspective, qualitative research plays a critical role in unpacking complex, multi-actor interactions, particularly in areas such as stakeholder engagement, governance structures, and ESG-related decision-making. Unlike quantitative approaches that prioritize optimization and efficiency, qualitative inquiry enables researchers to capture the socio-environmental dynamics, power relations, and contextual nuances embedded within supply chain systems. These interpretative processes are essential for understanding how sustainability practices are negotiated, implemented, and experienced across different nodes of the supply chain (Seuring & Müller, 2008; Carter & Rogers, 2008). In this context, the integration of AI into qualitative research introduces both opportunities and epistemological tensions. While AI tools can enhance analytical efficiency and support data processing across complex supply chain networks, they may also risk oversimplifying context-dependent insights that are critical for sustainable decision-making. As supply chains increasingly emphasize transparency, accountability, and ethical governance, the depth and integrity of qualitative interpretation become central to producing meaningful and responsible research outcomes. Therefore, examining how AI reshapes cognitive engagement and interpretative practices is not only a methodological concern but also a crucial issue for advancing sustainability-oriented supply chain research.

This study aims to fill this gap by exploring the ways AI tools alter the levels of intellectual involvement, decision-making, and interpretation associated with qualitative research. Drawing from the activity of researchers who integrate AI into their work, this paper attempts to expose the ethical, cognitive, and methodological issues that accompany unrestrained enthusiasm for technological advancement. The results will establish AI-integration

policies for qualitative research that undermine the autonomous role of AI while preserving critical human reasoning tailored to scholarly work within an automated environment. Against this backdrop, this study investigates how AI-mediated analytical processes influence researcher cognition, interpretative depth, and decision-making in qualitative sustainability and supply chain research, with the aim of identifying practices that preserve methodological rigor while leveraging technological efficiency.

Research Questions

1. How do AI-assisted analytical processes reshape researcher cognitive engagement and interpretative practices during qualitative data analysis in sustainability and supply chain research contexts?
2. To what extent does the use of AI influence the interpretative depth, contextual sensitivity, and analytical rigor of insights generated from qualitative data in sustainable supply chain studies?
3. What methodological and ethical strategies can be developed to ensure that AI functions as a complementary tool that enhances, rather than compromises, human judgment and interpretative quality in qualitative sustainability and supply chain research?

Literature Review

AI in Qualitative Research: Emerging Opportunities and Tensions

The integration of Artificial Intelligence (AI) into qualitative research is gaining momentum, prompting both optimism and concern within scholarly discourse. Traditionally, qualitative research emphasizes depth, reflexivity, and contextually grounded interpretation (Creswell & Poth, 2018). However, the emergence of AI tools such as ChatGPT, and other machine learning-based platforms has begun to reshape data processing, coding, and thematic analysis (Saldaña, 2021) (Flick, 2022).

AI and Cognitive Efficiency in Qualitative Analysis

Empirical studies report that AI can substantially reduce the cognitive load associated with repetitive analytic tasks, including transcript organization and theme generation (Marzuki, Hanim, & Kaeppl, 2023; Microsoft Research, 2023). These gains in efficiency may allow researchers to devote more attention to higher-order analytical tasks. Nonetheless, several scholars caution that reliance on AI can compromise the interpretative richness and contextual sensitivity central to qualitative inquiry (Gao, Liu, & Wang, 2022) (Barocas & Selbst, 2016) (O'Neil, .2016)

Ethical Risks and Interpretative Limitations of AI

A recurring concern is the tendency of AI systems to produce generalized, surface-level summaries that may overlook emotional and cultural nuance. This is particularly problematic in studies involving marginalized communities or sensitive topics, where misrepresentation may result in epistemic harm (Bender et al., 2021). Additionally, the potential for algorithmic bias, data privacy violations, and the opacity of AI decision-making processes—the so-called “black box” issue—poses ethical challenges for researchers (Floridi & Cowls, 2019; Stanford HAI, 2024).

Cognitive Augmentation and the Risk of Cognitive Outsourcing

From a cognitive perspective, AI functions as a decision-support mechanism, augmenting researcher engagement by reducing extraneous cognitive load and enhancing ideation (Jarrahi, 2018; Sweller, 1988). However, scholars caution against “cognitive outsourcing,” where critical reasoning and reflexive skills may atrophy due to overreliance on automated systems (Marzuki et al., 2023).

Prompt Engineering and AI Literacy as Emerging Research Competencies

The effectiveness of AI tools in qualitative contexts is further contingent on prompt engineering—a process that demands strategic and contextually informed input to generate meaningful outputs. Grawal et al. (.2019) and Mollick (.2024) argue that prompt quality directly influences the accuracy and relevance of AI responses, necessitating the inclusion of prompt engineering and AI literacy in research training curricula (Microsoft Research, 2023; Noble, 2018).

Hybrid Human–AI Approaches in Qualitative Research

In response to these challenges, the literature increasingly advocates for hybrid methodologies that combine AI-assisted efficiencies with human interpretive oversight. Such models involve iterative prompt revision, collaborative coding between human and AI agents, and rigorous validation techniques to preserve the epistemological integrity of qualitative analysis (Saldaña, 2021; Flick, 2022). (Brynjolfsson & McAfee, 2014) (Thomas, 2018)

Toward a Balanced and Ethical Integration of AI

Overall, the literature underscores the need for a balanced, ethically informed approach to AI integration in qualitative research—one that maintains the centrality of human judgment while leveraging the computational strengths of emerging technologies.

Conceptual Framework

Building on the reviewed literature, this study develops a conceptual framework to explain how AI-mediated processes influence qualitative analysis, with particular emphasis on cognitive engagement and interpretative depth.

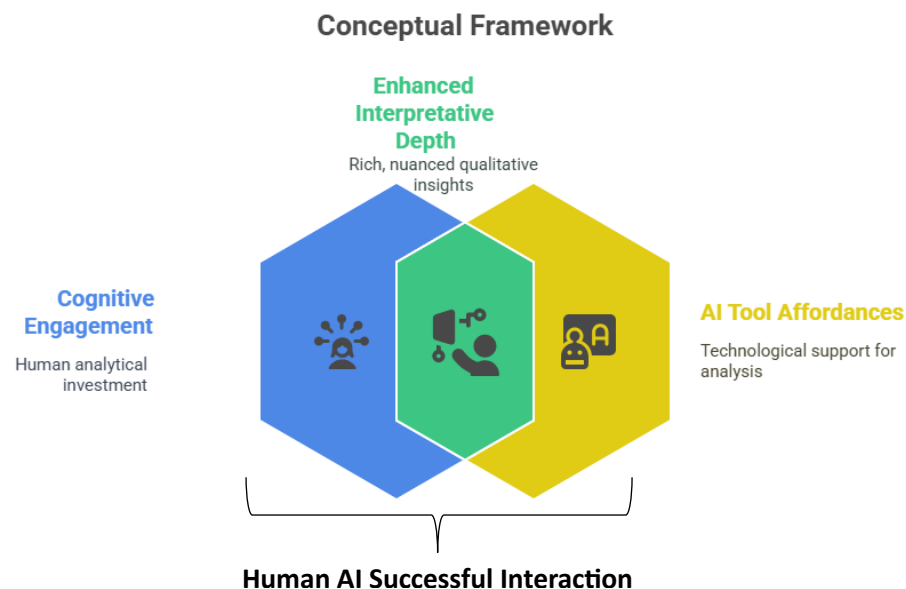


Figure 1. Conceptual Framework of AI-Mediated Cognitive Engagement and Interpretative Depth in Qualitative Research

The proposed framework centers on the interaction among three primary constructs: AI tool affordances, cognitive engagement, and interpretative depth.

AI tool affordances refer to the functional capabilities of AI systems, including coding assistance, text summarization, and theme generation. These affordances shape how researchers engage with qualitative data, either by reducing cognitive load and enhancing ideation or by encouraging overreliance and cognitive outsourcing. Cognitive engagement represents the extent to which researchers invest mental effort in data interpretation, critical thinking, and reflexive analysis. Higher levels of engagement are associated with more active sense-making processes, while reduced engagement may lead to passive reliance on AI-generated outputs. Interpretative depth reflects the richness, contextual sensitivity, and analytical rigor achieved in qualitative analysis. It captures the ability of researchers to uncover nuanced meanings, contradictions, and socio-cultural dimensions embedded in the data.

As illustrated in Figure 1, AI tool affordances influence cognitive engagement, which in turn shapes interpretative depth. This sequential relationship highlights the importance of maintaining active human involvement in AI-assisted qualitative research to ensure meaningful and contextually grounded interpretation. The framework also acknowledges the role of enabling conditions, such as prompt engineering, AI literacy, and ethical reflexivity, which can enhance the effectiveness of human–AI interaction and mitigate risks related to bias, hallucination, and loss of contextual nuance. Overall, the framework positions AI not as a substitute for human interpretation, but as a mediating force that reshapes the cognitive processes underlying qualitative analysis. It emphasizes the need for a balanced human–AI collaboration to preserve analytical depth and epistemological rigor.

Research Methodology

Research Design

This study adopts a qualitative interpretivist design, grounded in constructivist epistemology. It seeks to understand how researchers experience and make sense of AI integration in qualitative analysis, with a focus on cognitive engagement and interpretive depth outcomes.

Participants and Sampling

1. Target Population

Target Group: Academic researchers and postgraduate students using AI in qualitative workflows.

Sampling Method: Purposive and snowball sampling ensured participants had relevant experience.

Sample Size: 7 participants to achieve thematic saturation while maintaining manageability.

Data Collection Methods

1. Semi-Structured Interviews

2. Method: Semi-structured interviews lasting 45–60 minutes.

3. Format: Audio-recorded (with consent), then transcribed verbatim.

4. Focus: Participants' use of AI for coding, theme generation, and interpretation.

Data Analysis

To explore the cognitive and interpretative impact of AI tools on qualitative research, this study adopted a systematic thematic analysis approach, following the well-established framework by Braun and Clarke (2006). Thematic analysis was selected for its flexibility and capacity to uncover nuanced meanings within rich, descriptive data. It enabled the researcher to identify, analyze, and report patterns (themes) across interview transcripts in relation to the core research questions. The following phases were meticulously carried out

Phase 1: Familiarization with the Data

Immediately following transcription, the researcher engaged in intensive reading and re-reading of all interview transcripts to immerse in the dataset.

Phase 2: Initial Coding (Open Coding)

A line-by-line coding strategy was employed to generate open codes basic segments of meaning derived directly from participant narratives. Codes were tagged with short descriptors (e.g., *"time-saving," "lack of nuance," "boosted idea generation," "bias in AI"**) that captured their essence. These codes remained closely tied to the language and context of the participants, preserving emic perspectives.

Phase 3: Axial Coding and Theme Development

During axial coding, related codes were grouped into higher-order categories to identify central patterns and interrelationships. For example:

- Codes like *"AI makes me faster," "ChatGPT gives draft summaries,"* and *"saves mental energy"* were grouped under the theme "Enhanced Cognitive Efficiency".
- Codes like *"lost depth," "generalized summaries,"* and *"requires human checking"* were clustered into "Interpretative Shallowing".

Phase 4: Reviewing and Refining Themes

Preliminary themes were reviewed to evaluate:

1. Internal coherence (do all data excerpts within the theme align conceptually?)
2. External distinctiveness (are themes clearly distinguishable from each other?),
3. explanatory value (do the themes help answer the research questions?).

Some themes were merged, split, or renamed at this stage. For instance, initial themes "AI support" and "Reduced load" were merged into a broader theme: "AI as a Cognitive Partner", while a vague theme "ethical concerns" was refined into two sub-themes: "Bias in Output" and "Transparency and Trust".

Phase 5: Defining and Naming Themes

Each finalized theme was defined with a concise title, short paragraph capturing its conceptual boundaries, and illustrative quotes from participants to ground interpretations in empirical evidence.

Final themes included:

- AI as a Cognitive Partner

- Surface-Level Interpretation and Analytical Gaps
- Efficiency vs. Depth Trade-off
- Bias, Hallucination, and Ethical Vigilance
- Prompt Engineering and Researcher Agency
- Balanced Integration and Human Oversight

Ethical Considerations

This study received ethical clearance from the university's institutional review board. Ethical safeguards included Informed Consent, Anonymity, Confidentiality, Transparency.

Results and Discussions

This chapter presents the findings from in-depth interviews with researchers using AI tools in qualitative research. The results are thematically organized to respond to the three primary research questions:

Data from seven participants yielded six central themes, which reflect a complex and nuanced picture of AI's role in shaping contemporary qualitative research.

AI as a Cognitive Partner

AI tools were frequently described as “thinking companions” that enhanced researchers’ ability to conceptualize, synthesize, and mentally organize data. Rather than replacing researchers, AI acted as a form of cognitive scaffolding.

“Before, I would stare at the screen for hours trying to find a starting point. Now, I use ChatGPT to brainstorm and it gives me some direction. It doesn’t write for me—it just clears the fog.” – Participant 4

Participants identified three key ways AI supported their mental processes:

- **Mental Activation:** Generating lists of potential themes or literature areas jumpstarted mental engagement.
- **Idea Structuring:** Some participants used AI to develop outlines or to check the coherence of emerging categories.
- **Perspective Expansion:** AI sometimes offered unexpected angles or interpretations that participants had not initially considered, prompting further exploration.

These findings resonate with Sweller's (1988) theory of cognitive load, wherein AI reduces the “extraneous load” of searching, typing, and repetitive filtering, freeing up cognitive resources for deeper engagement.

Efficiency vs. Depth Trade-off

A dominant theme among participants was the trade-off between the efficiency provided by AI tools and the depth traditionally associated with qualitative research.

“Yes, it clustered responses quickly, but they were very surface-level. If I had submitted them as-is, I would have missed all the emotional subtext in the data.” – Participant 1

Participants described:

- **Fast Sorting, Shallow Meaning:** AI tools effectively categorized survey or interview responses, but outputs lacked depth and often needed extensive manual elaboration.

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- Reductionism Risk: AI grouped diverse participant voices into generalized themes, potentially erasing valuable nuance.

This mirrors the findings of Gao et al. (2022), who caution that AI-generated summaries may offer efficiency at the expense of interpretive accuracy and contextual relevance. The depth of thematic understanding especially in sensitive studies requires human insight, which machines cannot replicate.

Surface-Level Interpretation and Analytical Gaps

This theme underscores how AI tools, while grammatically competent, often lacked the interpretive and emotional intelligence required for rich qualitative insights.

“AI told me that my participants ‘liked their community’—but it missed how they said it through tears, through stories of loss and resilience. That matters.” – Participant 6 Key observations included:

- Lack of Cultural Sensitivity: AI often missed the socio-cultural context embedded in participant narratives.
- Tendency to Generalize: Responses like “participants are optimistic” glossed over critical contradictions and power dynamics evident in the original data.

The gap in analytical depth aligns with Bender et al. (2021), who argue that AI lacks lived experience and can only mimic rather than interpret language. For researchers working with marginalized or emotionally rich narratives, this lack of interpretative competence was particularly problematic.

Bias, Hallucination, and Ethical Vigilance

Nearly all participants expressed concerns about the reliability and objectivity of AI-generated outputs. Bias and factual errors (hallucinations) were commonly reported.

“ChatGPT gave me information about a journal article that didn’t exist. It sounded so real. If I didn’t cross-check, I would’ve cited a ghost.” – Participant 2

Subthemes:

- Embedded Bias: AI models reflected Western-centric epistemologies and often misinterpreted non-Western cultural references.
- Factual Errors and Hallucinations: AI sometimes “invented” plausible-sounding quotes, references, or summaries.
- Dependence on Prompt Quality: Poorly worded or vague prompts led to misleading outputs, increasing the risk of misinterpretation.

These concerns directly support ethical warnings issued by Floridi & Cowls (2019) and Stanford HAI (2024) about the potential for AI tools to reproduce systemic biases and fabricate information, particularly when used uncritically.

Prompt Engineering and Researcher Agency

A critical insight was that the researcher’s ability to effectively communicate with the AI through prompt engineering significantly shaped the quality of output.

“Once I learned to ask better questions like specifying tone, context, even assumptions my results got much better. You have to treat AI like a collaborator with strict instructions.” – Participant 3 Key observations:

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- Learning Curve: Participants developed better prompting skills over time, often through trial and error.
- Prompt Specificity: Clearer, more detailed prompts yielded more relevant, nuanced, and accurate responses.

- Empowered Use: Participants who mastered prompt engineering felt more in control of the research process and used AI more effectively and ethically.

This finding aligns with Liu et al. (2021), who emphasize prompt engineering as a critical skill for interacting meaningfully with generative models. It also supports Microsoft Research (2023) in advocating for AI literacy in academic training.

Balanced Integration and Human Oversight

Ultimately, participants advocated for a hybrid research model, combining AI's speed and structure with human critical thinking and contextual awareness.

"AI helps me prepare a skeleton but I flesh it out. I add the context, the emotion, the theoretical links. That's something only I can do." – Participant 5 Subthemes:

- Complementarity, Not Replacement: AI was most effective when used to support—not supplant - human interpretation.

- Peer Debriefing and Validation: Several participants cross-checked AI-generated categories with human colleagues for verification.

- Iterative Use: AI was used in cycles first for draft insights, then re-prompted or revised based on deeper manual analysis.

This hybrid approach echoes Johnson & Thomas (2024), who emphasize "collaborative human-AI workflows" that integrate automation with reflective interpretation.

Discussion

This chapter synthesizes the study's findings with existing literature to explore how AI tools influence cognitive engagement, interpretative practices, and ethical considerations in qualitative research. Through thematic analysis, this study identified six interrelated themes that collectively highlight both the transformative potential and critical limitations of AI integration in qualitative inquiry. The discussion is structured according to the study's three research questions

RQ1: How Do AI Tools Alter the Dynamics of Researcher Engagement During the Data Interpretation Phase?

The findings demonstrate that AI tools, particularly large language models like ChatGPT, serve as effective cognitive partners by enhancing mental activation, reducing analysis fatigue, and supporting ideation. This is consistent with Jarrahi (2018), who theorized that AI can augment rather than replace human cognitive functions in complex decision-making tasks. Participants in this study described AI as helpful for "clearing the fog" when beginning analysis or organizing chaotic data points—a role akin to cognitive scaffolding.

From a theoretical standpoint, Sweller's (1988) Cognitive Load Theory provides a useful lens: AI tools reduce extraneous cognitive load (e.g., repetitive sorting or summarization), allowing researchers to focus on germane

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load, such as drawing theoretical connections. However, these benefits must be balanced against the potential erosion of cognitive skills if researchers outsource too much of their analytical responsibility to machines (Marzuki et al., 2023). Furthermore, the interactive nature of AI introduces a new dynamic: researchers must learn not only how to think critically but also how to prompt effectively. Thus, AI alters engagement not just by reducing mental burden but by reshaping the skills required for scholarly inquiry prompt engineering becomes a new academic competency.

RQ2: How Does the Use of AI Affect the Richness and Depth of Insights Derived from Data?

While AI was found to enhance analytical speed, it often did so at the expense of depth and contextual nuance. Participants noted that AI-generated themes tended to be surface-level, lacking the emotional resonance or cultural specificity needed in interpretive work. This aligns with Gao et al. (2022) and Bender et al. (2021), who argue that AI lacks embodied knowledge and thus struggles with interpretative depth especially in contexts that demand empathy, reflexivity, and cultural understanding. In many cases, AI grouped emotionally rich or contradictory responses under generalized labels such as “satisfaction” or “positive perception,” effectively flattening diverse voices. This phenomenon poses ethical and methodological risks, particularly in studies involving marginalized communities or sensitive topics where participant voice is central.

These findings reaffirm the importance of human oversight and iterative analysis. While AI can provide a structural foundation, final interpretations must be guided by researchers’ contextual literacy and theoretical sensitivity. AI tools, in their current form, are not yet equipped to handle the hermeneutic complexity of deep qualitative interpretation on their own.

RQ3: What Best Practices Ensure That AI Complements, Rather Than Compromises, Human Interpretation in Qualitative Research?

Participants emphasized the need for hybrid methodologies that combine AI’s computational efficiency with the reflective and interpretive capabilities of human researchers. This confirms the recommendations of Saldaña (2021), Flick(2022), and Johnson & Thomas (2024), who advocate for collaborative workflows in which AI assists but does not dominate. Three core practices emerged:

1. Prompt Engineering: Researchers must develop advanced prompting skills to generate contextually relevant and accurate outputs (Liu et al., 2021).
2. Critical AI Literacy: Users must be trained to detect hallucinations, biases, and oversimplifications in AI-generated content (Microsoft Research, 2023).
3. Ethical Reflexivity: Ensuring ethical rigor involves questioning how AI tools may distort data and maintaining transparency about the limits of automation (Floridi & Cows, 2019; Stanford HAI, 2024).

A noteworthy implication is the evolving skillset required for future qualitative researchers. Beyond traditional analytical skills, scholars now need AI negotiation skills the ability to strategically collaborate with AI systems, just as they would with a co-researcher.

Theoretical and Practical Implications

Theoretical Contributions

- The study extends constructivist and interpretivist paradigms by demonstrating how meaning-making now occurs in dialogue not only with participants and data but also with AI.

- It introduces the notion of AI-mediated cognition in qualitative research, contributing to emerging theories in human-computer interaction and digital research methods.

Practical Contributions

- The findings offer a clear roadmap for integrating AI tools responsibly, emphasizing scaffolding (not replacement), validation through human judgment, and collaborative refinement.

- Educators and institutions can use these insights to design AI-integrated research training, including courses on prompt engineering, ethical use, and bias mitigation.

ESG and Governance Implications

- The findings of this study carry important implications for Environmental, Social, and Governance (ESG) practices within sustainable supply chain management. As organizations increasingly rely on qualitative insights to inform supplier selection, stakeholder engagement, and sustainability reporting, the integration of AI into analytical processes introduces both opportunities and governance risks. While AI can enhance the efficiency of data processing and support large-scale analysis across complex supply chain networks, the tendency toward surface-level interpretation and potential algorithmic bias may undermine the credibility and inclusiveness of ESG-related decision-making.

- From a governance perspective, the use of AI in qualitative analysis necessitates greater transparency, accountability, and methodological rigor. Organizations must ensure that AI-assisted insights are subject to human validation, particularly when dealing with sensitive social and environmental data. This includes establishing clear protocols for prompt design, data verification, and bias mitigation to prevent the misrepresentation of stakeholder voices—especially those from marginalized or underrepresented groups within the supply chain.

- Furthermore, the study highlights the need to embed AI literacy and ethical reflexivity into organizational governance structures. Training programs for analysts and decision-makers should emphasize critical engagement with AI outputs, rather than passive acceptance. In doing so, firms can better align AI adoption with ESG principles, ensuring that technological efficiency does not come at the expense of interpretative depth, ethical responsibility, or stakeholder trust.

- Ultimately, responsible AI integration in qualitative supply chain research supports more informed, transparent, and context-sensitive sustainability governance, reinforcing the role of human judgment as central to ethical and effective decision-making.

Limitations of the Study

While rich in detail, the study has several limitations:

- The sample size was small ($n=7$), and participants had varying levels of AI familiarity, which may influence the generalizability of findings.

- All participants were academic researchers, limiting the perspective from other fields such as journalism, public policy, or clinical research.

- The study focused on generative AI tools (e.g., ChatGPT), but did not explore more advanced domain-specific AI software (e.g., Dedoose, Atlas.ti).

Directions for Future Research

This study opens several avenues for future exploration:

- Longitudinal studies tracking how AI use impacts researcher cognition over time.
- Cross-cultural comparisons examining how researchers in different socio-cultural contexts perceive and engage with AI tools.
- Collaborative AI research models, especially in interdisciplinary or multilingual teams.
- Ethnographic research on AI in practice, documenting how researchers use, mistrust, and reinterpret AI outputs in real time.

Conclusion

This study highlights the dual role of AI in qualitative research as both a powerful ally and a potential disruptor. While AI tools can enhance cognitive engagement and streamline analysis, they also risk diminishing interpretive quality and reinforcing biases if used uncritically. The key lies in fostering human-centered, ethically reflective, and strategically hybrid research practices. By equipping researchers with the skills to engage with AI thoughtfully, we can harness its potential while safeguarding the depth, context, and humanity that define qualitative inquiry.

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