Comparing Human and AI-Driven Data Analysis in Qualitative Research in Agriculture Education

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Introduction

To compete with the technological advancement and change happening globally, it will be necessary to advantageously utilize technological innovations, like ChatGPT, Microsoft CoPilot, and other software, to aid in qualitative research (Hitch, 2023). These applications store and facilitate information, conditions, and advanced data to be accessible to the public (Pletnov, 2024; Richter, 2024). Simulating human behaviors through artificial intelligence (AI) can be used in qualitative research to generalize rich data, highlight codes or themes, and understand relationships data may present (Grossman et al., 2023). In this study, researchers aim to analyze the use of AI through Microsoft CoPilot versus human behavior in qualitative coding methodologies. Researchers argue that AI applications may effectively create qualitative codes and thematic analyses when employed purposefully and guided by the purpose and research questions (Grossman et al., 2023; Hitch, 2023).

Theoretical Framework

AI is a recent technological advancement for social scientists in terms of application to coding, but AI, transcription services, and transformational applications have existed for quite some time, especially in agriculture (Lee et al., 2024; Pletnov, 2024). Venkatesh et al. (2003) constructed a framework, the Unified Theory of Acceptance and Use of Technology Model (UTAUT), based on various factors influencing digital users' technology adoption. This model predicts that four main constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) will determine the “user acceptance and usage behavior” of varied technology implementations (Venkatesh et al., 2003). Specifically for this study, UTAUT aids in determining how these factors pertain to adopting AI tools for qualitative coding. Furthermore, are there benefits to using AI in qualitative research, and how can researchers be encouraged to use these practices?

Methodology

To understand the impact of CoPilot in qualitative coding, researchers used comparative analysis. Comparative analysis is a method of examination used to analyze, coordinate, and compare texts, scales, items, etc. (Harvard University, n.d.). Researchers in this study used a hybrid approach of comparative analysis, combining two sets of data to analyze through the lens of a theory to generalize and make inferences (Harvard University, n.d.). This method of analysis allows researchers to dive deeper into a topic to produce scaffolded results, which may be more influential than single-source analysis (Harvard University, n.d.). Researchers obtained a set of 16 complete qualitative interviews that were used for a separate research study, which will remain anonymous to preserve the initial data collected. The interviewees were given pseudonyms to promote anonymity. Researchers manually coded the interview transcriptions

with open and focused coding (Tracy, 2013). Once human-coded, Microsoft CoPilot Pro (paid-for version) was employed to analyze the data. The interviews were combined into one file and shared with CoPilot with an intentional and specific instruction: "Please help qualitatively code these 16 interviews for open coding initial themes." CoPilot responded, "Sure, I would be happy to help with that!" and produced a complex data set for researchers to interpret.

Results

Researchers compared findings once qualitative codes and themes were obtained from human coding and CoPilot. Human-coded themes included management actions, goals, knowledge, legacy, stewardship, and outside factors, distributed in several sub-themes. CoPilot codes were motivation, goals and practices, challenges, management, community, and personal connection. Even though the code's names differed, theme definitions were highly similar. However, AI coding unified management actions and knowledge in a single theme (management) and added the community and motivation themes. After identifying the emerging themes, researchers requested CoPilot identify supporting quotes for each theme, which were contrasted with manually selected quotes. Supporting quotes were associated with the identical/similar theme in both coding formats. Quotes were contextualized within the same themes and were presented in almost identical length and word counting. Even though some evident differences emerged, no relevant findings or context-based facts were identified.

Conclusions & Implications

Upon analyzing the result of both coding methods (human and AI), emerging themes were produced similarly, resulting in overlapping conclusions. Each AI-coded theme was also a human-coded theme or sub-theme. Likewise, CoPilot (paid version) was selected so as not to compromise the original data set's confidentiality. From these results, we argue that utilizing AI would result in a beneficial form of comparison, allegory, or cross-checking in qualitative research. Due to the accuracy, time, and complexity of results provided by CoPilot, qualitative researchers may continue to implement AI as a means of methodological analysis.

Under the UTAUT constructs, researchers will need to perceive how implementing AI in their qualitative research will benefit them (cut time and energy costs), ease their effort (click of a button as opposed to hours of mining), act as a social norm (innovative methodology v. easy loophole), and reduce barriers (researcher bias, reaching saturation) (Venkatesh et al., 2003). For qualitative researchers, AI applications could facilitate single-researcher studies, offering a counterpart for interceding reliability and agreement. Utilizing AI applications to produce rich thematic codes may have the potential to aid in data analysis and create powerful platforms for researchers to base their research upon, integrating strong evidence through meaningful supporting quotes (Morgan, 2023). This comparative analysis offers preliminary findings of how AI applications could positively impact qualitative research and academia when implemented responsively. Even though qualitative researchers could consider employing AI applications for data analysis and visualization, further research is required to ensure trustworthiness.

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