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Artificial Intelligence in Psychological Qualitative Data Analysis: Is It a Balance Between Efficiency and Originality?

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ABSTRACT

Technological advancements have ushered in significant changes in the way activities are carried out across the world, including within the research domain. Artificial Intelligence (AI) tools are increasingly being applied to support a range of research tasks, such as data analysis. This has received both enthusiasm and skepticism. The purpose of this scoping review was to explore the benefits and drawbacks of using AI tools in analysing psychological qualitative data to establish if there is a balance between efficiency and human originality. Eight studies formed the sample, as there is limited research that utilised AI tools in analysing qualitative psychological data. Findings show that AI tools have the potential to make data analysis accurate, efficient, and scalable, improving behaviour prediction and giving nuanced and objective analysis. On the other hand, it was noted that these tools may perpetuate inherent biases, raise some ethical concerns, lack transparency, and may generate misinformation. To create a balance between efficiency and human originality, cognisance must be given to the fact that these tools must not come as a substitute for traditional qualitative analysis of psychological data, but must be used in a hybrid form of approach. Of importance, training data for these tools should always be updated to avoid bias and possible violation of human rights.

INTRODUCTION

Artificial Intelligence (AI) can be regarded as one of the most profound technological advances that has changed many facets of life in today's world. Chetwynd (2024)defines it as a general concept that can be implemented in certain types of machine learning or generated computation whose growth came alongside the development of computers. Christou (2023c) notes that AI is a term used to describe how machines are utilised to imitate human intelligence to carry out tasks that are normally performed by human beings. The introduction of AI in society has been received with both skepticism and optimism. On one hand, it has been regarded as dangerous and fake, whilst on the other hand, it has been welcomed as innovative and an excellent problem solver. Across many sectors of society, it has sparked excitement and concern. The use of AI has also spread across the research community, where it has received the same sentiments shared above.

To begin with, I will explore the emergence of AI. The history of AI is an unfolding narrative of human creativity and technological advancement, which can be traced from the mid-20th century to date. Chetwynd (2024) states that most scholars associate modern technological developments with the work of Alan Mathison Turing in the 1950s, and the term artificial intelligence was first coined at a conference in 1956 by a group of experts comprising Marvin Minsky, John McCarthy, Claude Shannon, and Nathan Rochester. This is the period in which Logic Theory was developed as the earliest form of AI programs with the capability to prove mathematical theorems (Paramasivam, 2022). In the 1960s, IBM's data processing system was introduced, marking a shift from solely electrochemical systems to early data processing machines, having a significant effect on how businesses process data (Mucci, 2024).

The 1980s saw the emergence of the desktop computer, software development, networking and connectivity, and storage advancements associated with the IBM PC and Apple Macintosh. From the 1990s to the early 2000s, there was an introduction of expert systems, which are computer programs that use rule-based reasoning to make decisions. Specifically, in the early 2000s, there occurred a wide use of data mining and search engines for extracting patterns and information from large datasets for instance Google, which is an example of an early AI driven information retrieval (Dwivedi, 2023). In the mid-2000s, there was an advent of CNNs (Convolutional Neural Networks), deep learning, and natural language processing (NLP) models, which enhanced understanding of text, leading to the development of AI chatbots, voice assistants, and automated language translation systems.

Today, AI is increasingly being used in processing and analysing big data in industries like finance, healthcare, e-commerce, and as an analytical tool for qualitative research data (Kariyapperuma, 2022), where it engages in sentiment analysis and extraction of opinion from textual data (Acheampong, 2021). It has also influenced research significantly with the use of groundbreaking models like GPT, BERT, and advanced computer vision systems. There is a rapid integration of AI technologies in our daily lives from voice assistants and recommendation engines to autonomous vehicles and advanced healthcare diagnostics (Cochrane, 2025). In a blog by Nowak (2025), AI reflects its intelligence using Machine Learning (ML) and Natural Language Processing (NLP) in quickly detecting trends, patterns, and anomalies that may not be identified by human effort. The emphasis on ethical considerations and data privacy in today's research community thus asks for responsible AI development to ensure beneficial contributions to society, balanced with ethical and safe practices.

Existing literature has some significant insights on the positive and negative contributions of AI in qualitative data analysis (QDA) (Dwivedi et al., 2023; Hitch, 2024; Morgan, 2023; Zhang et al., 2025). A highlight of the types of AI and AI tools that are commonly used in QDA becomes necessary. These include Natural Language Processing (NLP), Machine Learning (ML), Large Language Models (LLMs), Speech Recognition (ASR), Computer Vision, and commonly used tools for QDA include ChatGPT, Claude, Gemini (LLMs/NLP); NVivo, Atlas.ti, MAXQDA (NLP +ML), Microsoft Copilot (LLM and Notion AI, Google Docs + Gemini (LLMs). Most literature has focused on evaluating the use of ChatGPT in QDA and the assumption is that its evaluation can set the base for insights of the pros and cons of using various AI tools for this purpose (Bennis & Mouwafaq, 2025; Dwivedi et al., 2023; Haman & Skolnik, 2024; Morgan, 2023; Zhang et al., 2025; Zheng & Zhan, 2023).

Qualitative research involves analysis of large datasets, which may be time-consuming and cumbersome. Deep learning models like GPTs have been regarded as helpful, especially in performing literature reviews as they have been programmed to detect themes and key concepts automatically in consolidating large datasets (Christou, 2023b; Watson, 2022; Zhang et al., 2025). AI systems have also been credited with the ability to perform complex analyses, such as reflecting the connection between words and concepts within a text, and may use machine learning algorithms to mine text data for themes and patterns without having prior knowledge (Radford, 2018). Other researchers have encouraged the use of AI in thematic analysis as a way of bringing innovation to streamline and enhance the process (Bazeley, 2013) and as a way of revolutionising qualitative research (Benbya, 2020). Though this is commendable, however, considering the basic requirements of QDA, there will still be a need for human involvement through some manual coding or categorisation, as well as verification of the task performed by AI tools. Researchers must also maintain the principles of familiarising themselves with data and cross-referencing as recommended by Braun and Clarke (2022) to verify reliability in the use of AI. In addition, it is recommended that researchers understand these tools' strengths and weaknesses to ensure that quality is enhanced.

AI has been valued as an important tool that can be useful in creating new theoretical conceptualisation through analysing existing data and theoretical frameworks (Dwivedi et al., 2023). Through its use, researchers may shorten the time they need to identify key themes and concepts that may be required in producing a conceptual paper (Williams, 2024). To support this view, Christou (2023a) gave an example of a study by Gururangan et.al (2020), which was conducted using AI to generate textual data for qualitative research on social and behavioural sciences, and another by Kesavan et.al. (2019), who utilised AI to analyse social media images and extracted recurring visual themes to develop captions. These examples reflect that AI can lessen the task of analysing large datasets, which promotes efficiency. Some areas that can benefit from using AI to analyse data and generate text data include language, culture, communication, and management (Christou, 2023b). However, the tools should be used wisely and in an ethical manner.

Though the use of AI in QDA is a welcome innovative and efficient way, it has got some drawbacks which researchers must take into consideration when utilising its tools. One of these is that, some deep learning models like GPT have been accused of sometimes failing to give authentic, correct or reliable information or picking errors and inconsistencies in literature (Buruk, 2023; Liu, 2023; Saliba, 2023; Zhou, 2023) which according to (Christou, 2023b) may result in inaccurate conclusions, false systematic reviews as well as incorrect conceptualisation of phenomena under study. Related to this, Lee (2022) and Qiu (2023) point that deep learning models have the potential to create fake stories which may lead to the spread of wrong information or infodemics and propaganda. Christou (2023b) further argued that if the training data is distorted or the model is erroneously calibrated, then there will be high chances that a GPT would produce faulty results. In addition, Christou (2023c) says that deep learning models are restricted in the sense that they cannot modify user-generated content and researchers may not have full control over the content generated (Qasem, 2023), which can be troublesome in conceptual research where the aim will be to create new theoretical frameworks and conceptual models. The models may lack the human capacity to understand the nuanced and intricate nature of academic writing and may fail to contrast reliable and unreliable sources. Grimmer (2021) added that sometimes overreliance on these models when conducting literature reviews may rob researchers of their independent and critical thinking. The implication being that qualitative researchers end up not keeping up to the expected standards of using their expertise and skills in synthesising data, forming connections, conceptualisations, and propositions.

Machine learning algorithms like GPTs have been associated with perpetuating some of the biases and misperceptions found in society. Arguments have been presented on how these models may be influenced by social and cultural factors used by the data that train them, thereby leading to consolidation and continuation of existing prejudices, hierarchies, and some dilemmas (Buolamwini, 2018; Chetwynd, 2024) as well as toxic stereotypes and inequalities (Bolukbasi, 2016). These authors stressed that there must be an epistemological stance that should be in place to recognise such influences to minimise the risk. Related to this, several researchers and users highlighted the lack of transparency as an issue of concern that has been raised against generative AI when used in qualitative studies (Adadi, 2018; Clark et al., 2025; Dwivedi et al., 2023). As a remedy to this, Bender (2018) emphasised that researchers need to be transparent and honest when they talk of the limitations and biases of language models, as transparency is critical in both qualitative research and AI-assisted analysis.

Another concern came from Sousa (2023), who states that as deep learning models use large datasets for effective training, it may arouse privacy and security issues where sensitive or personal data are concerned. For instance, private information like emails or social media posts has been given as examples of data that can be used to train these models, leading to the generation of relatively private content making people concerned about having their personal data being exposed (Schwartz, 2020). The fact that these models may fail to understand standards of handling data in the manner that humans do raises controversy in using AI in analysing qualitative research data.

This paper aims to explore how AI has been applied to enhance the efficiency of data analysis whilst maintaining integrity in qualitative psychological research focusing on its application, benefits, drawbacks, and future directions. The basic question being, does the use of AI tools in analysing psychological qualitative research data simultaneously enhance efficiency and promote human originality?.

METHODS

This paper takes the reader through a discussion of the use of AI in analysing data from qualitative psychological research using a critical approach. I conducted a scoping review of relevant articles from across the globe. The scoping review was not registered since it's not mandatory to register scoping reviews; however, I tried to follow the PRISMA ScR checklist to meet its reporting standards.

Eligibility Criteria

This study comprised of studied conducted using AI tools to analyse data or which reviewed the use of such tools in psychology qualitative studies. Studies that used AI tools to analyse psychological quantitative data were excluded. Studies that explored the benefits and drawbacks of using AI tools in analysing psychological qualitative data were included. Most of these studies would also give recommendations on how AI could be included in psychological research. This review did not focus on a specific context therefore studies from across the globe were included for as long as they focused on psychological qualitative data analysis using AI.

Types of Sources of Evidence

Sources of information were drawn from literature search platforms where primary and secondary research studies were extracted. The review included studies written in English only as there were no resources for translation. I searched and included the studies published between 2015 and 2025 since the use of AI tools in research became more common in the 2020s. Studies that included analysis of quantitative psychological data or any other research data which was not related to psychology were excluded.

Search Strategy

The sample for this scoping review was drawn from two databases, specifically ScienceDirect and APA PsycNet, and three publisher platforms, namely Taylor and Francis, Springer.com, and Frontiers, through a three-phase search strategy. The initial phase searched the two databases to identify relevant records. In the second phase, the search strategy was developed according to the previous phase using all identified key terms and databases and publisher platforms were searched. Search terms included:

1. 'AI' OR 'Artificial Intelligence' RR 'AI tools' OR 'machine learning' OR 'ML' or 'Natural Language Process' OR 'NLP' OR 'Large Language Models' OR 'LLM' AND
2. 'qualitative data analysis' OR 'textual analysis' OR 'thematic analysis' OR 'coding qualitative data' OR 'qualitative research methods' OR 'content analysis' AND
3. 'psychology' OR 'mental health' OR 'psychological research' OR 'psychosocial behaviour' AND
4. 'efficiency' OR 'automation' OR 'timesaving' AND
5. 'originality' OR 'interpretation' OR 'creativity' OR 'humanity' OR researcher insight' OR 'human judgment'

In the final phase, the reference lists of all the included studies were screened for additional records. The final sample was selected from empirical research, which included qualitative studies, mixed-methods studies, comparative studies, and case studies; methodological papers, conceptual/theoretical papers and reviews, reports, reviews, and grey literature.

Study Selection

After retrieving all related studies, I exported them to EndNote reference manager, where duplicates were carefully removed. The inclusion and exclusion criteria were followed in screening the titles and abstracts of studies from each database or publisher platform. At the end, full texts were retrieved for all studies that passed the title and abstract screening.

My search of databases and other sources yielded 956 records. Duplicates were removed to remain with 725, which were screened at the title and abstract level resulting in 85 records being evaluated for eligibility. From these, 77 were excluded as they were either focusing on qualitative research in general, not specifically on psychology, or they were focusing on psychological quantitative data. Eventually, 8 articles became the sample for the scoping review.

Analysis and Presentation of Results

Thematic analysis was conducted for this scoping review. The benefits and drawbacks of using AI tools in psychological qualitative data analysis were summarised for each study, then those that were related were presented under one theme.

RESULTS AND DISCUSSION

The Application of Artificial Intelligence in Qualitative Psychological Research

The most common tool that was analysed or used in the reviewed studies was ChatGPT. From the selected studies, two overarching themes emerged which had sub-themes under them. These include the benefits of using AI tools in qualitative analysis of psychological research and the drawbacks or limitations of such tools. They were further divided into subthemes showing specific concerns and advantages. Under the benefits, the subthemes included enhanced accuracy, improved efficiency, ability to analyse large datasets, pattern and trend identification, improved behaviour prediction, as well as nuanced and objective analysis. Subthemes for the drawbacks included inherent biases in training, opacity of AI systems (black box), risk of AI-generated misinformation, ethical challenges, theoretical concerns, dependence on human validation, and rapid technological advancement.

Enhanced accuracy was raised by several researchers as an advantage of using AI tools in qualitative data analysis. Salah et al. (2023) say use of ChatGPT can facilitate automation of coding and categorisation process, thereby reducing the risk of coder bias at the same time improving the reliability of the research results. Chen et al. (2024) also supported that it enhances the reliability of research outcomes. In addition to this, Bennis and Mouwafaq (2025) added that there will also be consistency in qualitative coding, which can yield perfect concordance. Ocana Flores and Luna (2024) note that these tools provide accurate assessments when compared to human judgments, which reduces bias and help in analysing large volumes of data. Dave et al. (2022) and Salah et al. (2024) support this by saying the tools improve accuracy in classification tasks. Overall, the researchers emphasise that using AI tools can help qualitative researchers to yield accurate analysis.

Another advantage related to accuracy is efficiency, which was also a common theme emerging from the reviewed studies. It was noted that by automating tasks, tools like ChatGPT significantly reduce the time needed for data analysis, thus giving researchers time to focus on other critical aspects of their work (Firmin et al., 2017; Salah et al., 2023; Salah et al., 2024). Other scholars emphasise that these tools are efficient to an extent that they can quickly analyse large qualitative datasets, which gives researchers room to engage in other subjective aspects like adjusting codes and theorising data (Bennis & Mouwafaq, 2025; Gibson & Beattie, 2024). Chen et al. (2024) added that besides efficiency, these tools also improve scalability, which improves research efficiency in comparison to manual coding and qualitative analysis. In connection with this, is that AI tools have been associated with the ability to analyse large datasets (Bennis & Mouwafaq, 2025; Firmin et al., 2017; Gibson & Beattie, 2024), for instance, when analysing social media posts or survey responses which may be challenging to analyse manually (Salah et al., 2023). Chen et al. (2024) acknowledge that this ability enables researchers to explore behavioural tendencies and emotional patterns that were previously difficult to attain.

Improved identification of patterns and trends has also been highlighted as a strength of using AI tools in qualitative data analysis. Salah et al. (2023) found that the use of ChatGPT facilitates the identification of patterns and trends in social data, which may not be that easy to discern manually and this provides in-depth knowledge into social phenomena. Other researchers found that AI tools can rapidly pick out frequent topics or linguistic patterns, which may be helpful in bringing out new areas of research or theory development. In addition, Ocana Flores and Luna (2024) note that these tools can show relationships in data that may be difficult for other practitioners to discern, giving deeper insights into individual and collective behavioural responses. Salah et al. (2024) also note that AI tools help in understanding complex relationships among variables, which may be difficult to conduct manually.

In addition, data analysis using AI tools has been associated with improved behaviour prediction. Salah et al. (2023) reiterate that tools like ChatGPT can model social interactions, leading them to analyse social data, which facilitates more accurate behaviour prediction. Related sentiments were shared by Ocana Flores and Luna (2024). The tools have been applauded for improving prediction and diagnosis of developmental risks of mental health, thereby promising accuracy (Dave et al., 2022). Hence, the tools have been associated with improvements in mental health risk detection which can lead to early intervention.

Nuanced and objective analysis is another theme that has been associated with the use of AI tools. Bennis and Mouwafaq (2025) pointed out that AI tools offer enhanced analytical depth, which unpacks nuanced insights and latent patterns that may be missed by human researchers. This may result in an in-depth psychosocial analysis. Related to this, Ocana Flores and Luna (2024) note that the use of these tools may help uncover hidden patterns as well as eliminate personal biases, hence ensuring the attainment of objective results. Moreover, they play a key role in facilitating understanding complex relationships by uncovering them, something which may be difficult to do manually (Dave et al., 2022). In other words, these findings reflect that AI tools may have the potential to dig deeper than human researchers, as well as enhance objectivity.

While AI tools offer numerous benefits for data analysis, some scholars have drawn attention to their potential drawbacks. One of the major drawbacks is the inherent bias embedded in the data training of these tools. It has been noted that AI models like ChatGPT are prone to biases which they gain from their training data posing the danger of reproducing cultural and social biases (Gibson & Beattie, 2024), or perpetuating harmful stereotypes, discriminatory language or biased perspectives which may impact negatively on objectivity and fairness of research findings (Bennis & Mouwafaq, 2025; Salah et al., 2023; Salah et al., 2024). They also have the potential to reflect gender, race, or cultural biases that may distort the validity of results (Chen et al., 2024). Ocana Flores and Luna (2024) noted that such biases are problematic in psychological contexts.

Another common drawback that came out was the opacity of AI systems, referred to as the 'Black box'. Salah et al. (2023) point out that AI models have complicated built-in systems, which make their internal workings unclear, thus compounding the assessment of the accuracy, reliability, and potential biases in the generated text. Gibson and Beattie (2024) raised concern over the integrity of data analysed by AI tools since researchers cannot verify the datasets or algorithms used to generate the responses. Chen et al. (2024) say the opacity of these tools creates interpretability challenges, which create difficulties in understanding their decision-making processes. Ocana Flores and Luna (2024) note that such black boxes rob the tools of transparency, as there will be limited insights into the rationale behind their predictions, which makes the users question their integrity. Overall, the complex nature of AI systems makes them lose credibility in some instances as users question how they make their decisions.

There are some conceptions that AI tools may sometimes generate misinformation. Some scholars state that tools like ChatGPT tend to produce 'hallucinated' text, which sounds very good yet entirely fabricated, posing the danger of coming up with flawed conclusions if there is no rigorous validation (Salah et al., 2023). Similarly, Firmin et al. (2017) say there is potential of misinterpretations from AI tools as they may generate surprising or contradictory results, which will require further human analysis to fathom the nuances surrounding the obtained results. In other words, these scholars are bringing out the idea that there is skepticism towards conclusions generated by AI tools, as sometimes the information may not be truthful.

Psychological qualitative research usually deals with sensitive data, hence failure of these tools to adhere to research ethical considerations poses some challenges. It has been noted that ethical concerns of informed consent, privacy, potential manipulation, and risk of deception may be infringed upon using AI tools in qualitative research (Salah et al., 2023). This has been supported by Chen et al. (2024), who say that these tools may not adhere to privacy concerns, especially when dealing with psychologically sensitive data. Data confidentiality, researcher bias, and failure to balance between AI and human experience have also been raised as some ethical challenges that may emanate from the use of these tools (Bennis & Mouwafaq, 2025). Ocana Flores and Luna (2024) reiterate that ethical concerns raised against the use of these tools also lead people to doubt the responsible implementation of AI technologies. In relation to this, Dave et al. (2022) note that these technologies lack social acceptance as there is a lot of skepticism and concern from the public on how personal data is collected, used, and secured. Thus, the lack of human involvement in AI data analysis raises serious ethical concerns that may affect the acceptance of the tools by the public and professionals.

Last, the use of AI tools has been associated with a negative impact on theoretical advancements as they overemphasise data creation and analysis to the neglect of further developing theories (Chen et al., 2024). Salah et al. (2023) acknowledge that AI tools can generate coherent text, but they lack dynamic creativity and innovation, evidenced by human effort, which threatens the introduction of groundbreaking insights or exploration of research areas that have not been explored. In this sense, the use of these tools may be regarded as detrimental to theoretical development.

Implications and Future Directions for AI Integration in Qualitative Psychology

The findings of this scoping review suggest that, although AI tools are increasingly being adopted in qualitative research, their application remains marked by both significant strengths and notable limitations. Moreover, the current review largely echoes what other scholars have observed regarding the use of AI in data analysis more generally, without offering insights that are unique to psychological research. In addition, ChatGPT was found to be the most used AI tool in psychological research, which was also found to be common by other researchers (Bennis & Mouwafaq, 2025; Dwivedi, 2023; Haman & Skolnik, 2024; Morgan, 2023; Zhang et al., 2025; Zheng & Zhan, 2023). This means that common issues in using AI tools in psychological qualitative research resonate with what was found also in other fields.

Utilisation of AI tools has been associated with positive outcomes like improved accuracy and efficiency, which was noted to lessen the burden on the researcher as large datasets were reported to be analysed swiftly and with accuracy. These positive outcomes have also been confirmed by other researchers who looked at this issue across different fields (Christou, 2023b; Radford, 2018; Watson, 2022; Zhang et al., 2025). This asks researchers to embrace these tools, taking into consideration that they still need to be involved and maintain integrity.

On the other hand, a lot of negatives have been found by the studies reviewed in this study. This shows that although AI tools can make research fast and reduce the pressure on the researchers, concerns must be raised about the information that they generate and how they make decisions as well as the implications of their conclusions on society. Concerns of ethical issues, misinformation, black box effect, lack of creativity, and that of transparency have also been noted in other studies (Buruk, 2023; Christou, 2023b; Lee, 2022; Liu, 2023; Qiu, 2023; Saliba, 2023; Zhou, 2023). Lack of transparency creates a significant tension with the core values of qualitative psychological research, which prioritise interpretive depth, reflexivity, and researcher subjectivity. The ‘Black box’ nature of the systems limits researchers’ ability to be fully involved with the data, challenging assumptions or making nuanced interpretive decisions, which are critical factors for ensuring originality and richness of qualitative insights. Taking this into consideration, a lot needs to be done to make researchers have confidence to use these tools in a trusting manner. The use of AI tools then becomes double-wedged wedged where on one end, the tools offer efficiency and scalability at the same time, heavily costing creativity and contextual meaning-making processes that define human-led analysis.

Conclusion

A growing interest in the use of AI tools for psychological qualitative data analysis has been highlighted by this scoping review and it revealed both their transformative potential and inherent limitations. AI tools have significant benefits in terms of accuracy, efficiency, scalability, and consistency, which facilitate the management and exploration of increasingly large and complex qualitative datasets. However, there are concerns around opacity, interpretive shallowness, biases, and lack of contextual sensitivity of these tools, which raises issues on their compatibility with the core principles of qualitative inquiry, such as reflexivity, subjectivity, and creative interpretation. As a result, utilisation of AI tools need not be regarded as a substitution of human insight but as a dynamic balance between automation and originality. Future work must consider how training data should be developed in such a way that it embraces all without perpetuating some social biases and they must be consistently updated to make the analysis relevant. Human involvement must not be an option but should be a prerequisite, hence the need for adoption of hybrid approaches that will enhance rigour and richness of human-led analysis while thoughtfully leveraging AI to enhance, not to substitute the traditional interpretive process.

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