

## A tutorial for integrating generative AI in mixed methods data analysis

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### Abstract

The current article used real data to demonstrate the analysis and synthesis of Mixed Methods Research (MMR) data with generative Artificial Intelligence (Gen AI). I explore how reliable and valid Gen AI data outputs are and how to improve their use. The current content is geared towards enhancing methodological application regardless of field or discipline and includes access to a prompt library and examples of using outputs. The demonstration data used emanated from a study done in South Africa, with a quantitative sample size of 969 first-year engineering students and, for the qualitative part, 14 first-year students. In the current article, I compare my original analysis to ChatGPT results. Generative AI as a mind tool is best used with human insight, and I found this to be especially true when coding qualitative data. ChatGPT produced generic codes if asked to do inductive coding, and the results improved when training the Gen AI on human examples, which led to moderate and significant correlations between human and machine coding. The quantitative analysis was accurate for the descriptive statistics, but the researcher had to use best judgment to select the correct inferential analysis. Quantitative and qualitative analysis should be conducted separately in generative AI before asking the Chatbot for help with mixed methods results. In the current paper, I give guidelines and a tutorial on how to use chatbots in an ethically responsible and scientifically sound manner for research in social and human sciences.

**Keywords** Generative Artificial Intelligence (Gen AI) · Chat Generative Pre-Trained Transformer (ChatGPT also known as the Chad) · Mixed Methods Research (MMR) · Data Analysis Tutorial · Chatbots

## 1 Introduction

Recent advances in generative Artificial Intelligence (Gen AI) are changing how we conduct scholarly research. We are challenged to use new tools in all educational disciplines [1–4], adapt to rapidly shifting technological landscapes, share what we have learned to support one another and engage in intellectual curiosity [5, 6]. Therefore, I showcase in this article how to use a generative AI platform to analyse quantitative and qualitative data and integrate findings for Mixed Methods Research (MMR). The current manuscript demonstrates the use of ChatGPT for a novel application and convergent MMR design. For exploratory and explanatory designs, the Gen AI could help the researcher identify participants for the qualitative phase or assist in designing an interview protocol based on the qualitative findings. The current paper presents a case study of one platform, ChatGPT, and when I tried the prompts on a newer Gen AI platform, Julius AI [7], I found they worked just as well. While the current paper's demonstrations were done with ChatGPT-4, I applied them in ChatGPT-4o [8] and found the prompts work even better in the latest model.

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Chat Generative Pre-Trained Transformer (ChatGPT) has emerged as a dominant role player in the generative AI field, and higher institutions are reporting that students and academics are using the platform increasingly [9–11]. Some researchers [12] focus on the positive role that generative AI can play in higher education, for example, aiding in managing large classes and online learning. Other researchers focus on how generative AI will impact assessment [13], how it can be used to promote student learning and motivation [14] and which frameworks to use when integrating Chatbots into teaching and learning [15]. Most articles conclude that we need more research and guidelines on using generative AI in higher education [15, 16].

The popularity of Mixed Methods Research (MMR) is evidenced by more published articles reporting the methodology; consequently, issues of methodological integrity have also arisen [17]. MMR is gaining traction due to an awareness in many fields (social and behavioural) that MMR provides more comprehensive insights and solutions [18]. Analysing, combining, and making sense of both qualitative and quantitative results is challenging as it requires knowledge and expertise of both [19]. Using technology to facilitate MMR presents opportunities and challenges as the researcher needs to handle complex datasets and work with various software packages [17]. Software packages, such as MAXQDA, are available for an integrated analysis of MMR, and researchers vary in whether they separately analyse their QUAL and QUANT or use one platform to analyse concurrently [20]. With the Gen AI revolution, it is unsurprising that technology is even more critical in processing and interpreting MMR results [21]. The current paper offers a roadmap for using Gen AI for MMR analysis, as I suspect that using one Gen AI platform that the researcher is familiar with is a more likely route in the future rather than paying for many individual software packages.

The current article is not the first exploration of how to use generative AI in higher education research [22]; many good publications exist [23–25]. The current article adds a new approach by demonstrating the application of generative AI in Mixed Methods Research (MMR) and providing prompts and guidelines for use. My work here is intended to be a resource for students and the academy, showing how generative AI can feed into the research process for academic advancement [24]. Consequently, I use the following terms, which are distinct but related: generative Artificial Intelligence (Gen AI), Chatbots and Large-Language Models (LLMs). By generative Artificial Intelligence, I mean AI systems trained to produce new content based on but divergent from their training data [26]. Chatbots interface AI and humans by applying LLMs to interact through text or voice [27]. LLMs serve as the basis for many types of generative AI and were designed to understand and function through human language [28]. Gen AI uses human language as the medium of interaction. LLMs were designed to mimic natural human interactions, making it seem like you are speaking with someone [29]. I take a similar approach in this article, treating ChatGPT as an assistant and telling the story of using its functionalities in a more approachable, humanistic way [30]. Generative AI continues to evolve; for example, ChatGPT-3.5 is a text-to-text model, and ChatGPT-4 is a data-to-text model [31]. The usefulness of the current article is in its practical application to broaden our understanding of generative AI in higher education, and I present a tutorial which researchers can use [32]. I used Mixed Methods Research (MMR) for the Tutorial and application because MMR offers us a robust framework for addressing many multifaceted issues in research. MMR explores complex human phenomena [33, 34]. Moreover, by analysing mixed methods data in ChatGPT, I create sections on quantitative and qualitative analysis that researchers from these disciplines could use even if they are not interested in MMR.

The prompts and exercises in the current paper were piloted on over 100 academics at the University of Pretoria (UP), South Africa. Academy members from all Faculties and most departments at UP attended the training and provided feedback. I presented the workshop, which covered five topics: an introduction to using Gen AI for data analysis, evaluating and improving your writing with Gen AI, qualitative data analysis, quantitative data analysis, and Mixed Methods Research (MMR) in ChatGPT. Feedback was obtained from attendees, and they rated the workshop's usefulness as 8.5 out of 10 ( $n = 60$ ), emphasising that the most valuable characteristic was the applicability of the experience and information. Considering that the workshop was held in a hall for a large group, it was no surprise that participants said they would have preferred a smaller group to facilitate collegial interaction. Participants who came to learn about one type of analysis (for example, quantitative) did not like that other types were also presented and would have preferred a workshop focused only on their interests. There was also a broad range of participant preparedness, which made pacing the workshop challenging. Based on the experiences during the sessions and the feedback form, I refined the Tutorial and present the revised version in the current text.

## 1.1 Technological revolutions

Before the 2000s, software was syntax-based, and researchers had to write instructions [35–37]. Writing code often led to considerable effort to fix and manage mistakes in writing syntax, apart from the knowledge and skills needed to conduct and interpret the data analysis [38]. The Graphical User Interface (GUI, 'goosey') revolution brought about easier use of statistics, where pointing and clicking was all the programming knowledge required [39]. At each phase of software evolution, the researcher needs to understand what they are doing and the statistical choices [40] or qualitative methods they employ [41]. The roles and responsibilities remain; the researcher must be well grounded in their understanding of data analysis theory and application. However, the researcher can now use the Chatbot as an assistant to suggest further analyses, conduct some of the analysis, and obtain help interpreting outputs. At each step of the evolutionary process, there is less pressure on the researcher to know the underlying nuts and bolts of software and more opportunity to focus on the data. Researchers are only beginning to explore all the options that generative Artificial Intelligence offers [42]. Understandably, significant shifts are frightening, and the generative AI revolution in the academic world is no different. Luca Mari summarises this experience eloquently (2023, p.29):

*Copernicus showed us our cosmological non-centrality*  
*Darwin showed us our biological non-originality*  
*Chatbots are showing us our cognitive non-uniqueness*

Some of our shared fears include the idea that AI will fundamentally replace us, for example, being able to do work for which we were once considered crucial [43]. Another fear is that AI will reduce creativity, innovation and original work, replacing our humanity [44]. Hinks [45] found that negative expectations of artificial intelligence's role in society are associated with reduced life satisfaction. Students are worried about the impact generative AI will have on their development, and the academy is concerned about academic integrity and the impact on assessment [46]. The Council on Higher Education [47] suggests that treating generative AI as a "crime" or plagiarism will negatively impact teaching and learning.

How should we deal with Gen AI in scholarly research? To navigate these existential crises and our trepidation, we need to engage with our fears reasonably, as Chatbots are here to stay [48]. We must find ethically sound ways to use the new tools to advance human knowledge and development. Our friends from the philosophy of science can help us to think critically about the latest existential crises. Heidegger was worried that technology would strip us of our humanity (forgetting to "be"), Ihde was concerned with its role in our daily lives, and Stiegler focused on how technology could disrupt our cultural memories [49, 50]. Hui [50] merges these ideas and sees technology as the conduit through which we understand our world (he calls this "cosmotronics"). Baker and Hui are linked to the idea from Ihde [51] that science is the conceptual side of a technological society and that scientists should reimagine the role of technology and its ethical use. Metaphysics, cultural shifts and geopolitical implications cannot be ignored when significant technological changes occur [52]. New technologies shape the world around us, reshape how we see ourselves and lead to new traditions, potentially replacing our cultural heritages and requiring profound pluralism from us [50, 53]. In the research world, we measure what we value, pushing us to question what is valuable. While I focus on the practicalities in the current paper, I am also proposing a person-centred, meaning-making approach to scholarship and integrating artificial intelligence into our research [54]. I explore this idea further by examining how researchers can ethically apply the new Gen AI tools.

## 1.2 Ethical and safe use of generative AI in research

There is nothing inherently wrong with using generative AI during data analysis as long as the researcher does so responsibly [55]. For the reader's purposes, I recommend using generally established ethical guidelines for generative AI use in research [56, 57]:

- being transparent in your use of generative AI during your research processes
- being responsible for the inputs and how you use the outputs
- protecting the data privacy of your participants
- using AI for specific purposes in the research process and reporting the use as one would with any software [58]
- considering and limiting potential bias from the AI platform
- emphasis on the humanisation and centrality of participants in research

As a researcher, you need to understand that Chatbots are tools. The user still needs to have the required foundational knowledge to use the instrument for the intended purpose in the same way you need to know why you select statistical tests when using GUI software.

Designers of Chatbots add guardrails to prevent offensive, inflammatory or dangerous outputs in attempts to protect the users [59, 60]. However, jailbreaking still occurs; some individuals can find ways around the guardrails [61]. Jailbreaking is a complex issue and can be part of the innovative strategies of users. Guardrails have downsides, such as over-correction and replacing one type of bias with another—users need to be aware of this when employing Chatbots [62]. While the designers of generative AI try to protect users with guardrails, the researcher needs to understand settings to ensure safer use. To enhance the ethical use of ChatGPT and your data, you can go to privacy settings, choose “Settings”—“Data controls”; then switch off the “improve model for everyone” option [31]. In Fig. 1, I show the guidelines for the ethical use of AI and Chatbots in MMR and data analysis.

I advise that you refrain from uploading any sensitive data. Ensure you remove any identifying information from data sets before using generative AI to analyse the data. Use resources such as ChatGPT responsibly by rephrasing, repurposing, and reintegrating responses, just as you would information from other sources [63, 64]. Critically evaluate all the information you receive from AI platforms and apply your interpretation. Be transparent about how and when you used artificial intelligence in your writing, analysis, and presentation. Cite the Large-Language Model (LLM) you used. Chatbots are sophisticated but only sometimes reliable, explainable and never accountable for what they produce [65]. Therefore, the researcher is responsible for fair and ethical use.

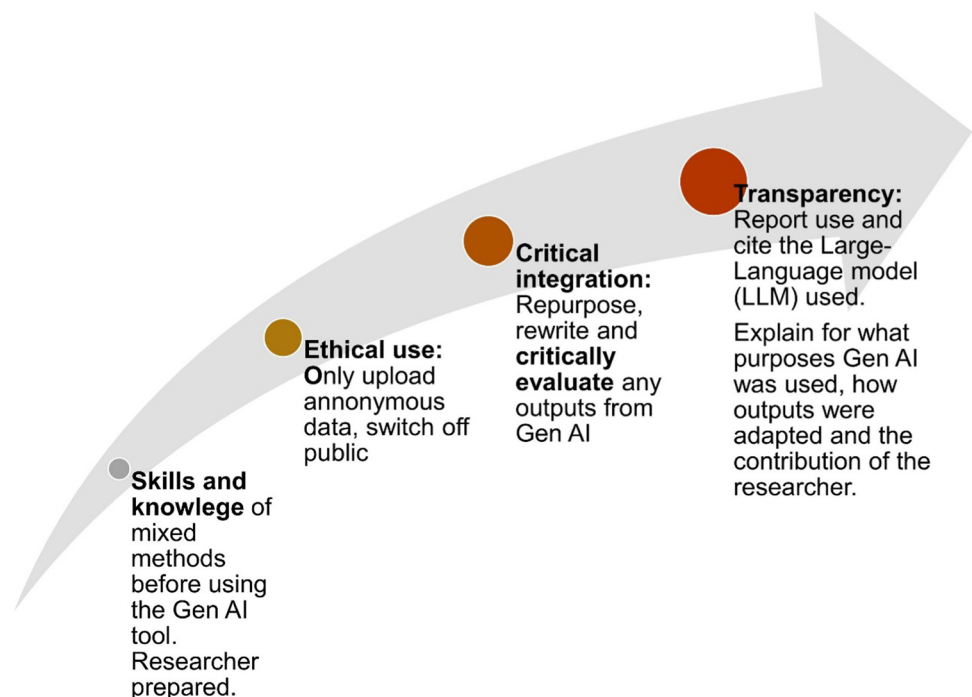
### 1.3 Research questions

1. *How can generative Artificial Intelligence assist with data analysis of Mixed Methods Research (MMR)?*
2. *To what extent does generative Artificial Intelligence yield reliable and valid findings for MMR data analysis?*

### 1.4 Novel uses of Gen AI in scholarly research

Many of the approaches discussed in the current article are known generally. I support users’ knowledge by showing them how to use Gen AI for research analysis, which is especially relevant for scholars who are hesitant or trying to analyse with Gen AI for the first time.

**Fig. 1** A framework for the ethical use of artificial intelligence in mixed method data analysis



A more novel use of LLMs is to ask it to work as your research coach. For example, I have wanted to learn how to use the R software package for years, but as this requires much dedicated time, I have been unable to do so. I could learn much faster if I had direct access to a person who could give me quick tutorials and help me when I get stuck. After all, I have tried attending workshops and doing courses on R, but I need direct help daily. After asking ChatGPT 4-o to act as my guide, my skills and knowledge of the software increased rapidly. This assistance is no small thing; many of us want to learn specific data analytics but need more time or resources to do so, and this is one of the most novel and revolutionary uses of Chatbots.

The other novel use of Chatbots is to use it as a peer reviewer, feed it the journal's requirements and ask it what you can do to improve the manuscript. Using LLMs to evaluate my writing has enhanced my work and ideas considerably. Of course, here, we need to exercise caution. Do not let the Gen AI do the writing or thinking for you; it needs to be a platform from which you spring and enhance your ideas and work. Language and technology are already modes through which we must communicate; if we allow LLMs to automate our knowledge work, our ideas will flatten and become superficial misrepresentations, and worse, the reader will not know where we end and the artificial begins.

### 1.5 Positionality statement

Enhancing critical positionality and reflexivity in the age of Gen AI requires transparency, contextual awareness, iterative and collaborative review, and critical engagement [1]. Researchers should be transparent by acknowledging the role of Gen AI and by detailing how the technology was used and interpreted [2]. Furthermore, we need to know how our positionality will intersect with Gen AI and how these assumptions might shape the outputs. Collaborating with more researchers is one way to check for hidden biases and assumptions, and one can ask Gen AI to scan for these. In the next paragraph, I demonstrate the process by adding my positionality and reflexivity.

I am a Caucasian academic working in a multi-cultural and multi-racial country, South Africa. I identify as female and acknowledge my middle-class economic status in a country with a large gap between the wealthy and the poor. I come from a privileged position where I could explore new technology like ChatGPT. As a White South African in higher education, I am aware of my perspectives and expectations of technology use and the barriers that disadvantaged students and academics may face. I take responsibility for reflecting on the structural biases in my environment, and I seek to address these barriers in part by sharing my knowledge in this article. The development of generative AI has built-in threats to ethical and fair use, such as access to devices for students, problems with data privacy, the potential erosion of local languages and the amplification of existing inequalities for students and academics who cannot afford to pay for access to better AI versions. As a researcher and member of the academy, I recognise that these challenges cannot be quickly resolved, but sharing knowledge within the higher education setting is part of addressing the issues and finding solutions. Therefore, I have held free workshops for colleagues and students, where we co-constructed knowledge gained from ChatGPT. I have added to student assignment papers the explicit requirement that they report prompts, how information was gained, and what they learned from the process. As I reflect on my own position, I encourage my students and colleagues to do the same, and I have learned much from them during this process.

## 2 Materials and methods data used for tutorial

Here, I describe the data used in the examples in the Tutorial; feel free to skip this part if you are not interested in the origin of the illustration data.

The data used as a demonstration in the current article comes from a project that focused on enhancing first-year engineering education in South Africa. The data were collected as part of a concurrent triangulation research design, and the findings were reported in publications [66, 67]. We wanted to help first-year engineering students by understanding student motivation, expectations, and perspectives and how these align with lecturer insights and curriculum design. Methodological integrity was built into the study through multiple encoders and special inspection of the data analysis. Three coders worked on the data, met regularly and eventually reached a consensus. After that, the codes and themes were reviewed by two specialist inspectors from the field of engineering education. The quantitative data were analysed by a research psychologist who worked with the team to make sense of the findings.

## 2.1 Instruments

The quantitative data were collected using the *Academic Pathways of People Learning Engineering Survey* (APPLES), which contains sections on learning expectations, beneficial and enjoyable educational experiences, skills and abilities required to become an engineer, motivation for studying engineering and post-graduate expectations [68, 69]. The qualitative data were collected using in-depth interviews for which the researchers designed a guide. The survey contained two open-ended questions where additional qualitative data were collected. In the open-ended questions, students were asked to explain why they chose engineering and provided any other information they deemed appropriate.

## 2.2 Sample

The quantitative data collection yielded a sample of 969 first-year engineering students, who were primarily men (71%), Caucasian (58%) or Black African (26%) and came from middle-class or affluent homes (81%). Students were, on average, 19 years old. The students who participated in the in-depth interviews (14) were all Black African by the study's design, predominantly male (9 out of 14 participants) and came from varied socio-economic backgrounds.

## 2.3 Data analysis

In the original analysis, I used the Rasch dichotomous model via Winsteps© 5.4.0.0 [70] and SPSS (Statistical Package for the Social Sciences) to generate descriptive and inferential statistics [71]. Two research psychologists transcribed and analysed the qualitative interview data using reflexive thematic analysis (TA) [67]. After that, the specialist inspection was conducted by two engineering educators, and the final themes and write-up were the result of a consensus being reached among the team of four researchers [72–74].

For the current article and demonstration, I reran the analysis through ChatGPT's *Advanced Data Analysis bot*, and my custom settings are shown Table 1. Custom ChatGPTs are available, and instructions can be customised [31]. I recommend that the user try out custom GPTs for themselves; the current Tutorial utilises the *Advanced Data Analyst*, one of the original custom ChatGPTs [31] for quantitative analysis and ChatGPT-4.o for qualitative analysis. Setting up custom instructions by clicking on your profile is recommended, and many good resources are available online for custom instructions [75].

To use the custom instruction shown in Table 1, click on your profile icon in ChatGPT, choose the *Custom Instructions* option, and paste the text. The text provided is a generic guideline which can be adjusted to suit specific individual preferences, and should reflect the type of research you are conducting [76].

## 2.4 Ethical considerations

The Faculty of Engineering, Built Environment, and Information Technology (EBIT) ethics committee approved the study at the University of Pretoria (EBIT/46/2020). The ethical guidelines of the University of Pretoria were followed during the study. All participants in this work have freely given informed consent to participate in the study. The author affirms that the participants also provided informed consent for their data to be used for publication purposes.

## 3 Tutorial and results–application

Here, I present the roles that generative AI can play in the various types of data analysis. I give prompt examples and evaluate the reliability and validity of using Gen AI for MMR. When asking a chatbot to conduct analysis, I recommend that you give it frameworks, evaluation criteria or any other standards that it could use to improve outputs [77]. Ask the GenAI to be brutally honest, to look for problems and lack of cohesion, to evaluate your writing critically, and to find ways to overcome positivity bias. Gen AI can act as an available, teachable, and inexpensive research assistant. Meet your artificial assistant, ChatGPT, also referred to here as Chad (the only good Chad you will ever meet). Chad is a naïve but

**Table 1** Custom instructions for mixed methods analysis in ChatGPT

Question	Heading	Specification
What would you like ChatGPT to know about you to provide better responses?	Key Responsibilities	Integration of qualitative and quantitative data analysis Coding, thematic analysis, and statistical analysis Synthesis of findings from both data types to generate comprehensive insights
	Knowledge or expertise	Expertise in qualitative coding, thematic analysis, and quantitative statistical methods Familiarity with integrating data from different sources to form cohesive conclusions Proficiency in software tools for both qualitative (e.g., NVivo, ATLAS.ti) and quantitative analysis (e.g., SPSS, R) [Add your projects here]
	Current Projects	Qualitative coding, Reflexive Thematic Analysis, mixed methods integration, statistical analysis, multimodal data analysis, Rasch Analysis
	Jargon or Terminology	
	Goals and Objectives	To create rich, multidimensional interpretations from diverse data sets, consider context, and apply interdisciplinary knowledge to enrich interpretations Create meaningful interpretations from textual data, consider context, apply interdisciplinary knowledge to interpretations, and limit bias
	Interactions	Engage in both social science and statistical data analysis Narrative and analytical writing for diverse audiences, including academic, policy, and public sectors Educational and practical application of mixed methods research findings
	Tone	Professional, empathetic, understanding, and clear
	Level of detail	Provide comprehensive narratives that integrate findings from both qualitative and quantitative data, supported by quotes and statistical evidence
	Preferred References	Scientific papers, psychological and educational frameworks, academic journals, primary sources across both qualitative and quantitative fields
	Examples of analogies	Use examples from journal articles, research reports, or thesis chapters that effectively demonstrate the integration of mixed methods
How would you like ChatGPT to respond?	Avoidance of Ambiguity	Present clear, analytical findings that seamlessly blend insights from both qualitative and quantitative research, grounded in theory and empirical evidence
	Resources links	Access to interdisciplinary data science libraries, mixed methods research papers, and online courses focusing on integrated data analysis techniques
	Follow up questions	Research impact, future studies
	Problem-solving method	Apply a systematic approach to mixed methods data analysis, detailing the process of qualitative coding, thematic generation, and quantitative statistical analysis, including the integration phase, to draw overarching conclusions
	Confidence of answers	Include a confidence level with each piece of advice or information provided, especially regarding integrating data and interpreting mixed methods analysis results

well-meaning intern working for \$20 monthly. Chad needs much supervision and makes silly mistakes but can add value when managed well. Chad is a well-mannered Chatbot (thanks to the guardrails) with much potential. Unfortunately, he/it is a people-pleaser, which can sometimes be annoying.

To enhance the practicality of this paper, I have recorded YouTube tutorials which can be used in conjunction with my article. Moreover, dear reader, please watch videos from Andy Stapleton's YouTube channel [78] as he tries out different Gen AI platforms for data analysis; for example, his video is entitled "*I Tested 3 AI Tools for Research Data Analysis—Which One Truly Delivers!?*"; this video can be found at the link: [https://www.youtube.com/watch?v=\\_7JyuA1nAKk](https://www.youtube.com/watch?v=_7JyuA1nAKk). Andy's analysis is limited to quantitative data, and my paper includes the steps to evaluate quantitative, qualitative, and MMR analysis.

### 3.1 Qualitative data analysis with ChatGPT

Before starting this paper-based Tutorial, I first need to ask: *Are you a human currently operating in energy-saving mode?* If yes, you might want to watch my tutorials on YouTube; the links are here: Gen AI QUAL coding of open-ended survey responses (<https://youtu.be/BBG1kVF3Yk8>), Gen AI QUAL analysis of Interviews (<https://youtu.be/G4HJCP-h86U>) and Gen AI Mixed Methods Data Analysis (<https://youtu.be/6EDJBdBsTE0>).

ChatGPT and similar generative AI platforms can analyse multimodal data [23] and play several roles in qualitative analysis, including coding, where you ask ChatGPT to generate codes for textual data based on frameworks or theories. In addition to textual analysis, Gen AIs can detect sentiment, such as the emotional tone of the text [79]. Gen AIs can generate themes and evaluate qualitative analysis for consistency by acting as a specialist inspector. The possibility of generating visualisations and tables with Gen AI is also helpful in quantifying or summarising aspects of the qualitative data. You can paste a limited amount of qualitative text into ChatGPT-3.5. ChatGPT-4o allows for uploading data, where you can ask for Excel codes per line, doing more checks and comparisons, and creating figures. Consider Gen AI as an additional coder or a research assistant in this process. However, crucially, do your own analysis and rely on something other than the Chatbot, as it may miss rich aspects of your data or misinterpret the text (more about this in my next section).

#### 3.1.1 Modifications of QUAL data for gen AI use

I only made a few modifications to the qualitative data before using it in a Gen AI environment. I remove any identifying information and am careful about which demographics to keep in the data set. For the current examples I show, I made sure the interviews had no names, and for the Excel spreadsheet with open-ended responses, I removed the identifying numbers and the empty responses.

#### 3.1.2 Practical application of QUAL data analysis in gen AI

In my experience, inductive coding does not work well in generative Artificial Intelligence settings, and I advise you to avoid asking the Chatbot to cold code. Instead, the Gen AI should be given both an analytical framework and a theoretical or conceptual framework to guide the coding and theme generation, as shown in Prompt 1 in [Appendix–Prompt Library](#). Examples of analytical frameworks to consider using include thematic, narrative, content, and discourse analysis. Another suggestion is to code the first few lines or paragraphs to show ChatGPT as examples.

Gen AI assigns generic codes such as "other" or "uncoded" when unsure or struggling to interpret the text. Such codes and themes require additional investigation as complex and valuable information is often submerged into these commonly named themes. When facing token restrictions, analyse a few interviews at a time; then, ask the Gen AI to adjust themes based on additional interviews. As shown in [Fig. 2](#), Chad provides well-written themes and quotes the participants as requested when given adequate guidance. The theoretical framework has also been woven into his answers.

[Figure 2](#) demonstrates the prompt to ask ChatGPT to code open-ended survey items (see also [Appendix–Prompt Library](#)). I uploaded the Excel file with the responses and labelled the columns where I wanted the bot to add the codes per line.

### 3.2 Quantitative data analysis with ChatGPT

Gen AI fulfils additional roles that GUI software did to a limited extent or not at all. ChatGPT can assist with cleaning data, for example, finding out-of-range values in data files. The *Advanced Data Analysis* custom ChatGPT can also scan your data file and recommend analysis. Here, I suggest sharing a codebook with the Chatbot with variables, labels, categories,



**You**

Attached are open-ended responses. Code and classify the responses so that you create themes, write up the themes as narratives with quotes from respondents to support your argument. Cite frequencies of how many times a theme was mentioned. Make the excel sheet available as a downloadable file with the codes completed.

**ChatGPT**

**1. Personal Interest and Passion (mentioned 213 times):** A significant number of students mentioned words like "enjoy," indicating that personal interest and passion for engineering and technology are major factors in their decision to pursue this field. For example, one respondent stated, "I've always enjoyed creating and tinkering with things since I was young. Engineering felt like the natural path for me," highlighting the personal connection to the field.

**2. Influence of Technology and Innovation (mentioned 46 times):** Words such as "world" and "things" suggest that the influence of technology and innovation on the world, and a desire to contribute to this, is a theme in students' motivations. Respondents expressed a desire to be at the forefront of technological advancements and to contribute to meaningful innovations. "I want to be part of the future, to innovate and make a difference in the world through technology," exemplifies this motivation.

**3. Career Aspirations (mentioned 33 times):** The word "work" implies that career aspirations, including specific industries or roles within engineering, are important considerations for students. Students mentioned the appeal of engineering as a pathway to diverse and rewarding career opportunities. "Engineering opens so many doors. I'm excited about the possibility of working in the space industry," illustrates this forward-looking perspective.

**4. Curiosity and Problem-Solving (mentioned 14 times):** The frequent use of "how" points to a theme of curiosity about how things work and a desire to solve problems, which is fundamental to engineering. "I'm driven by the challenge of solving problems and the satisfaction of finding solutions," reflects this curiosity and the problem-solving nature inherent to engineering.

**Fig. 2** Prompt 2a and response from ChatGPT to show the coding of open-ended survey questions

and any required explanations, such as the Level of measurement. Use the suggestions from the Chatbot with care, as the Gen AI might suggest analysis that cannot or should not be done with the type of data presented. Chad can quickly generate descriptive statistics, as I will demonstrate here, and a paragraph with initial interpretation for the researcher to consider using. Commonly used inferential statistics can also be conducted in ChatGPT, with the bonus of interpretation. Currently, generative AI is fine for run-of-the-mill statistical analysis. Using generative AI to run more sophisticated statistical models requires further exploration. For example, I conducted some structural equation modelling (SEM) with ChatGPT, but the Chatbot found this challenging.

### 3.2.1 Modifications of QUANT data for gen AI use

I did not modify my quantitative data for the prompts shown, but I provided the Gen AI with a codebook to correctly interpret the variables. Suppose one wants to do a more complex analysis in Gen AI, such as multi-level modelling. Preparing the data in a format that would aid the analysis process may be necessary. However, you could also ask the Chatbot to assist you as it can reformat data sets.

### 3.2.2 Practical application of QUANT data analysis in Gen AI

Figure 3 shows the prompt asking for Chad's recommended data analysis.

As shown in Fig. 3, Chad recommends many different types of analysis for my specific data set. However, not all of them are feasible or applicable. Nonetheless, this is a good starting point, and the Gen AI may suggest types of analysis you have yet to consider.

Figure 4 is where I asked ChatGPT to produce descriptive statistics in a specified table format. I also asked for an interpretation and write-up of the table. While I did not fully agree with its interpretation, this again provides a good departure point to help the researcher start the writing process.

In Fig. 5, I illustrate the prompt for asking for inferential statistics from the Chad. Instead of asking for specific analysis, I asked ChatGPT to explore various relationships and to report statistical significance in an interpretative paragraph.

As can be seen from the response, the Gen AI accurately interprets the  $p$ -values, though it fails to report the effect sizes. I continued prompting beyond this point to obtain all the information I needed. Remember that just like a real assistant, you should keep speaking with the bot until you receive everything you need. See the [Appendix](#) for the other prompts used.

**You**

I have cross-sectional survey data, please recommend analyses I could do with my data set. The variables include demographic questions, such as gender, age, and race. The constructs measured in the questionnaire include motivation to attend university and long-term career goals.

**ChatGPT**

With the dataset you've provided and considering the variables and their options, your study presents a rich opportunity for both descriptive and inferential statistical analyses.

**1. Descriptive Statistics**

- **Demographic Profiles:** Use frequency distributions to describe the demographic characteristics of your sample (Gender, Ethnicity, Age).
- **GPA Distribution:** Analyze the distribution of GPA scores to understand academic achievement levels within your sample. This can include measures of central tendency (mean, median) and dispersion (standard deviation, range).
- **Preferences and Expectations:** Summarize the top choices for the constructs to identify trends in learning expectations, beneficial and enjoyable educational experiences, important skills and abilities, reasons for studying engineering, and post-graduation opportunities.

**2. Cross-tabulations and Chi-square Tests**

- **Demographics vs. Expectations/Experiences:** Explore relationships between demographic variables (Gender, Chi-square tests can help determine if there are significant associations).
- **GPA and Educational Experiences:** Investigate if there's a correlation between students' GPA and their views on what educational experiences are most beneficial or enjoyable.

**3. Multivariate Analysis**

- **Factor Analysis:** If Q1-Q6 options can be interpreted as reflecting underlying dimensions (e.g., attitudes towards teamwork, innovation, professional development), factor analysis could reduce these items into fewer dimensions for further analysis.
- **Cluster Analysis:** Group students based on their responses to Q1-Q6 to identify distinct profiles within the engineering student population, such as those highly motivated by innovation versus those focused on practical skills.

**4. Regression Analysis**

- **Predictors of GPA:** Use linear regression to identify if any of the categorical variables (e.g., ethnicity, first to attend university) or responses to Q1-Q6 are significant predictors of GPA.
- **Outcomes Based on Educational Preferences:** Logistic regression could explore whether certain preferences or expectations (e.g., valuing team-based problem solving) predict specific outcomes, like the desire to work internationally after graduation (Q6.5).

Fig. 3 Prompt 3 to ask for suggestions on analysing a quantitative data set

### 3.3 Mixed methods research data analysis with gen AI

A wide range of MMR analyses can be aided by generative AI, including concurrent triangulation, sequential explanatory and exploratory analysis, transformative designs (here, you must supply the paradigm) and multi-stage evaluations. ChatGPT can also produce more complex figures and tables based on its own or your analysis, for example, side-by-side joint displays, statistics displayed by theme or vice versa and interview questions joint displays [80]. I have also created some infographics with ChatGPT-4, but these still require much input from the researcher, and it may be easier to create your own in a different software environment. To successfully use Gen AI for mixed methods analysis, I recommend that you separately analyse the quantitative and qualitative data and combine the findings into a single document before asking the bot to assist with MMR analysis.

#### 3.3.1 Modifications of MIXED data for Gen AI use

The researcher creates the combined qualitative and quantitative findings for the mixed methods analysis, as I suggest running the analysis for each separately (for QUAL and QUANT) and combining the outputs into a single document for the Gen AI to interpret. This part then requires many modifications from the researcher regarding what to include, how to present the information in the documents and how to request integration from the bot. I pasted tables from the quantitative data in the current analysis, starting with sample descriptives. I added headings to the document and presented the qualitative data as themes with participant quotes.

#### 3.3.2 Practical application of MIXED data analysis in Gen AI

In Fig. 6, I prompt ChatGPT to use my combined quantitative and qualitative findings document and conduct a sequential explanatory analysis using this study's theoretical framework. I specified both the analytical and the theoretical (or

**You**

Summarize the demographic variables in the attached data set. Create a table and write a paragraph to illustrate your findings.

**ChatGPT**

The demographic profile of students surveyed reveals a diverse group with a predominant male representation, comprising 71% of respondents, while females account for 29%. The ethnicity distribution indicates a majority of White students at 58%, followed by African students at 25%, and Indian or Coloured students at 17%. Regarding family background in engineering, 55% of the students do not have a family member with an engineering degree, whereas 43% do, highlighting a mix of first-generation students and those with familial ties to the field. Notably, a vast majority (82%) are not the first in their immediate family to attend university, suggesting a significant portion of students come from families with a history of higher education. The age range primarily centers around 19 years, indicating a young cohort, and the GPA data, with an average of approximately 55.55, suggests a broad range of academic achievement among the students.

Category	Description	Percentage (%) or Summary
<b>Gender</b>	Male	71%
	Female	29%
<b>Ethnicity</b>	White	58%
	African	25%
	Indian or Coloured	17%
<b>Family Member with Engineering Degree</b>	No	55%
	Yes	43%
	Prefer not to say	2%
<b>First to Attend University</b>	No	82%
	Yes	17%
	Prefer not to say	1%
<b>Age</b>	Mean (Average)	19 years
	Std (Standard Deviation)	1.04 years
	Min (Minimum)	18 years
	Max (Maximum)	33 years
<b>GPA</b>	Mean (Average)	55.55
	Std (Standard Deviation)	15.84
	Min (Minimum)	0
	Max (Maximum)	91.17

**Fig. 4** Prompt 4 descriptive statistical table output and interpretation from ChatGPT

conceptual) frameworks as this yields the best results. Researchers should use comprehensive frameworks when conducting and analysing MMR data, as shown by Corrigan and Onwuegbuzie [81].

The output received in Fig. 6 was sparse, but further prompting into aspects reported by Chad led to more valuable outputs.

Based on the findings, I asked ChatGPT to create a joint table (see Fig. 7). While I would not use the table in its current format in a publication, I would use this summary to guide my writing and inform the creation of other graphics.

I recommend using generative AI to create initial tables, figures and text based on the quantitative and qualitative data. The final integration should be based on the aims of the study. When asking ChatGPT to create side by side type of tables, check this against your own version to make sure everything relevant is included. Write your interpretations based on your research aims and objectives; do not rely solely on the bot.

### 3.4 The quality of gen AI analysis

In Table 2, I compare the original analysis done by the research team and the outputs received from ChatGPT-4's *Advanced Data Analysis* Chatbot.

Most were similar when comparing the original qualitative analysis done by the researchers to the ChatGPT themes. The content of the themes is also consistent, but the most significant difference was related to the extent of coverage. ChatGPT found most of the same themes but gave shorter, less rich write-ups. ChatGPT also missed a theme we identified (behavioural and attitudinal factors). Regarding the quantitative analysis, the Chatbot suggested creating demographic profiles (for example, gender, age, and ethnicity), mean distributions (for continuous variables) and summaries for the categorical variables. Other suggestions included cross-tabulations, non-parametric analysis, factor analysis (for

<p><b>You</b></p> <p>Explore relationships between demographic variables and constructs. Report any statistically significant findings, adding p-values and effect sizes. Write interpretations for your findings and report statistics in APA 7 style.</p>
<p><b>ChatGPT</b></p> <p>Gender shows a statistically significant association with certain preferences, notably Q1.1 (Build technical knowledge, <math>p=0.000022</math>) and Q5.1 (Technology plays an important role, <math>p=0.036243</math>), where male students are significantly more likely to select the option suggesting gender differences in these educational preferences.</p> <p>Ethnicity also shows significant associations, particularly with Q5.1 (<math>p=0.000035</math>), indicating varied preferences across different ethnic groups in the role of technology in solving society's problems, with White students being significantly more likely to choose this option.</p> <p>A Family member with an engineering degree has a notable association with Q5.1 (<math>p=0.003913</math>), suggesting that having a family background in engineering might influence the value placed on technology's role in society.</p> <p>First to attend university does not show strong statistical significance with the top options, indicating that being the first in the family to attend university does not markedly affect these specific educational preferences or expectations.</p> <p>The significant p-values, especially those below 0.05, suggest that certain demographic factors are associated with specific educational preferences and expectations among engineering students. For instance, gender differences are apparent in the emphasis on technical knowledge and the perceived role of technology in addressing societal issues. Ethnicity also plays a role in how students value technology's impact on society, with varying preferences observed across different ethnic groups</p>

Fig. 5 Prompt 7 Inferential statistics and interpretation from ChatGPT

<p><b>You</b></p> <p>I have findings from a questionnaire, and I also conducted 14 in-depth interviews. The results from the quantitative and qualitative analyses are attached. Please conduct a sequential explanatory analysis and help me to identify patterns, achieve triangulation and integrate the results. Use the Incentive Theory to interpret the results. Write a page based on the sequential explanatory analysis.</p>
<p><b>ChatGPT</b></p> <p>The document outlines mixed-methods findings from first year engineering students, integrating quantitative survey results with qualitative interviews. It covers demographics, motivations for studying engineering, and educational experiences. Key themes include Transition Challenges, emphasizing adaptation difficulties from high school to university; Importance of Social Connections, highlighting the role of peer support; and Academic and Personal Growth, reflecting on self-development. Using Incentive Theory, these findings suggest that both intrinsic motivations (interest in engineering) and extrinsic incentives (career aspirations, social connections) drive students' academic journeys, aligning with the theory's emphasis on external and internal motivators in shaping behavior. The importance of supportive environments and opportunities for personal and academic development in engineering education emerged from the study. This integrated analysis underscores the complex interplay between students' backgrounds, motivations, and educational experiences, offering valuable perspectives for enhancing engineering curricula and support services.</p>

Fig. 6 Prompt 8—request integration of qualitative and quantitative data for MMR analysis

**You**

Based on the findings from the previous prompt, create a statistics-by-themes joint table display of the findings. Make the table a downloadable Excel.

**ChatGPT**

Themes	Description	Findings
Demographic Profile	Diverse group with a predominantly male representation; variance in ethnicity and family educational background.	Male: 71%, Female: 29%; Ethnicity: White 58%, African 25%, Indian or Coloured 17%
Gender and Educational Preferences	Male students showed a significant preference for building technical knowledge and recognizing technology's important role.	Q1.1 ( $p=0.000022$ ), Q5.1 ( $p=0.036243$ )
Ethnicity and Technology's Role	Varied preferences across different ethnic groups regarding technology's impact on society.	Q5.1 ( $p=0.000035$ )
Family Background in Engineering	Having a family member with an engineering degree influences the value placed on technology's role in society.	Q5.1 ( $p=0.003913$ )
First to Attend University Impact	Being the first in the family to attend university does not markedly affect educational preferences or expectations.	No strong statistical significance
Transition Challenges	Adapting to new study methods, managing time effectively, and navigating a competitive academic environment.	Transition from high school to university; managing new academic expectations and social environment.
Importance of Social Connections	The formation of social connections and study groups is crucial for academic success.	Benefits of working with others; forming study groups and friendships.
Academic and Personal Growth	Realization of the need for self-reliance, highlighting a journey of personal and academic growth.	Self-reliance and adaptation; personal and academic development.
Personal Interest and Passion	Personal interest and passion for engineering and technology are major factors in pursuing the field.	Mentioned 213 times; passion for creating and tinkering.
Influence of Technology and Innovation	Desire to be at the forefront of technological advancements and contribute to meaningful innovations.	Mentioned 46 times; desire to innovate and make a difference through technology.
Career Aspirations	Engineering viewed as a pathway to diverse and rewarding career opportunities.	Mentioned 33 times; engineering as a pathway to diverse careers.
Curiosity and Problem-Solving	Curiosity about how things work and a desire to solve problems.	Mentioned 14 times; driven by problem-solving and finding solutions.

**Fig. 7** Statistics-by-themes joint display generated by ChatGPT

constructs in the survey) and regression analysis to estimate predictors of the continuous variables. All the former suggestions I considered myself and are reasonable.

Further suggestions, which I had yet to consider, included cluster analysis to group the students (this was not feasible with the data set), creating profiles within the engineering student population, and outcomes based on educational preferences. These last suggestions were exciting but irrelevant for my data set, once again pointing to the fact that the scholar needs to understand their data and the statistical possibilities. The demographic tables, figures, and interpretations provided by ChatGPT were of high quality and a good match for our own demographic profiles. When I asked ChatGPT to suggest inferential analysis, it did suggest the same non-parametric tests that I initially used, but it also suggested less useful and sometimes irrelevant analysis.

While descriptive statistics can quickly and reliably be done using ChatGPT, researchers should use their knowledge and judgment of statistics when deciding which tests to run in generative AI. The outputs are deemed acceptable and accurate and could be used in a research report or journal article, with the caveat that the text interpretation should be rewritten. Look for inaccuracies or exaggerations in the Chatbot's output; for example, in my outputs, I found the claim that the sample is diverse to be an exaggeration.

The open-ended survey questions revealed most of the same themes, but again, ChatGPT's descriptions and unpacking of the themes were shallow compared to human analysis. To check how consistent the Gen AI's coding was with human coding in the open-ended questions, I created a dataset in which the themes were labelled as:

**Table 2** Comparison of original quantitative and qualitative analysis with ChatGPT

Type	Original (Researchers)	ChatGPT version
Qualitative interviews	Theme: The academic program	Theme: Academic and Personal Growth
Qualitative interviews	Theme: Student support	Theme: Transition Challenges
Qualitative interviews	Theme: The role of peers in student success	Theme: Importance of Social Connections
Qualitative interviews	Theme: Behavioral and attitudinal factors	
Quantitative data analysis	Demographic profile (Table & Text)	Demographic profile (Table & Text)
Quantitative data analysis	Recommended non-parametric analysis	Recommended non-parametric but also other not applicable analysis
Quantitative data analysis	Non-parametric analysis and interpretation	Non-parametric analysis was done, but less detail was provided
Open-ended survey questions	Theme: Intrinsic Psychological Motivation	Theme: Personal Interest and Passion
Open-ended survey questions	Theme: Engineering as Social Good	
Open-ended survey questions	Theme: Focused on career opportunities	Theme: Career aspirations
Open-ended survey questions	Theme: Intrinsic behavioural motivation	Theme: Influence of Technology and Innovation
Open-ended survey questions		Theme: Curiosity and Problem-Solving

**Table 3** Correlation comparison between codes assigned by a human and Gen AI coder

	Cramer's V value	Approximate significance
ChatGPT Cold Coding	0.133	0.919
ChatGPT Coding with human example	0.355	0.000
Julius AI Cold Coding	0.132	0.339

Social good = 1

Intrinsic psychological = 2

Intrinsic behavioural = 3

Financial = 4

Parental influence = 5

Diverse career opportunities = 6

Unsure = 7

Other = 8

In the first round, I asked ChatGPT to merely cold code and transform his answers into the above numbers. My colleague's coding had already been converted to the numbers. As these were two nominal variables ranging in values from one to eight, I chose Cramer's V in SPSS to assess how well the Gen AI classified the responses [40] as shown in Table 3. I was using human coding as the ideal as this was done by a qualitative researcher and checked by me.

When ChatGPT and Julius AI cold code, they both have negligible associations with the human coder's choices. When the human coding is given as an example (see Prompt 2b in Appendix), the association increases to moderate and significant with Cramer's  $V=0.355$ ,  $p=0.000$ . In Table 4, I show examples of the text coded by my colleague (human coder), then ChatGPT and Julius AI cold coding and in the last column, the results from ChatGPT after it reviewed the human codes.

The more broad or vague the responses from the sample, like the text "It seems interesting", the more difficult it was for the Gen AI to assign meaning to the phrase. Of course, this table also shows that more than one code can exist in a textual response, and my colleague had more than one column of codes. Table 5 gives an overview of counts for alignment between the human and Gen AI coders.

The Gen AI initially over-assigned the category "Other", showing a lack of specificity. After training with the human codes, the Gen AI improves, but there are still aspects of contextual clues it struggles with coding these types of responses, and I do not expect the correlation to be more than moderate, as shown in Table 3. I repeated this experiment with the interview data, and similar results were found: The Gen AI's coding assigned "Uncategorized" to most lines, and with training on human responses, the coding and theme assignment improved. Note that more rounds of training may be required depending on your data.

My brief section about the reliability and validity of using Gen AI for MMR data analysis is superficial and I included it to give a cursory overview of the methodological integrity of Gen AI for scholarly research. A detailed and critical analysis of the subject matter is needed but beyond the scope of the current paper.

### 3.5 Troubleshooting

As is the case with all technology, ChatGPT and other Gen AIs can experience technical difficulties. Troubleshooting includes clearing the history, cookies, and cache for the "all-time" option. Next, you can restart the session. Lastly, use different browsers (for example, Firefox works well for me) or disable all the Chrome extensions.

## 4 Discussion and key findings

Generative AI is here to stay, and we must find ways to use it ethically and responsibly [3]. Therefore, the current study demonstrates how to conduct MMR analysis and integration using an artificial intelligence platform, ChatGPT. All types of technology have drawbacks, and a lack of transparency could call into question our methodological integrity, one of the biggest threats we face with Gen AI [82]. In this paper, I provide guidelines on using generative AI for MMR data analysis while balancing potential pitfalls. The main findings and recommendations from the current article are shown in Fig. 8.

**Table 4** Examples of how human and Gen AI coding for text compares

Text	Human Code	ChatGPT Cold Code	Julius AI Cold Code	ChatGPT with human codes as an example
Building stuff is my passion	Intrinsic behavioural	Other	Other	Intrinsic behavioural
It seems interesting	Intrinsic psychological	Other	Other	Unsure
To participate in the team that helps South Africa transition into the 4th industrial revolution	Social Good	Other	Social Good	Social Good
To be able to create new and innovative ways to improve our society	Social Good	Other	Other	Intrinsic behavioural
I have a passion for physics and mathematics and its applications in the world	Intrinsic psychological	Diverse career opportunities	Diverse career opportunities	Social Good
After taking IT and EGD in high school I realised how fun it is to be able to create working apps or mechanisms. I have been interested in building and designing things since I was very small. Engineering has a wide range of job opportunities	Intrinsic behavioural	Intrinsic psychological	Intrinsic psychological	Intrinsic psychological
I chose engineering because it has been a study I am passionate about since a young age wanting to explore how to fix things, make them work and build different stuff. I have always been interested in the practical aspect of building and designing new things hence driven by interest, passion and something that makes me happy	Intrinsic psychological	Diverse career opportunities	Diverse career opportunities	Intrinsic psychological



**Table 5** Human versus machine—code comparison based on counts

Codes assigned	Human Codes	ChatGPT Cold Code	ChatGPT with Human Codes as example
Social Good	36	7	86
Intrinsic psychological	202	12	101
Intrinsic behavioural	75	1	22
Financial	15	0	5
Parental or Mentor influence	7	0	0
Diverse career opportunities	34	25	25
Student unsure	7	1	136
Other	0	365	0

## Quantitative

- Gen AI scans data & suggests analyses
- Researcher critically evaluate suggestions
- Gen AI creates descriptive statistics
- Gen AI runs inferential tests
- Gen AI produces tables & figures
- Researcher interprets outputs with Gen AI assistance

## Qualitative

- Researcher provides an analytical framework to Gen AI
- Researcher provides theoretical / conceptual framework for Gen AI to use
- Researcher asks Gen AI to analyse textual data & produce codes
- Researcher asks Gen AI to create narrative themes with direct quotes from participants
- Compare Gen AI analysis to researcher's findings and collate

## Mixed

- Researcher conducts qualitative & quantitative analyses separately (using Gen AI or other software)
- Researcher compiles qualitative and quantitative findings into one document with clear headings
- Gen AI use as an assistant to synthesize and derive meaning from compiled document
- Gen AI to generate figures and tables for mixed method findings

**Fig. 8** Summary of recommendations for generative AI mixed methods data analysis use

In the quantitative section, I demonstrate how ChatGPT can quickly provide suggestions for data analysis techniques. Most of the suggestions are valid, and the bot has also improved since I used it last year, as it can now more accurately identify parametric from non-parametric statistical models. Providing the Chatbot with a codebook facilitates data analysis. Generative AI can provide accurate descriptive and inferential statistical outputs, but its ability to conduct more sophisticated analysis, such as structural equation modelling (SEM), has yet to be tested.

In the qualitative section, the Chatbot should be provided with an analytical and a theoretical model to improve the analysis. Gen AI does not handle inductive coding well, and I suggest providing the bot with examples of how you want it to code (train the Gen AI on human-coded texts). You could also specify if you want it to act as a splitter or lumper. For more informative text, such as interviews, ChatGPT produces coherent narrative themes and can quote participants. The Gen AI was less useful for shallow qualitative data, such as answers to open-ended questions. I suspect the latter is due to the inherent vagueness of the responses, which even human coders find challenging.

Mixed Methods Research (MMR) analysis works best if the quantitative and qualitative analyses are done separately before asking the bot to help integrate the findings. When the QUAL and QUANT are neatly combined in a document with clear headings, a prompt can be provided to the Gen AI wherein one asks it to help synthesise the findings. Here, I recommend specifying which MMR analytical approach you want it to use. The side-by-side tables it produces are also helpful, but as always, the researcher must add their insights.

The reliability and validity of straightforward tasks, such as producing descriptive statistics, are perfect in the generative AI environment. More interpretative outputs, such as narratives derived from qualitative data, are less reliable and valid when using ChatGPT, as I demonstrated when correlating the human and machine coding. While it can detect most of the same themes, it sometimes misses them. Therefore, the researcher can consider the Gen AI an assistant in coding but should still create their own themes and write-ups to compare to bot outputs. Overall, the reliability and validity of using generative AI in analysing MMR data is acceptable if the researcher specifies frameworks, provides codebooks and trains the Gen AI on human versions. The researcher must have the required foundational knowledge and be discerning, rephrasing, repurposing, and reintegrating the outputs before final publication. One of the main advantages of using generative AI is the quick turnaround time for data analysis. Speedier analysis is desirable in a world where rapid publication is required in higher education [41]. Here, I do not wish to endorse hustle culture; instead, I want to spend less time on manual and pseudo tasks. As scholars, we need more opportunities for deep work and life, as discussed in Newport [83]. New technology should free us up to create and do meaningful work that contributes to the good of our collective lives.

We may ask ourselves why we would create new knowledge in a world where artificial intelligence can produce equivalent artefacts. Yet there have always been others doing something similar, and who could do it better than we could. Excellent poets, writers, scholars, artists, and every type of creator have existed for millennia. We continue to create despite others doing the similar work because everyone has a unique point of view. Different from another person or Chatbot. We create new knowledge as scholars because we need to contextualise what we do for our settings. We add value through our humanity, and others crave that human connection. Human production of creative work will become even more desirable when machines make so much. Creativity is a natural part of who we are—we are our most authentic selves when we create and recreate [84]. Authentic self-expression through knowledge creation can fulfil an identity need, helping us to feel connected to ourselves and our world through adding new insights and intellectual artefacts.

#### 4.1 Significance of the findings

The current paper demonstrates innovative ways to use Gen AI for quantitative, qualitative, and Mixed Methods Research data analysis. I also showcase new ways to integrate findings with the assistance of generative AI to improve the interpretation of MMR data. The reader is provided with guidelines on using Gen AI for efficiency and automation to make handling large quantities of data easier. Generative AI misses themes sometimes but can also reveal themes and patterns humans overlook. Therefore, I state the case for combining human insight with generative artificial intelligence to obtain results beyond the abilities of either; the sum of the parts is indeed greater. My study can be used across many disciplines or for cross-disciplinary work where mixed methods are prominent. I have detailed my steps and provided a prompt library for easy replicability and application. The current paper serves as capacity building for researchers globally to advance their use and understanding of AI tools in research methodology. In this paper, I explicitly addressed ethical considerations to clarify privacy, consent, and practical implications for researchers who want to use generative AI. My findings here are meant to strengthen digital literacy in a fast-developing technological landscape.

#### 4.2 Limitations of the study

The Tutorial and application were limited to an available data set, and the example was drawn from higher education. I only used one platform, ChatGPT, and I used the paid version. Using Gen AI in data analysis has limitations, as discussed in the paper. The quality of the results depends on the researcher's knowledge and skills. The platform user should have the requisite knowledge of MMR data analysis, synthesis, and application. Chatbots cannot replace human insight.

Furthermore, the fact that bias and unfairness are built into artificial generative intelligence is well known [85]. Therefore, the researcher must actively manage the inputs and how the outputs are used, aware that there may be systemic, computational and human biases embedded in chats [86]. The landscape of generative AI is also changing rapidly [87],

and the current paper is limited to the time and space in which it was written. ChatGPT is not the only platform available to researchers, and future researchers could look at platforms such as Perplexity (see <https://www.perplexity.ai/>), Jenni (see <https://jenni.ai/>) and Consensus (<https://consensus.app/>). A limitation of the current paper is that some of the ideas presented here may be obsolete soon. However, there are aspects of the current paper that I believe will remain relevant: the prompt library and the recommendations emerging from the paper, as these will be applicable in newer LLMs, the reflections on the role that humans play in knowledge creation and the guidelines on how to use Gen AI responsibly and ethically.

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**Author contributions** The author, Celeste Combrinck, conceptualized the paper. Celeste Combrinck designed the methodology and conducted the data collection and analysis. Celeste Combrinck wrote the draft and was responsible for synthesis, revision, and final approval. Celeste Combrinck generated all figures and tables. Celeste Combrinck conducted the literature review included in the article.

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**Data availability** The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

**Code availability** Not applicable.

## Declarations

**Consent for publications** All participants in this work have provided informed consent to participants in the study. The author affirms that the participants also provided informed consent for their data to be used for publication purposes.

**Competing interests** There is no conflict of interest.

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## Appendix—prompt library

### Prompts for qualitative analysis

Square brackets indicate aspects you should modify to suit your needs.

**Prompt 1**—You are a qualitative researcher. Use Reflexive thematic analysis according to Braun and Clark, to analyse the interviews and generate themes. Use the [add theory or conceptual framework here] to interpret the data with the following labels for the themes:

[Add list of codes or themes here].

The themes should be written as narrative findings in paragraphs, and each theme should be named to reflect the main finding of that theme. Use quotes from the interviewee to support your themes. Please add to every theme how many participants cited the reason associated with the theme.

**Prompt 2a**—Attached are open-ended responses to the question “Briefly explain why you chose to study engineering?” in column B. Code and classify the responses according to the codes shown below and add these labels to each line of the Excel Spreadsheet in Column C:

Social Good  
Intrinsic psychological  
Intrinsic behavioural

Financial  
Parental or Mentor influence  
Diverse career opportunities  
Student is Unsure

Make the Excel sheet available with the codes completed in Column C.

### **Prompt 2b:**

Attached are open-ended responses to the question: “Briefly explain why you chose to study engineering?” in column B. A human has already generated themes in Columns C and D. I want you to read the text and the human codes and then add your own themes to Column E and use the following categories:

Social Good  
Intrinsic psychological  
Intrinsic behavioural  
Financial  
Parental or Mentor influence  
Diverse career opportunities  
Student is Unsure

Make the Excel sheet downloadable with the completed themes.

### **Prompts for quantitative analysis**

**Prompt 3**—I have cross-sectional survey data; please recommend analyses I could do with my data set. The variables include [demographic questions, such as gender, age, and race]. The constructs measured in the questionnaire include [motivation to attend university and long-term career goals]. [Codebook pasted with prompt].

**Prompt 4**—Summarise the constructs [add list here] in the attached data set to identify trends. Create a table and write a paragraph to illustrate your findings.

**Prompt 5**—Please create demographic profiles for my data. Create a table in [APA 7] as the output with a paragraph briefly describing the student profile.

**Prompt 6**—Redo the analysis; consider that most of the demographic variables are categorical in nature. Add the categories to the table to make it easier for the reader to understand.

**Prompt 7**—Based on the previous data, run inferential statistical analysis and identify any significant items. Include p-values and effect sizes. Show the results in tables with a summary of your interpretation.

### **Prompts for mixed method analysis**

**Prompt 8**—I have findings from [a questionnaire], and I also conducted [in-depth interviews]. The results from the quantitative and qualitative analyses are attached. Please conduct a [sequential explanatory analysis] and help me identify patterns, achieve triangulation, and integrate the results. Use the [Incentive Theory] to interpret the results. Write two pages based on your sequential explanatory analysis.

**Prompt 9**—Based on the findings from the previous prompt, create a statistics-by-themes joint table display of the findings. Make the table a downloadable Excel.

**OR**

Create a side-by-side joint display of the quantitative and qualitative findings. Make the display downloadable.

**Prompt 10**—Produce a two-page document of your findings and ensure your report clearly distinguishes between quantitative and qualitative findings and how they integrate. Based on your findings, suggest practical or theoretical implications. Reflect on the effectiveness of the mixed-methods approach for the data collected.

## Prompts for obtaining more from chatbots

**Prompt 11**—Please give me more information about your analysis and findings.

**Prompt 12**—You are the student’s supervisor. Evaluate the problem statement according to the guidelines. Identify the shortcomings and list them. Give the student valuable tips to improve the problem statement. Problem statement guidelines: a) What do we already know about the problem? (Use recent and relevant studies to substantiate, preferably studies no older than ten years) b) What do we need to know about the problem? (Gap in literature/scholarly field) c) Why does it matter? (importance of the study) d) Conclude with how your study will address the problem.

**Prompt 13**—I want you to evaluate the writing. Act as a critic; be ruthless. Analyse the text and tell me where it can be better.

**Prompt 14**—Please write a review of the attached document and highlight both the strengths and the weaknesses of the submission. Please be as constructive and specific as possible when offering recommendations. Use the following guidelines when examining the document [insert journal guidelines or evaluation criteria here].

## References

1. Howard J. Artificial intelligence: implications for the future of work. *Am J Ind Med.* 2019;62(11):917–26. <https://doi.org/10.1002/ajim.23037>.
2. Dwivedi YK, et al. Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int J Inf Manage.* 2021;57: 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>.
3. Ågerfalk PJ. Artificial intelligence as digital agency. *Eur J Inf Syst.* 2020;29(1):1–8. <https://doi.org/10.1080/0960085x.2020.1721947>.
4. Ooi KB, et al. The potential of generative artificial intelligence across disciplines: perspectives and future directions. *J Comput Informat Syst.* 2023. <https://doi.org/10.1080/08874417.2023.2261010>.
5. Dewey J, Pautz MC, Diede MK. How do we address faculty burnout? Start by exploring faculty motivation. *Innov High Educ.* 2023. <https://doi.org/10.1007/s10755-023-09685-2>.
6. Strzelecki A. Students’ Acceptance of ChatGPT in higher education: an extended unified theory of acceptance and use of technology. *Innov High Educ.* 2023. <https://doi.org/10.1007/s10755-023-09686-1>.
7. Caesar Labs, I. Julius AI. 2024; April,7, 2024. <https://github.com/julius-ai/julius-ai>.
8. OpenAI. ChatGPT-4o [Large language model]. 2024. <https://chat.openai.com>.
9. Bahroun Z, et al. Transforming education: a comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability.* 2023;15(17):12983. <https://doi.org/10.3390/su151712983>.
10. Wikipedia. *ChatGPT*. 2024. <https://en.wikipedia.org/wiki/ChatGPT>. 4 March 2024
11. Rawas S. ChatGPT: empowering lifelong learning in the digital age of higher education. *Educ Inf Technol.* 2023. <https://doi.org/10.1007/s10639-023-12114-8>.
12. Ruiz-Rojas LI, et al. Empowering education with generative artificial intelligence tools: approach with an instructional design matrix. *Sustainability.* 2023;15(15):11524. <https://doi.org/10.3390/su151511524>.
13. Ratten V, Jones P. Generative artificial intelligence (ChatGPT): implications for management educators. *Int J Manage Educat.* 2023;21(3): 100857. <https://doi.org/10.1016/j.ijme.2023.100857>.
14. Hmoud M, et al. Higher education students’ task motivation in the generative artificial intelligence context: the case of ChatGPT. *Information.* 2024;15(1):33. <https://doi.org/10.3390/info15010033>.
15. Koh E, Doroudi S. Learning, teaching, and assessment with generative artificial intelligence: towards a plateau of productivity. *Learn Res Pract.* 2023;9(2):109–16. <https://doi.org/10.1080/23735082.2023.2264086>.
16. Dempere J, Modugu K, Hesham A, Ramasamy LK. The impact of ChatGPT on higher education. *Front Educ.* 2023;8:1206936. <https://doi.org/10.3389/educ.2023.1206936>.
17. Fàbregues S, Molina-Azorin JF, Fietters MD. Virtual special issue on “quality in mixed methods research”. SAGE publications sage CA: Los Angeles. 2021: 146–151. <https://doi.org/10.1177/1558689821100197>
18. Timans R, Wouters P, Heilbron J. Mixed methods research: what it is and what it could be. *Theory Soc.* 2019;48(2):193–216. <https://doi.org/10.1007/s11186-019-09345-5>.
19. Warfa AM. Mixed-methods design in biology education research: approach and uses. *CBE Life Sci Educat.* 2016;15(4):5. <https://doi.org/10.1187/cbe.16-01-0022>.
20. Kuckartz U, Rädiker S. Using Maxqda for integration in mixed methods research, in *The Routledge handbook for advancing integration in mixed methods research.* 2022, Routledge. p. 540-562
21. Herrmann H, Cameron R. Responsible mixed methods research (RMMR): a case for managing ethics and AI in MMR, in *Handbook of Mixed Methods Research in Business and Management.* 2023, Edward Elgar Publishing. p. 55–75. <https://doi.org/10.4337/9781800887954.00012>
22. Islam I, Islam MN. Exploring the opportunities and challenges of ChatGPT in academia. *Discov Educat.* 2024. <https://doi.org/10.1007/s44217-024-00114-w>.
23. Davidson T. Start generating: harnessing generative artificial intelligence for sociological research. *osf.io/preprints/socarxiv/u9nft*, 2023. <https://osf.io/u9nft/download>
24. Pack A, Maloney J. Using generative artificial intelligence for language education research: insights from using <sc>OpenAI</sc>’s <sc>ChatGPT</sc>. *TESOL Q.* 2023;57(4):1571–82. <https://doi.org/10.1002/tesq.3253>.

25. Barros A, Prasad A, Śliwa M. Generative artificial intelligence and academia: implication for research, teaching and service. *Manag Learn.* 2023;54(5):597–604. <https://doi.org/10.1177/13505076231201445>.
26. Goodfellow I, et al. Generative adversarial networks. *Commun ACM.* 2020;63(11):139–44. <https://doi.org/10.1145/3422622>.
27. Adamopoulou E, Moussiades L. An overview of chatbot technology. in *IFIP international conference on artificial intelligence applications and innovations.* 2020. Springer. <https://doi.org/10.1109/ACCESS.2022.3143323>
28. Hadi MU et al. A survey on large language models: applications, challenges, limitations, and practical usage. *Authorea Preprints,* 2023. <https://doi.org/10.36227/techrxiv.23589741.v1>
29. Korteling J, et al. Human-versus artificial intelligence. *Front Artif Intell.* 2021;4: 622364. <https://doi.org/10.3389/frai.2021.622364>.
30. Cooms S, Saunders V. Poetic inquiry: a tool for decolonising qualitative research. *Qual Res J.* 2024;24(1):3–22. <https://doi.org/10.1108/QRJ-05-2023-0071>.
31. OpenAI. ChatGPT (September 25 Version) [Large language model]. 2024. <https://chat.openai.com>.
32. Costello GR, Davis KR, Crocco OS. Learning by doing: student & faculty reflections on a collaborative model for conducting and publishing mixed methods research in a graduate course. *Innov High Educ.* 2022;47(6):1067–84. <https://doi.org/10.1007/s10755-022-09629-2>.
33. Malina MA, Nørreklit HS, Selto FH. Lessons learned: advantages and disadvantages of mixed method research. *Qual Res Account Manag.* 2011;8(1):59–71.
34. Onwuegbuzie AJ, Poth C. Special issue mixed methods. *Int J Qualitat Methods.* 2015;14(2):122–5. <https://doi.org/10.1177/160940691501400203>.
35. Coolidge FL. *Statistics: a gentle introduction.* 2020: Sage Publications.
36. Chambers JM. *Statistical computing: history and trends.* Am Statistic. 1980;34:238–43.
37. Abatan SM, Olayemi M. The role of statistical software in data analysis. *Int J Appl Res Stud* 2014; 3(8). <https://ssrn.com/abstract=2532326>
38. Klinke S. *Statistical user interfaces.* Center for Applied Statistics and Economics (CASE) REport, 2004; 35. [https://www.econstor.eu/bitstream/10419/22208/1/35\\_sk.pdf](https://www.econstor.eu/bitstream/10419/22208/1/35_sk.pdf)
39. Martinez WL. *Graphical user interfaces.* Wiley Interdiscipl Rev Comput Statist. 2011;3(2):119–33. <https://doi.org/10.1002/wics.150>.
40. Field AP. *Discovering statistics using IBM SPSS statistics.* 2024: Sage publications limited.
41. Vindrola-Padros C, Johnson GA. Rapid techniques in qualitative research: a critical review of the literature. *Qual Health Res.* 2020;30(10):1596–604. <https://doi.org/10.1177/1049732320921835>.
42. Kantor J. Best practices for implementing ChatGPT, large language models, and artificial intelligence in qualitative and survey-based research. *JAAD Int.* 2024;14:22–3. <https://doi.org/10.1016/j.jdin.2023.10.001>.
43. Cave S, Dihal K. Hopes and fears for intelligent machines in fiction and reality. *Nat Mach Intell.* 2019;1(2):74–8. <https://doi.org/10.1038/s42256-019-0020-9>.
44. McClure PK. “You’re fired”, says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Soc Sci Comput Rev.* 2018;36(2):139–56. <https://doi.org/10.1177/0894439317698637>.
45. Hinks T. Artificial intelligence perceptions and life satisfaction. *J Happiness Stud.* 2024;25(1):1–14. <https://doi.org/10.1007/s10902-024-00727-w>.
46. Smolansky A et al. Educator and student perspectives on the impact of generative AI on assessments in higher education. In *Proceedings of the tenth ACM conference on Learning@ Scale.* 2023. <https://doi.org/10.1145/3573051.3596191>
47. Council on Higher Education, C. A closer look at plagiarism within the context of student academic writing in an era of generative artificial intelligence. Briefly Speaking, 2024. 27. <https://www.che.ac.za/file/7452/download?token=Zk5fYHd3>
48. Atkinson R. Don't fear AI (Volume 2). European Investment Bank. 2019. <https://doi.org/10.2867/939083>
49. Baker M. The western mathematic and the ontological turn: ethnomathematics and cosmotechnics for the pluriverse, in *Indigenous knowledge and ethnomathematics.* 2023, Springer. p. 243–276. [https://doi.org/10.1007/978-3-030-97482-4\\_9](https://doi.org/10.1007/978-3-030-97482-4_9)
50. Hui Y. For a cosmotechnical event: In honor of Don Ihde and Bernard Stiegler. *Reimag Philo Technol Reinvent Ihde.* 2020. [https://doi.org/10.1007/978-3-030-35967-6\\_6](https://doi.org/10.1007/978-3-030-35967-6_6).
51. Ihde D. *Technology and the lifeworld: from garden to earth.* 1990.
52. Fisher WP. Meaning and method in the social sciences1. *Hum Stud.* 2004;27(4):429–54. <https://doi.org/10.1007/s10746-004-3339-z>.
53. Roth PA. *Meaning and method in the social sciences: a case for methodological pluralism.* 2019: Cornell University Press.
54. Fisher Jr WP, Cano SJ. Ideas and methods in person-centered outcome metrology. *Person-Centered Outcome Metrology,* 2023: p. 1. [file:///C:/Users/u27313192/Downloads/978-3-031-07465-3%20\(1\).pdf](file:///C:/Users/u27313192/Downloads/978-3-031-07465-3%20(1).pdf)
55. Schlagwein D, Willcocks L. ‘ChatGPT et al’: The ethics of using (generative) artificial intelligence in research and science. *J Informat Technol.* 2023;38(3):232–8. <https://doi.org/10.1177/02683962231200411>.
56. Rothenberger L, Fabian B, Arunov E. Relevance of ethical guidelines for artificial intelligence-a survey and evaluation. in *ECIS.* 2019. <https://core.ac.uk/download/pdf/301379344.pdf>
57. Skorburg JA, O’Doherty K, Friesen P. Persons or data points? Ethics, artificial intelligence, and the participatory turn in mental health research. *Am Psychol.* 2024;79(1):137. <https://doi.org/10.1037/amp0001168>.
58. O’Kane P, Smith A, Lerman MP. Building transparency and trustworthiness in inductive research through computer-aided qualitative data analysis software. *Organ Res Methods.* 2021;24(1):104–39. <https://doi.org/10.1177/1094428119865016>.
59. Wang Y, Singh L. Adding guardrails to advanced chatbots. *arXiv preprint arXiv:2306.07500,* 2023. <https://doi.org/10.48550/arXiv.2306.07500>.
60. Abdelkader H, et al. ML-On-Rails: safeguarding machine learning models in software systems a case study. *arXiv preprint arXiv:2401.06513,* 2024. <https://doi.org/10.48550/arXiv.2401.06513>
61. Boxleitner A. Pushing boundaries or crossing lines? The complex ethics of ChatGPT Jailbreaking. *The Complex Ethics of ChatGPT Jailbreaking* (October 17, 2023), 2023. <https://doi.org/10.2139/ssrn.4604736>
62. Kamalov F, SantandreuCalonge D, Gurrib I. New era of artificial intelligence in education: towards a sustainable multifaceted revolution. *Sustainability.* 2023;15(16):12451. <https://doi.org/10.3390/su151612451>.

63. Cheng MWT, Yim IHY. Examining the use of ChatGPT in public universities in Hong Kong: a case study of restricted access areas. *Discover Educat.* 2024. <https://doi.org/10.1007/s44217-023-00081-8>.
64. Daniela F-T. Academic writing and ChatGPT: Students transitioning into college in the shadow of the COVID-19 pandemic. *Discov Educat.* 2024;3:1–10. <https://doi.org/10.1007/s44217-023-00076-5>.
65. Mari L. Chatbots: facing a cultural revolution and trying to understand it (a non-technical perspective), B. Seminar, Editor. 2023: UC Berkeley. <https://bearcenter.berkeley.edu/seminars-fall-2023>
66. Combrinck C, Inglis H. The validity of international instruments for assessing South African engineering students, in 2020 IFEEES World Engineering Education Forum–Global Engineering Deans Council (WEEF-GEDC). 2020, IEEE: Cape Town. p. 1–5. <https://doi.org/10.1109/WEEF-GEDC49885.2020.9293636>
67. Inglis H, Combrinck C, Simpson Z. Disrupted access and success: Students' transition to university in the time of Covid-19. 2022. <https://doi.org/10.36615/sotls.v6i2.227>
68. Donaldson KM et al. Scaling up: taking the academic pathways of people learning engineering survey (APPLES) national, in 2008 IEEE Frontiers in Education Conference. 2008, IEEE Computer Society. p. F4H-6-F4H-11. <https://doi.org/10.1109/fie.2008.4720596>
69. Sheppard SD et al. Exploring the engineering student experience: findings from the academic pathways of people learning engineering survey (APPLES). 2010, center for the advancement of engineering education technical report CAEE-TR-10–01. <https://files.eric.ed.gov/fulltext/ED540124.pdf>
70. Linacre JM. *Winsteps® (Version 5.4.0.0)* 2023: Portland, Oregon: Winsteps.com. <https://www.winsteps.com/>
71. IBM, IBM SPSS Statistics for Windows (Version 28.0). 2023, IBM Corp.
72. Braun V, Clarke V. One size fits all? What counts as quality practice in (reflexive) thematic analysis? *Qualitat Res Psychol.* 2021;18(3):328–52.
73. Braun V, Clarke V. *Thematic analysis: a practical guide.* 2022, London: SAGE.
74. Braun V, Clarke V. Using thematic analysis in psychology. *Qual Res Psychol.* 2006;3(2):77–101. <https://doi.org/10.1191/1478088706qp063oa>.
75. Surach D. AI foundations: Learn to leverage market moving AI tools. 2024, YouTube: YouTube. <https://www.youtube.com/@ai-foundations>
76. Surach D. 5 ChatGPT Hacks | Take ChatGPT to the NEXT Level!, in AI Foundations. 2023: YouTube. [https://www.youtube.com/watch?v=J8L6J9U\\_KzY](https://www.youtube.com/watch?v=J8L6J9U_KzY)
77. Stapleton A. How to write an a+ essay using AI in 3 simple steps. 2023: YouTube. <https://www.youtube.com/watch?v=EeMm-kaYgI0&t=68s>
78. Stapleton A. Andy Stapleton: Teaching you the insider secrets of academia to make it work for YOU. 2024, YouTube: YouTube. <https://www.youtube.com/@DrAndyStapleton>
79. Owoahene Acheampong K, Nyaaba M. Review of qualitative research in the era of generative artificial intelligence. Matthew, review of qualitative research in the era of generative artificial intelligence (January 7, 2024), 2024. <https://doi.org/10.2139/ssrn.4686920>
80. Guetterman TC, Feters MD, Creswell JW. Integrating quantitative and qualitative results in health science mixed methods research through joint displays. *Ann Fam Med.* 2015;13(6):554–61. <https://doi.org/10.1370/afm.1865>.
81. Corrigan JA, Onwuegbuzie AJ. Toward a meta-framework for conducting mixed methods representation analyses to optimize meta-inferences. 2020. <https://hdl.handle.net/10210/460756>
82. Grimes M, et al. From scarcity to abundance: Scholars and scholarship in an age of generative artificial intelligence. *Acad Manag J.* 2023;66(6):1617–24. <https://doi.org/10.5465/amj.2023.4006>.
83. Newport C. *Slow productivity: the lost art of accomplishment without burnout.* 2024: Portfolio.
84. Mirkin PJ. Exploring student experiences of learning chemistry using holism evolution infused poetry. *Discov Educat.* 2024;3(1):1–13. <https://doi.org/10.1007/s44217-024-00095-w>.
85. Schwartz R, et al. Towards a standard for identifying and managing bias in artificial intelligence. *NIST Spec Publicat.* 2022. <https://doi.org/10.6028/NIST.SP.1270>.
86. Hwang G-J et al., Vision, challenges, roles and research issues of artificial intelligence in education. 2020, Elsevier. p. 100001. <https://doi.org/10.1016/j.caeai.2020.100001>
87. Nishant R, Kennedy M, Corbett J. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. *Int J Informat Manage.* 2020. <https://doi.org/10.1016/j.ijinfomgt.2020.102104>.

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