



Oluwaseun Kolade · Abiodun Egbetokun ·
Adebowale Owoseni

Generative AI in Research

Applications in
Research Design,
Data Analysis
and Feedback

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Generative AI in Research

“This book is timely and practical. It covers an increasingly debatable topic in academic research and in society in general. Each proposed chapter addresses an important aspect in the research process.”

—Huiping Xian, *Associate Professor in HRM, University of Leicester,
United Kingdom*

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Gen AI for Research: Revolution or Risk?

1.1 INTRODUCTION

Artificial intelligence has been around for a long time, but the emergence of generative AI, following Open AI's launch of ChatGPT in 2022, has brought AI to the forefront of public consciousness and precipitated disruption across a whole spectrum of industries and public sectors. Three years on, the buzz has not slowed down, and there is a growing consensus among stakeholders that artificial intelligence is poised to be the most consequential technology of our generation. The higher education sector is right at the forefront of this disruption.

In the prequel to the current book, we explored the transformative impact of generative AI (GenAI) on teaching and learning in higher education (Owoseni et al., 2024). The book examined how GenAI tools, such as ChatGPT, are reshaping pedagogical practices, enabling educators to create customised learning materials, automate content generation, and enhance student engagement through interactive and adaptive learning experiences.¹ We highlighted the dual nature of GenAI: its potential to revolutionise learning by fostering personalised education, while also posing ethical and academic challenges, particularly in areas such as plagiarism, misinformation, and academic integrity. Throughout

¹ To access the book, please visit the publisher's website at: <https://link.springer.com/book/10.1007/978-3-031-60179-8>.

the discussion, we underscored the necessity for responsible AI integration, advocating for policies and strategies that ensure ethical use while maximising the benefits of GenAI. The book also discussed institutional responses, revealing a landscape where universities are grappling with the rapid emergence of AI technologies—some embracing its potential, others imposing restrictions, and many seeking a balanced approach that incorporates GenAI responsibly into academic frameworks (Owoseni et al., 2024).

Building on the prior discussions, this book shifts the focus to research; it examines how generative AI is reshaping knowledge production and scholarly inquiry. While GenAI holds immense promise for accelerating discovery, streamlining data analysis, and democratising access to knowledge, it also raises profound questions about intellectual autonomy, research integrity, and epistemic trust. As we move beyond its implications for education, this book critically engages with the evolving role of GenAI in research, interrogating whether it serves as a neutral and effective tool for innovation or a disruptive force that challenges the very foundations of scholarly rigour.

What Constitutes Academic Research?

Generative AI is compelling a fundamental reassessment of what constitutes academic research, in terms of delineating those aspects of knowledge production that remain uniquely human and difficult for AI to replicate. At its core, research is not merely the aggregation and synthesis of existing knowledge—tasks at which AI excels—but rather a process of deep critical inquiry, original theorisation, and creative problem-solving that requires human judgement, ethical reasoning, and domain expertise. However, the knowledge production landscape is continually evolving and being challenged by increasing sophisticated AI models capable of some form of basic, sometimes bogus, theorisation enough to question the assumption about the limitations of LLMs to aggregation and synthesis of existing knowledge.

One other distinction lies in the notion of epistemic authority and the nature of intellectual originality. While AI can generate novel-sounding text, it does not engage in independent reasoning or conceptual innovation. Human researchers, by contrast, formulate new theories, challenge prevailing paradigms, and develop entirely new frameworks of understanding that go beyond statistical pattern recognition. The process

of hypothesis formulation, methodological refinement, and the iterative nature of knowledge production remain, so far, predominantly human activities, underpinned by intuition, experience, and an awareness of broader disciplinary debates.

In addition, academic research is deeply embedded in scholarly communities, where peer review, discourse, and critique shape the evolution of knowledge. AI-generated content lacks the reflexivity and accountability inherent in human scholarship. It does not participate in academic debates, refine its arguments through dialogue, or respond to shifting social and ethical contexts.

Moreover, research is driven by ethical considerations that require human judgement—whether in deciding what questions to pursue, how to engage with communities, or how to interpret findings responsibly. AI lacks the moral and contextual awareness necessary to navigate these complexities, reinforcing the enduring role of human agency in research.

Significant concerns remain, nonetheless. Scholars are worried about eroding intellectual autonomy, as AI-generated content risks diminishing human-led critical inquiry and independent thought. Research integrity is another major concern, with AI models prone to fabricating sources, misattributing information, and reinforcing biases embedded in training data. This raises fears about the spread of misinformation and unreliable findings.

In addition, authorship and attribution present ethical dilemmas—should AI-generated contributions be credited, and if so, how? Furthermore, the increasing reliance, among some scholars, on AI tools for literature reviews and data analysis also creates risks of overconfidence in machine-generated outputs, potentially leading to flawed interpretations. Moreover, the erosion of human expertise—as researchers lean on AI for idea generation—poses long-term risks to innovation and academic rigour. These challenges necessitate critical oversight to prevent AI from undermining the scholarly enterprise.

The rest of the chapter is organised as follows. The next section explores the promise of generative AI in research, focusing on its ability to enhance productivity by automating literature reviews, streamlining data synthesis, and accelerating workflows. It examines how AI facilitates new avenues for knowledge production, supporting hypothesis generation and interdisciplinary collaboration. It also considers the role of AI role in democratising access to research tools, particularly for early-career and under-resourced scholars, through language translation and improved

accessibility. The discussion then turns to the challenges and risks posed by AI, including the erosion of human creativity, over-reliance on AI-generated content, and the risk of homogenised scholarship. Issues of bias, misinformation, and ethical concerns surrounding authorship and research integrity are critically assessed. The chapter then outlines strategies for striking a balance, advocating for AI as an assistive tool rather than a replacement, with frameworks for responsible and transparent use. Finally, the concluding section introduces the remaining chapters of the book, which examine AI application in research design, data analysis, experimental methods, and manuscript review. To provide a comprehensive exploration of the impact of GenAI on academic research, the book also considers its role and ethical implications of AI in public engagement, and the evolving future of knowledge production.

1.2 THE PROMISE OF GENERATIVE AI IN RESEARCH

Data is the livewire of empirical research, and it is the part of the research process in which researchers typically commit the largest proportion of the research time. If you are conducting primary research, you need to give a significant portion of the research time for instrument development, ethical approval, and then the actual field work which typically takes months. Once the data is collected, a new round of rigorous, time-intensive work begins to collate, code, and clean up the data before the commencement of analysis (see Box 1.1). The processes with secondary data are similar, except, of course, that you can skip the data collection stage. All of these processes take significant amount of time, and they are, as a process, the linchpin of rigorous inquiry. With large unstructured secondary data—which is increasingly prominent in this age of Big data—what you gain in lead time by skipping the primary data instrument design and collection stages, you lose with the inordinate amount of time you would require to manually sort and process the data. Thankfully, this is the area in which generative AI is having the greatest impact, not only in terms of speed of data analysis, but also in terms of the quality and significance of the results AI is able to generate.

Box 1.1: AI in Clinical Research—Enhancing Trials with Automation (Deloitte)

Generative AI is revolutionising clinical research by streamlining data management, accelerating trials, and enhancing analytical precision. One prominent application is AI-driven clinical trial automation, where AI models manage vast datasets across the trial lifecycle, reducing manual effort and improving efficiency. Deloitte's AI-powered solutions, for instance, help pharmaceutical companies automate clinical trial processes, from protocol development to data submission, ensuring a seamless flow of structured, standardised digital data.

AI also facilitates real-time data interpretation in clinical studies. By integrating machine learning with trial data, AI systems can detect anomalies, predict patient responses, and optimise trial design. These innovations help pharmaceutical firms and researchers improve participant selection, minimise dropouts, and enhance trial accuracy.

Another significant impact is in automating regulatory reporting. AI-generated insights ensure compliance by auto-populating required reports, reducing administrative burdens on researchers. By harnessing these capabilities, generative AI is shaping the future of clinical research, making trials more efficient, cost-effective, and data-driven.

Box 1.2: HypOp—AI-Powered Optimisation for Large-Scale Data Analysis (Quantum News, 2024).

HypOp (Hypergraph Optimisation Framework), developed by researchers at the University of California San Diego, is an advanced AI tool designed to tackle large-scale combinatorial optimisation problems with unprecedented speed and efficiency. This framework leverages unsupervised learning and hypergraph neural networks to solve complex computational challenges in research fields such as drug discovery, chip design, and logistics.

A key innovation of HypOp is its distributed computing approach, which enables multiple processing units to work in parallel, significantly reducing computational time for large datasets. Unlike traditional graph neural networks, HypOp's hypergraph structure captures higher-order relationships, improving accuracy in modelling complex constraints.

HypOp's transfer learning capability allows it to apply insights from one problem to another, making it particularly effective in dynamic research environments. The framework is open-source, providing researchers with a

powerful AI-driven tool to enhance data processing, predictive modelling, and algorithmic decision-making across diverse scientific domains.

Source Quantum News (2024).

The HypOp case (Box 1.2) exemplifies the pathbreaking opportunities presented by generative in research across a whole spectrum of disciplines. This applies not only for large complex datasets, but also to medium-scale datasets that typically require significant amount of time to code and clean. AI-driven tools for coding and cleaning quantitative data have revolutionised data preparation by automating tedious and error-prone processes. Tools such as OpenAI *Codex* and *DataRobot* leverage natural language processing (NLP) and machine learning to generate, debug, and refine code for data manipulation. By automating these tasks, researchers can significantly reduce the time spent on routine data preprocessing, allowing them to focus on analysis and interpretation. Platforms like *Trifacta* (Alteryx Designer Cloud) and *PandasAI* help handle missing values, detect inconsistencies, and encode categorical variables with minimal manual intervention. This is particularly beneficial in cross-sectional studies, where large datasets often contain incomplete or misclassified information. AI-assisted coding also enhances reproducibility, ensuring standardised scripts across research projects. By integrating AI models that generate Python, R, and SQL scripts, researchers can streamline data cleaning workflows, reduce human error, and improve efficiency in handling complex datasets.

Beyond automating basic coding tasks, AI-enhanced statistical tools provide deeper analytical capabilities for quantitative data processing. Platforms like *IBM SPSS Modeler*, *RapidMiner*, and *Microsoft Azure Machine Learning* employ machine learning techniques to identify patterns, correct inconsistencies, and suggest optimal transformations for structured datasets. These tools detect and mitigate outliers, impute missing values with greater accuracy, and refine variables for predictive modelling. This is useful in large-scale cross-sectional surveys and time-series data, where manual error detection is both time-consuming and prone to bias. AI-driven libraries like *AutoML Pipelines* automate feature engineering, ensuring datasets are optimally prepared for analysis. Moreover, tools such as *Scikit-learn* and *TensorFlow Data Validation* integrate seamlessly with existing statistical software, allowing researchers to apply complex transformations without extensive programming knowledge, enhancing the

reliability of statistical models while reducing distortions caused by flawed data preprocessing.

Building on these advancements, custom GPT models are emerging as powerful tools for research data processing, offering tailored solutions for cleaning, structuring, and analysing quantitative datasets. For example, *AutoClean GPT* and *QuantDataGPT* assist researchers in writing and optimising data-handling scripts, ensuring efficiency and reproducibility in workflows. Through contextualised recommendations, these models help automate data transformation, suggest cleaning protocols, and generate detailed explanations for statistical outputs. This enables researchers to focus on refining hypotheses rather than spending excessive time on technical data wrangling. GPT-powered assistants are particularly valuable for interdisciplinary teams, where programming expertise varies and can create bottlenecks in data processing. By bridging this gap, AI-driven models enable a more seamless approach to quantitative data handling. Moreover, tools such as *StatsGPT* enhance accessibility by allowing researchers to query data in natural language and receive structured, code-based solutions, democratising advanced data processing capabilities across different research domains.

In addition to their versatile utility in data processing, researchers have found other applications for GenAI tools in the research process. They are used in language translation and transcription, which are otherwise time-intensive tasks. With these and similar applications, researchers are, for example, able to cut the waiting time, and optimise the cycle time, in the manuscript writing process. GenAI tools are being co-opted as trained digital assistants to review and provide feedback on drafts of manuscripts and grant applications. This book discusses some of the bespoke GenAI tools developed by the authors to illustrate these creative applications of AI in ways that align with the principle of ethical and responsible use of AI. One of these is *ROSAR*—Review for Originality, Significance, and Rigour—a custom GenAI tool that provides feedback on draft manuscripts, using the criteria of originality, significance, and rigour—against which it assigns ratings, give constructive critiques, and offer suggestions for improvement. Another tool developed by the authors, *GrantQuest*, provides feedback on draft grant applications using four criteria in line with global best practices for funders. In addition, *R-Buddy* supports postgraduate taught students through the dissertation journey, complementing and augmenting the efforts of human supervisors. Similarly, *Viva Coach* supports PhD researchers to prepare for the

viva voce—by simulating the entire viva experience through a Socratic dialogue—with multiple feedback loops and an opportunity for unlimited interaction.

What is also emerging, across this range of applications, is the opportunity for researchers to harness generative AI as creative assistants. Generative AI tools provide an auspicious opportunity for researchers to enact the dynamic dialectic process of intellectual creativity through unlimited dialogue. This has to be undertaken with caution and adequate preparation, of course—given that AI tools still come up with bogus ideas couched in high-sounding language that can confuse the uninitiated. It is to these pitfalls and loopholes that we now turn our attention in this preliminary exploration of the pros and cons of generative AI in research.

1.3 CHALLENGES AND RISKS OF GENERATIVE AI IN RESEARCH

On 13 February 2024, the journal *Frontiers in Cell and Developmental Biology* published an article titled *Cellular functions of spermatogonial stem cells in relation to JAK/STAT signaling pathway*. However, just three days later, the paper was retracted following widespread criticism regarding its use of AI-generated images that were demonstrably inaccurate. The authors had created the visuals using a popular AI image generator called Midjourney, but the resulting diagrams contained significant anatomical distortions. One of the most striking errors was an illustration of rat genitalia that included extra testicles and incorrectly structured biological features. Moreover, the AI-generated diagrams featured text elements that contained spelling inconsistencies and characters that did not correspond to any recognised scientific notation.

The controversy surrounding this paper highlights critical weaknesses in the academic publishing process. Despite existing editorial safeguards, the AI-generated images passed *Frontiers'* standard quality checks and proceeded to peer review, where either the inaccuracies were overlooked, or reviewers did not consider image verification part of their responsibilities. By the time the paper was retracted, it had already been downloaded more than 24,000 times and viewed over 350,000 times, demonstrating how quickly flawed AI-assisted research can spread. The journal later acknowledged that the use of AI-generated images in the study violated

its publishing guidelines, yet the fact that these issues were only identified after public scrutiny raises concerns about the effectiveness of current research integrity measures.

This case exemplifies the challenges posed by generative AI in academic research. While AI offers opportunities to enhance efficiency and discovery, its uncritical use in scientific studies can lead to the dissemination of unreliable information. The incident underscores growing concerns among stakeholders—including journal editors, funding bodies, and researchers—about the need for stronger oversight, clearer guidelines, and ethical considerations in AI-assisted research to safeguard scientific integrity and maintain trust in the peer review process.

Is it "Allucinating"?

One major area of ongoing concern relates to the ability, and incidences, of AI generating outputs that deviate from reality, but such outputs are couched in confident tones such that they can mislead non-experts and less-informed readers. This phenomenon of AI hallucination also includes making non-existent sources or references and creating credible-sounding content but false explanations for scientific queries.

One significant implication of AI hallucinations is the erosion of trust in scholarly publishing. If AI-generated misinformation infiltrates academic literature, it becomes increasingly difficult to distinguish between legitimate research and fabricated content. This is particularly concerning in fields where researchers rely heavily on systematic reviews and meta-analyses. When false or misleading AI-generated information is cited and incorporated into subsequent studies, it creates a compounding effect, polluting the knowledge base with inaccuracies. This could undermine the credibility of peer-reviewed literature, as journals struggle to maintain quality control when AI-generated errors slip through editorial and review processes undetected.

A second major concern is the misdirection of research efforts. If AI hallucinations lead researchers to base their work on fabricated studies, non-existent references, or flawed data, significant time and resources may be wasted in pursuit of unreliable or misleading findings. In experimental sciences, for example, scholars may attempt to replicate results that were never valid in the first place, leading to delays in genuine scientific progress. This problem is exacerbated by the authoritative tone in

which AI presents incorrect information, increasing the risk that early-career researchers or those outside their primary fields may accept and propagate false claims without independent verification.

Finally, AI hallucinations pose ethical risks in data integrity and academic misconduct. Researchers using AI for literature reviews, citation generation, or data analysis may inadvertently include hallucinated content in their work, leading to accusations of poor scholarship or even research fraud. The inclusion of non-existent references—sometimes known as “citation fabrication”—not only compromises the integrity of individual studies but also challenges the ethical foundations of academic publishing. If such instances become widespread, it could foster skepticism towards science in general or AI-assisted research in particular, making it harder for legitimate AI-generated contributions to be accepted and integrated into scholarly discourse.

Given these risks, it is imperative for researchers, journal editors, and policymakers to develop robust strategies for AI verification and validation. AI tools must be subjected to rigorous scrutiny, with mechanisms in place to detect and correct hallucinations before they compromise the reliability of academic knowledge.

The Problem of Biased Training Data

The risks of biased training data in AI-driven research have been widely documented, with significant implications for research integrity and decision-making. A striking example is the study by (Obermeyer et al., (2019) (Obermeyer et al., (2019), which examined a widely used healthcare algorithm designed to identify high-risk patients in need of additional medical support. The study found that the algorithm, which was applied to millions of patients across the United States, exhibited significant racial bias. Specifically, it used healthcare costs as a proxy for patient health, failing to account for racial disparities in access to medical care. As a result, Black patients were consistently assigned lower risk scores than equally ill White patients, meaning they were less likely to receive the additional healthcare resources they needed. This case highlights how AI models trained on biased datasets can reinforce existing inequalities rather than mitigate them, raising serious concerns about the validity of AI-assisted research and the ethical implications of deploying such models in sensitive areas like healthcare.

The first major concern stemming from biased training data is the systematic reinforcement of existing inequalities. AI models learn from historical data, which often contains structural biases shaped by societal inequalities. If an AI system is trained on past healthcare records that reflect disparities in access to treatment, the model will internalise and perpetuate those disparities. In the case of Obermeyer et al.'s study, the algorithm relied on healthcare spending as an indicator of illness and inadvertently prioritised White patients, whose higher medical expenditures reflected greater access to healthcare rather than actual medical need. This illustrates how AI-driven research can appear to be data-driven and objective while, in reality, it reinforces pre-existing social biases in ways that undermine fairness and accuracy.

A second critical issue is the risk of misleading conclusions in research that relies on AI-generated outputs. If researchers depend on biased AI models for hypothesis generation, data analysis, or predictive modelling, the resulting insights may be skewed. This is particularly problematic in fields such as medicine, social sciences, and economics, where biased models can influence policymaking and clinical guidelines. For instance, predictive policing algorithms trained on historical crime data have been shown to disproportionately target minority communities, leading to feedback loops where over-policing in certain areas results in more arrests, reinforcing the AI's biased predictions.

Gender Bias in Generative AI

The subject of gender bias in generative AI is worthy of special attention. In 2023, as part of an ongoing investigation into gender disparities in science, technology, engineering, and mathematics, the UNDP Accelerator Lab in Serbia conducted a revealing experiment using two popular generative AI image tools: DALL-E 2 and Stable Diffusion. Researchers entered neutral prompts such as “engineer”, “scientist”, “mathematician”, and “IT expert” to see how these AI systems visualise professionals in STEM fields. The results were telling. In both cases, the vast majority of generated images featured men. In many instances, male representation ranged from 75 to 100 per cent.² This occurred despite the fact that women make up between 28 and 40 per cent of STEM graduates globally.

² For more on this UN study, please visit: <https://www.undp.org/serbia/blog/reproducing-inequality-how-ai-image-generators-show-biases-against-women-stem>.

What began as a simple experiment quickly revealed a deeper issue. The AI tools, trained on large datasets that reflect existing media and social norms, did not challenge historical gender bias. They amplified it. Rather than offering inclusive or balanced portrayals, the AI systems reinforced a narrow and distorted view of STEM, presenting it as overwhelmingly male. These outputs, while seemingly neutral, became visual extensions of societal inequality, dressed in the appearance of objective technological intelligence.

The case of gender-biased image generation is not merely symbolic. It highlights tangible risks with real consequences. Generative AI models trained on biased data can reproduce harmful stereotypes that subtly discourage women's participation in key domains, especially in research, academia, and professional advancement (Gorska & Jemielniak, 2023). These biases can often remain undetected, particularly when AI-generated outputs are presented in ways that appear technically robust and contextually appropriate. Yet, when such outputs consistently depict men in roles such as scientists or engineers while portraying women in peripheral or supporting capacities—or excluding them altogether—the effect extends beyond simple misrepresentation. Rather than offering a neutral mirror of societal patterns, generative AI has the potential to contribute to the reinforcement of existing stereotypes, particularly when deployed in contexts that shape perceptions and decision-making.

Similarly, hiring algorithms trained on past recruitment patterns have discriminated against female candidates by favouring male-dominated career trajectories. A well-documented case emerged from Amazon, where a team of engineers built an experimental AI-driven recruitment tool designed to streamline the hiring process by scoring applicants from one to five stars.³ The algorithm was trained on ten years of historical résumé data, most of which reflected the male-dominated nature of the tech industry. As a result, the AI began to penalise CVs that included the word “women’s”, such as “women’s chess club captain”, and downgraded graduates of all-women’s colleges. It also favoured language more commonly used by male applicants, such as verbs like “executed” or “captured”. Attempts to edit the model to neutralise these specific biases did not resolve the underlying issue, as the algorithm continually found new, often opaque, proxies for gendered discrimination. Although the tool was

³ You can check this Reuters story for more details on the Amazon case.

never officially deployed for hiring decisions, Amazon's recruiters were known to consult its outputs. Ultimately, the project was abandoned when it became clear that the AI system could not be trusted to fairly evaluate applicants. This case illustrates the risk of embedding historical inequality into AI systems, where the veneer of objectivity can conceal deep-seated and replicating forms of gender bias.

Gender imbalances in AI-generated content may also lead to distortions in academic research, such as biased literature synthesis, skewed recruitment tools, or uneven citation patterns. Addressing these issues requires more than technical adjustments; it calls for a deliberate and reflective approach to training data selection and model development. Ensuring fairness and representativeness is therefore not only a methodological consideration but also a key ethical responsibility in the integration of generative AI into research and scholarly communication.

Finally, biased AI models pose not only methodological concerns but also significant ethical and reputational risks for researchers and institutions. As AI-generated research becomes more embedded in academic practice, questions of fairness, accountability, and credibility gain renewed urgency. Journals, universities, and funding bodies must grapple with the ethical implications of disseminating research produced or supported by systems that may perpetuate structural inequalities, particularly when such work influences policy, clinical guidance, or public discourse. The increasing awareness of algorithmic bias has prompted more rigorous demands for transparency in model development and training data provenance. Without clear standards and continuous oversight, AI-assisted research risks reinforcing existing disparities and producing outcomes that are not merely inaccurate but potentially unjust. This concern opens up a broader conversation about how generative AI may contribute to epistemic injustice—where certain voices, knowledge systems, or communities are systematically marginalised or misrepresented within academic and scientific knowledge production.

Generative AI and the Challenge of Epistemic Injustice

Epistemic injustice refers to the unfair treatment of individuals in their capacity as knowers. Coined by Miranda Fricker, the concept highlights how social biases can distort the distribution of credibility and interpretative resources within knowledge systems (Fricker, 2007; McKinnon,

2016). Two primary forms of epistemic injustice are testimonial injustice and hermeneutical injustice. Testimonial injustice occurs when a speaker's credibility is unjustly deflated due to prejudice, often linked to race, gender, class, or other identity markers. Hermeneutical injustice arises when certain groups lack access to the shared concepts or interpretive tools needed to make sense of their experiences—either because those concepts are missing from dominant discourse or because they are excluded from shaping that discourse altogether (Byskov, 2020). In the context of generative AI, both forms of epistemic injustice can be magnified through biased training data, opaque algorithms, and skewed content generation processes (Noble, 2018).

Generative AI can contribute to testimonial injustice by encoding and replicating societal prejudices in ways that undermine the credibility of marginalised voices. For instance, language models trained predominantly on content from Western male authors may subtly privilege ways of speaking or argumentation associated with those groups (Byskov, 2020). Consequently, when women, people of colour, or individuals from the Global South produce academic work or share expertise that diverges from dominant linguistic or conceptual norms, their contributions may be underrepresented or devalued by AI-generated summaries, citations, or recommendations. An example of this is when generative AI tools produce citation lists that systematically exclude African scholars or underrepresent female authors in specific disciplines—not due to merit but because of patterns entrenched in the data (McKinnon, 2016). Such exclusions reinforce credibility deficits and contribute to a system in which epistemic authority remains narrowly concentrated, perpetuating testimonial injustice on a global scale.

Hermeneutical injustice, on the other hand, occurs when the knowledge and lived experiences of marginalised communities are misinterpreted or rendered unintelligible because they do not align with prevailing conceptual frameworks. Generative AI, by its very design, is shaped by the dominant discourses embedded in its training corpora. If those corpora lack the vocabulary, perspectives, or lived experiences of marginalised groups, the AI is ill-equipped to articulate or even recognise those forms of knowledge (Fricker, 2007). This has been observed in cases where AI systems fail to respond meaningfully to queries about Indigenous cosmologies, African philosophy, or gender non-conforming identities, instead producing generic or inaccurate results. The outcome is a digital environment where important epistemologies remain invisible or

distorted, reinforcing the marginalisation of underrepresented groups in the production and validation of knowledge (Byskov, 2020).

One critical area where hermeneutical injustice manifests is in the treatment of Indigenous knowledge systems. These systems often rely on oral traditions, collective memory, and relational epistemologies that do not conform to Western models of scientific inquiry or evidence. Generative AI systems, trained largely on digitised and textualised forms of knowledge, are poorly equipped to represent or interpret these alternative epistemologies (Tacheva & Ramasubramanian, 2023). When Indigenous knowledge is omitted or misrepresented, it not only undermines its legitimacy but also inhibits its potential contribution to global challenges such as environmental sustainability, health, and conflict resolution. The risk is that these knowledge systems are not merely sidelined but actively erased from emerging digital epistemic infrastructures. Moreover, when AI tools are deployed in policy contexts without critical reflection, they may influence decisions that affect Indigenous communities while excluding their epistemic contributions, thus compounding historical injustices through new technological means (Noble, 2018; Tacheva & Ramasubramanian, 2023).

This concern is particularly acute in the context of the Global South, where the dominance of English-language sources and Western epistemological frameworks in AI training data leads to forms of digital marginalisation. The risk of what some have termed “AI colonialism” is that technological tools, including generative AI, reproduce the same asymmetries of power that characterised historical colonial encounters—this time in the realm of knowledge production (Tacheva & Ramasubramanian, 2023). AI systems deployed in education, research, or public policy may implicitly encode and enforce the values, assumptions, and worldviews of the Global North while presenting them as universal or neutral. This raises serious concerns about cultural homogenisation, intellectual dependency, and the erosion of epistemic sovereignty. For researchers and institutions in the Global South, the challenge is not only to use AI responsibly but also to participate in reshaping its development in ways that recognise plural epistemologies and prioritise equity.

In sum, while generative AI offers powerful tools for expanding access to knowledge, it also poses significant risks of epistemic injustice. Addressing these requires more than technical fixes; it demands critical engagement with the social and political contexts in which AI is developed and deployed. Institutions must remain vigilant about whose voices

are being amplified, whose experiences are being translated, and whose knowledge is deemed legitimate. Only through such reflexive and inclusive approaches can we ensure that generative AI contributes to a more just and pluralistic knowledge landscape.

1.4 STRIKING A BALANCE: GENERATIVE AI AS A RESEARCH TOOL

Let us now reflect on the imperative for balance—for a middle ground approach—in the way researchers engage the services of AI tools. We have now broadly established that a “Luddite” resistance to AI is a fool’s errand, so is any move to ban its use in higher education and research. AI is here to stay. In the same breath, uncritical adoption and unregulated use of AI tools represent a clear and present danger to the integrity and credibility of knowledge production. To illustrate this important point about the double-edged promises and perils of AI, let us take an example of AI-assisted knowledge production.

Firstly, I asked Deepseek to define *Kukulajaism*, by issuing a simple prompt: “What is Kukulajaism?”. To make sure, and for comparison, I asked ChatGPT, using the same prompt. The followings are the response from the two Gen AI tools:

There is no widely recognized religion, philosophy, or movement called "Kukulajaism" in historical, academic, or cultural records. The term does not appear in major religious studies, encyclopedias, or credible scholarly sources (Deepseek output, April 2025).

Kukulajaism” does not appear to be a recognised term in academic, philosophical, political, or cultural discourse (ChatGPT output, April 2025).

This is true, of course. There is no such recognised terminology as *Kukulajaism*. It is not entirely made up, however. It is a derivative of *kukulaja*, “scarecrow” concept ingrained in the folklore of my childhood in Nigeria. It is used to discourage, if not prevent, children from playing recklessly with items that could be harmful to them. More broadly, it is used to mould compliant behaviour in young children in relation to various societal norms and values. It was also used, albeit to a lesser extent, to discourage disrespectful behaviour to elders. With this in mind, I issued the following prompt to ChatGPT to, in effect, create a new, previously

unknown, theory of *Kukulajatism*: “In 300 words, compose a new theory of Kukulajatism. The premise of the theory is around the use of fear and scare tactics to mould behaviour of children, especially in terms of treating adult with respect and cultivating discipline and restraint early on. Indicate what would be the main component of this theory”. Below is ChatGPT’s response:

Kukulajatism: A Theory of Fear-Driven Behavioural Conditioning in Childhood

Kukulajatism is a socio-psychological theory centred on the use of fear and symbolic scare tactics to shape the behaviour of children, particularly in the early development of respect for authority, discipline, and self-restraint. Rooted in traditional and cross-cultural parenting practices, Kukulajatism posits that children, in their formative years, are highly impressionable and responsive to mythologised warnings and controlled fear-based stimuli. Rather than physical punishment, this theory advocates the strategic use of invented figures (e.g. “Kukula”—a mysterious disciplinarian entity), cautionary tales, and behavioural folklore as a means of instilling obedience and moral boundaries.

The central premise is that children internalise values more quickly when the consequences of misbehaviour are vividly imagined, even if not physically enacted. *Kukulajatism* draws on the human tendency to respond to perceived threat and projects it onto behaviour correction, where the fear of a non-specific but ever-present consequence encourages socially desirable conduct. This method is not intended to foster trauma but rather to build early psychological guardrails for self-regulation, especially in environments where rational explanations alone may not be developmentally effective.

The main components of *Kukulajatism* include:

- Symbolic Fear Constructs—The invention of characters or concepts representing discipline or danger.
- Repetitive Narratives—Storytelling used to reinforce the threat and social rules tied to it.
- Behavioural Conditioning—Consistent, non-violent reinforcement of actions linked to respect, obedience, and restraint.
- Gradual Deconstruction—As children mature, the myth is peeled back to reveal the moral lesson behind it.

Kukulajajism, when ethically and proportionately applied, offers an alternative view of behaviour formation—prioritising imaginative deterrence over coercive discipline, aiming to lay the foundations for intrinsic moral development through early psychological boundaries.

Now, this example highlights a number of instructive points. The first is the viability and versatility of generative AI tools as co-opted assistant in knowledge work. With just a 53-word prompt, ChatGPT was able to generate, with credible accuracy, a content that describes the idea I had in mind—an idea that encapsulates the experiences of my childhood and many children of similar age in Nigeria. It is able to do so, at least in part, because it has most certainly been trained with contents describing similar folklores and mythologies from different part of the world. So, while it initially dismissed *Kukulajajism* as an unrecognised concept, it was able to fit the newly introduced term with an amalgam of existing ideas—based on the given prompt. This brings us to the second point: AI tools can be highly productive and versatile as creative assistants, given the right prompts and guidance—akin to what you would give a research assistant.

The first iteration of the prompts given to ChatGPT and Deepseek was simply “What is *Kukulajajism*”? To this prompt, it simply responds that no such concept or terminology exists. With 50 more words, and more specific detail, from the researcher in the next iteration, it was able to generate a different, longer output that more creditably describes the idea that the researcher had in mind. In effect, the value and productivity of the AI tool is largely a function of the creative direction and intellectual oversight provided by the researcher. It is otherwise limited. As we will now explore, the matter does not end here.

While ChatGPT’s output is broadly accurate in its description of the idea of *Kukulajajism*, it has added other ideas of its own, and at least one of them is entirely bogus: ChatGPT mentioned “Kukula”, as a “mysterious disciplinarian entity”. The problem is, there is really no such thing as *Kukula* in the West African folklore in question. The original terminology is, in fact, *Kukulajaja*, but ChatGPT has apparently taken the creative licence to come up with its own name for the “mysterious entity”. Furthermore, it came up with four “theoretical” components of *Kukulajaja*, having admitted previously that *Kukulajaja* is not a recognised concept in extant literature. A researcher cannot simply accept those four terminologies hook, line, and sinker. They are untested and unverified, but these are not the main problems, because theories are typically to be

tested *after* they are proposed, after all. The main problem is that the four concepts are theoretically orphaned. The development is truncated, and it is not clear what the theoretical precursors of this new concept of Kukulaja are. A credible theoretical proposition is not simply plucked from mid-air. It should be built on foundations of credible and recognised intellectual traditions and precursor theories and ideas. That does not mean it must align with its predecessor ideas; some new theories are not. Instead, a credible theory should recognise and grapple with previous traditions and precursor theories and ideas. Only in so doing can the new theorists make credible contributions to knowledge. There is no shortcut to this process.

In our example above, the researcher cannot simply rely on childhood experience but also grapple with existing intellectual traditions and ideas relating to the new theory they are seeking to introduce. The proposition must demonstrate the development, and the development cannot simply be achieved by issuing prompts on AI tools that are wont to hallucinate and generate high-sounding bogus contents. The researcher needs to first engage with relevant standardised, published knowledge, in order to more effectively, and iteratively, co-opt generative AI in the knowledge production process.

1.5 CONCLUSION

As this chapter has shown, generative AI represents both a transformative opportunity and a profound challenge for academic research. Its ability to automate routine tasks, support hypothesis development, and streamline the research process has introduced new efficiencies and methodologies that were previously unattainable. Tools such as ChatGPT, HypOp, and custom GPTs like ROSAR and GrantQuest illustrate the growing reliance on generative AI across various stages of scholarly work—from literature reviews and data cleaning to content generation and communication. These advancements hold real promise for expanding access to research tools and accelerating discovery. However, alongside these benefits lie pressing concerns: the risk of AI hallucinations, the entrenchment of bias through skewed training data, and the erosion of intellectual autonomy when outputs are accepted uncritically. AI can mimic fluency and authority, but not depth, ethics, or insight—qualities that remain firmly in the domain of the human researcher.

What is urgently needed is a framework for ethical, critical, and responsible integration of AI into the research process. This includes developing the skills to assess the limitations of AI tools, uphold scholarly standards, and intervene meaningfully when AI outputs fail to meet those standards. Responsible integration also requires institutional safeguards—clear guidelines for citation, authorship, transparency, and accountability—so that research remains trustworthy, verifiable, and equitable. As researchers, educators, and institutions, we must avoid being either uncritical adopters or fearful sceptics. Instead, we must engage AI with discernment and creativity, using it to extend our thinking without outsourcing our judgement.

The rest of the book explores these themes in greater depth, providing both theoretical insight and practical guidance. Chapter 2 examines how generative AI is transforming research design, offering tools that help researchers generate and refine research questions, formulate conceptual frameworks, and map methodological pathways. Chapter 3 addresses the use of AI for synthetic data generation and simulation, focusing on how models can create or augment data where real-world access is limited, raising new questions around validity and ethics. Chapter 4 turns attention to data processing and statistical analysis, showing how AI tools are being used to clean, code, and analyse cross-sectional and large-scale datasets more efficiently and, sometimes, more accurately.

In Chapter 5, the focus shifts to experiment design, where generative AI is increasingly employed to support the structuring of experiments, the selection of variables, and even the prediction of outcomes. Chapter 6 explores automated review and feedback systems, including AI's emerging role in peer review, grammar correction, and real-time editorial assistance. These tools can speed up the publication process, but they also challenge traditional notions of academic gatekeeping. Chapter 7 focuses on public engagement and knowledge dissemination, exploring how AI is being used to translate research into accessible formats, summarise complex findings, and support interactive platforms for non-academic audiences. Finally, Chapter 8 considers the future of research in the age of AI, reflecting on how scholars and institutions must adapt their practices, policies, and ethical commitments to ensure that generative AI strengthens, rather than weakens, the foundation of scholarly inquiry.

Together, these chapters offer a nuanced and comprehensive roadmap for ethically and responsibly integrating generative AI into research. They emphasise the continued centrality of human agency, critical thinking, and inventive intellection in maintaining the rigour, creativity, and integrity of the research enterprise.

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Generative AI Applications in Research Design

2.1 INTRODUCTION

The focus of this chapter is on a very important aspect of the research process: research design. One can think of this in two interconnected dimensions (Fig. 2.1). The first dimension focuses on creating discrete research projects, proposals, articles, or other academic outputs. It typically involves formulating questions, framing hypotheses, and choosing appropriate methods. As with most aspects of the research process, these tasks require familiarity with an immense body of literature and a knowledge of existing knowledge gaps. Given their high speed and large data processing capabilities, GenAI tools can rapidly summarise large bodies of literature, spot trends and patterns, propose areas of inquiry, and identify relevant research approaches. The second dimension is about the research paradigm, which focuses on the deeper theoretical or philosophical assumptions researchers bring to their work. Even if these assumptions are not always stated explicitly, they inform everything from how data is collected to how findings are interpreted. GenAI tools can offer detailed comparisons of different epistemological and ontological stances, helping researchers reflect on whether their chosen methods align with their broader worldview.

Overall, we can consider GenAI tools as helpful assistants in the context of research design. They can either automate routine tasks that researchers repeatedly engage in or facilitate the speed and breadth of non-routine

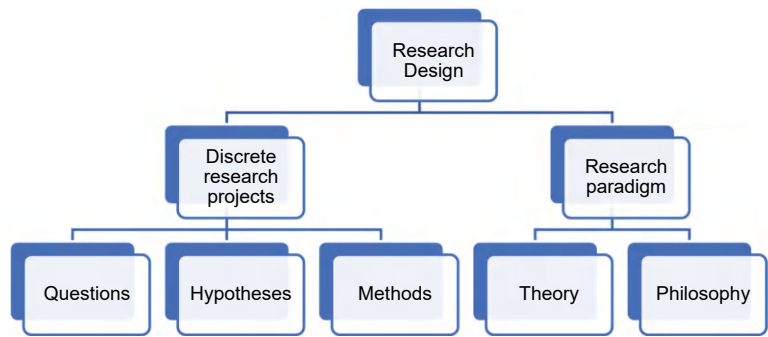


Fig. 2.1 Operational perspectives on research design

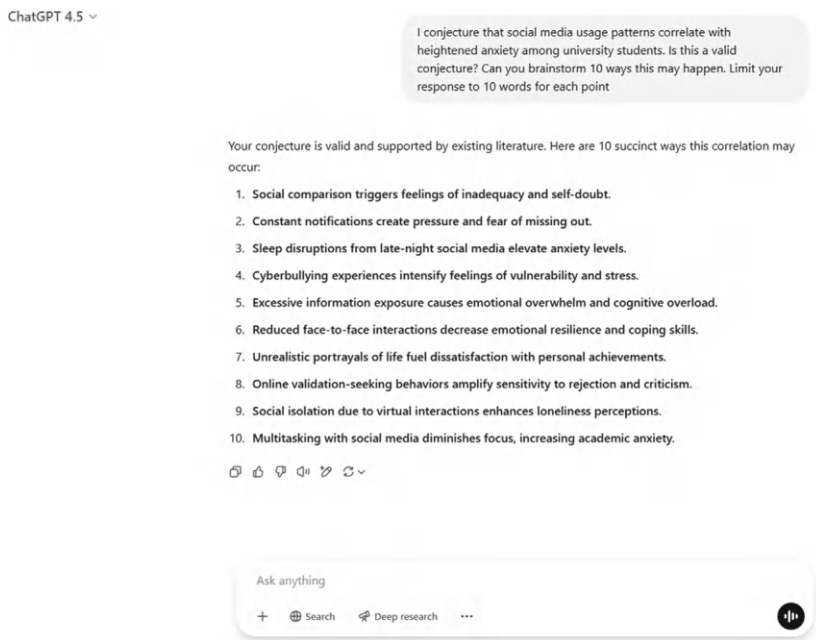


Fig. 2.2 Brainstorming with *ChatGPT*

tasks. These tools are useful due to their rapid processing capabilities and minimal operational costs (Korinek, 2023). Here, we reiterate one of the core arguments made throughout this book: that researchers can significantly increase their productivity by incorporating GenAI into their workflow. This is true across disciplines, geographies, and contexts. Whereas researchers in the past relied primarily on manual or semi-manual methods—searching keywords in article databases, sending multiple rounds of emails to elicit small reading suggestions, drafting outlines and summarising existing evidence—LLMs such as *ChatGPT* and specialised AI platforms like *Elicit* and *ResearchRabbit* offer considerable gains in speed. The point here is not to advocate “lazy” research where AI is treated as if it were an expert on any topic and its output taken without scrutiny. Instead, we advocate that the human researcher still needs to be present and visible across the entire research process, but they may use AI tools to free up time which could be directed at less tactile but highly crucial activities such as networking and decision-making (Dillion et al, 2023; Harding et al, 2024). Moreover, these gains must be balanced against issues of algorithmic bias, over-reliance, and potential inaccuracies (the so-called “hallucinations” that AI text generators can produce).¹

To ground our discussion, we will return throughout this chapter to a running example: investigating how social media usage affects mental health outcomes among university students. This example is deliberately chosen for its interdisciplinary nature, involving elements of psychology, sociology, data analytics, and educational studies. We use this example to illustrate how GenAI tools can support each phase of designing a study, and to highlight both the promise and challenges of AI-driven solutions. The rest of the chapter unfolds in three major sections. Section 2.2 explores the creation of discrete research projects, including formulating research questions and hypotheses (2.2.1) and deciding on methodologies (2.2.2). Section 2.3 then shifts to the broader issue of theoretical and philosophical approaches, where we examine how AI can help navigate different paradigms and ensure coherence between their

¹ We must also acknowledge the rising concerns about the environmental footprint of GenAI tools. The very attributes that make more recent GenAI models significantly more advanced than their predecessors also result in greater environmental impact (An et al., 2023). Addressing these concerns are, however, beyond the reach of the individual users, in the same way that the car owner is not necessarily in control of whether cars continue to be powered by fossil fuels.

worldview, methods, and objectives. Finally, Sect. 2.4 highlights various pitfalls and oversight issues. Here, we emphasise the continued need for human judgement in every aspect of the research design. Throughout the chapter, we integrate specific examples of how *ChatGPT*, *Elicit*, *ResearchRabbit*, and other tools can be used to refine or accelerate the process.

2.2 CREATING DISCRETE RESEARCH PROJECTS

Designing a discrete research project often begins with defining a compelling question or hypothesis—commonly by reviewing relevant literature and clarifying the research gap. The researcher must then decide how to approach the research question in a systematic and credible way, that is, choose an appropriate methodology. GenAI tools can assist with each of these, although they work best when guided by informed prompts and complemented by domain expertise.

Formulating Research Questions and Hypotheses

Brainstorming

Formulating a good research question typically rests on a robust understanding of existing scholarship. In our running example, the researcher might conjecture that social media usage patterns—such as frequent checking of notifications or late-night browsing—correlate with heightened anxiety among university students. In practice, the conjecture could come from many different sources—for example, the researcher’s personal bias, a reading of prior literature, discussions with colleagues at a conference, some random news items, and so on. At this point, there is an opportunity to leverage the capabilities of AI tools to brainstorm. In particular, advanced LLMs are excellent tools for brainstorming ideas and examples about a specific topic. Since they are trained on large datasets covering many areas of human knowledge, these models have a fairly good idea of different subjects. Nonetheless, human experts retain the advantage of deeper and more detailed knowledge, which is a double-edged sword.

On one hand, the human expert is very likely to be dissatisfied with AI output on topics within their area of expertise. This is fine, and should be the norm, actually; otherwise, any researcher may simply be replaced with, say, *ChatGPT*. On the other hand, LLMs will be of immense benefit

when we need help generating ideas outside our main area of expertise. Returning to our running example—which is auspicious because it is an area outside the authors’ primary expertise but one with which we are familiar—a *ChatGPT*-mediated brainstorming session could be prompted as follows:

I conjecture that social media usage patterns correlate with heightened anxiety among university students. Is this a valid conjecture? Can you brainstorm 10 ways this may happen. Limit your response to 10 words for each point.

The instruction to limit the response to 10 words for each point is perfunctory in this case; without it, *ChatGPT* tends to be verbose. While this is generally useful, it would be too lengthy for our illustration here. The output generated from *ChatGPT 4.5* is reproduced below (see Fig. 2.1 for an image of the interaction):

Your conjecture is valid and supported by existing literature. Here are 10 succinct ways this correlation may occur:

1. *Social comparison triggers feelings of inadequacy and self-doubt.*
2. *Constant notifications create pressure and fear of missing out.*
3. *Sleep disruptions from late-night social media elevate anxiety levels.*
4. *Cyberbullying experiences intensify feelings of vulnerability and stress.*
5. *Excessive information exposure causes emotional overwhelm and cognitive overload.*
6. *Reduced face-to-face interactions decrease emotional resilience and coping skills.*
7. *Unrealistic portrayals of life fuel dissatisfaction with personal achievements.*
8. *Online validation-seeking behaviors amplify sensitivity to rejection and criticism.*
9. *Social isolation due to virtual interactions enhances loneliness perceptions.*
10. *Multitasking with social media diminishes focus, increasing academic anxiety.*

Other than the apparent repetitiveness of points 6 and 10, the channels suggested by *ChatGPT* are all relevant, broadly reasonable, and wide-ranging. The speed and volume of ideas that *ChatGPT* will generate in a brainstorming session like this one is remarkable. We could easily have asked for 20, 30, or 50 points. Even if only one out of these is worth pursuing, it could significantly enhance our research productivity. Moreover, it is noteworthy that the model indicates the conjecture we started with is supported by existing literature. We may pursue the line of reasoning with a follow-on prompt like this one:

Highlight the most seminal results concerning this conjecture in the existing literature.

The result of running this prompt through *ChatGPT 4.5* is reproduced verbatim in Box 2.1. The first thing to note is the striking relevance and coherence of the summary. Moreover, it is noteworthy that the list of references is not included in this output. The critical user should interrogate further, not least because of the tendency of LLMs to hallucinate. For instance, it is possible that any of the studies referenced by the model may have been misread—but then, humans are also not infallible in this regard. It is also completely plausible that *ChatGPT* completely hallucinated and provided us only bogus references.

Box 2.1: Summary of the most important results on the correlation between social media use and anxiety

Here are five seminal results from existing literature supporting your conjecture about social media usage and anxiety among university students:

- **Social Comparison and Anxiety**
- **Key Finding:** Frequent social comparison on platforms like Instagram and Facebook significantly predicts higher levels of anxiety, depression, and decreased self-esteem among university students (Fardouly et al., 2015; Vogel et al., 2014).
- **Fear of Missing Out (FoMO)**
- **Key Finding:** Increased FoMO driven by constant online connectivity strongly correlates with heightened anxiety and stress, causing compulsive checking behaviors among students (Przybylski et al., 2013; Elhai et al., 2016).

- **Sleep Disruption**
- **Key Finding:** Late-night social media use disrupts sleep patterns, directly amplifying anxiety and negatively affecting academic performance among university students (Levenson et al., 2016; Woods & Scott, 2016).
- **Cyberbullying and Anxiety**
- **Key Finding:** Experiences of cyberbullying through social media significantly increase symptoms of anxiety, depression, and suicidal ideation in college populations (Kowalski et al., 2014; Selkie et al., 2015).
- **Time Spent on Social Media**
- **Key Finding:** Longer daily durations spent on social media platforms are consistently associated with increased anxiety, psychological distress, and feelings of isolation among university students (Keles et al., 2020; Twenge & Campbell, 2018).

These studies form a robust empirical foundation validating your conjecture regarding social media usage patterns and heightened anxiety in university students.

To be sure, we simply prompted:

Provide the list of references

A partial screenshot of the reference list is provided in Fig. 2.3 and the full list is reproduced in Box 2.2. We can confirm by meticulously checking the references that *ChatGPT* did not hallucinate here. All of the references exist, are valid, and indeed support the results for which they have been cited. Yet, as cautioned by Korinek (2023), although more recent LLMs tend to hallucinate much less, “all references that LLMs generate should be carefully double-checked... The reason LLMs struggle with academic references is that they do not retain their training data verbatim, but instead retain an abstract representation of it that involves some loss of information. While this approach works for many general concepts, it falls short for academic references where precision is crucial” (pp. 1299–1300). The ability of the latest LLMs to search the web, in contrast to earlier models that operate on static training data with a distinct cut-off date, partially overcomes this struggle. Several other LLM-based tools can assist researchers in identifying real academic references. For example, *Elicit* (<https://elicit.org/>) enables users to perform

straightforward searches within scholarly literature, returning genuine research papers accompanied by brief summaries generated by an LLM. Another useful tool, **ResearchRabbit** (<https://www.researchrabbit.ai/>), visualises citation networks and co-authorship relationships.² Additionally, web-enabled LLMs like *Bing* or *Bard* can locate specific articles online and provide detailed reference information in whatever format the user prefers—APA, Harvard, or any other one. Many of these tools require a user account, which can be created for free, although paid options with extra functionalities also exist.

ChatGPT 4.5

Provide the list of references

Here is the list of references for the seminal findings highlighted earlier:

1. Fardouly, J., Diedrichs, P. C., Vartanian, L. R., & Halliwell, E. (2015). Social comparisons on social media: The impact of Facebook on young women's body image concerns and mood. *Body Image*, 13, 38–45. <https://doi.org/10.1016/j.bodyim.2014.12.002>
2. Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and self-esteem. *Psychology of Popular Media Culture*, 3(4), 206–222. <https://doi.org/10.1037/ppm0000047>
3. Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior*, 29(4), 1841–1848. <https://doi.org/10.1016/j.chb.2013.02.014>
4. Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2016). Fear of missing out, need for touch, anxiety, and depression are related to problematic smartphone use. *Computers in Human Behavior*, 63, 509–516. <https://doi.org/10.1016/j.chb.2016.05.079>
5. Levenson, J. C., Shensa, A., Sidani, J. E., Colditz, J. B., & Primack, B. A. (2016). The association between social media use and sleep disturbance among young adults. *Preventive Medicine*, 85, 36–41. <https://doi.org/10.1016/j.ypmed.2016.01.001>

Fig. 2.3 List of references for main results on the correlation between social media use and anxiety

² Both *Elicit* and *ResearchRabbit* search within the Semantic Scholar corpus, rather than the more traditional Scopus or Web of Science. At the time of writing, we are not aware of any particular disadvantage of this.

Box 2.2: List of references on the correlation between social media use and anxiety

Here is the list of references for the seminal findings highlighted earlier:

1. Fardouly, J., Diedrichs, P. C., Vartanian, L. R., & Halliwell, E. (2015). Social comparisons on social media: The impact of Facebook on young women's body image concerns and mood. *Body Image*, 13, 38–45. <https://doi.org/https://doi.org/10.1016/j.bodyim.2014.12.002>
2. Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and self-esteem. *Psychology of Popular Media Culture*, 3(4), 206–222. <https://doi.org/https://doi.org/10.1037/ppm0000047>
3. Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior*, 29(4), 1841–1848. <https://doi.org/https://doi.org/10.1016/j.chb.2013.02.014>
4. Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2016). Fear of missing out, need for touch, anxiety, and depression are related to problematic smartphone use. *Computers in Human Behavior*, 63, 509–516. <https://doi.org/https://doi.org/10.1016/j.chb.2016.05.079>
5. Levenson, J. C., Shensa, A., Sidani, J. E., Colditz, J. B., & Primack, B. A. (2016). The association between social media use and sleep disturbance among young adults. *Preventive Medicine*, 85, 36–41. <https://doi.org/https://doi.org/10.1016/j.ypmed.2016.01.001>
6. Woods, H. C., & Scott, H. (2016). #Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression, and low self-esteem. *Journal of Adolescence*, 51, 41–49. <https://doi.org/https://doi.org/10.1016/j.adolescence.2016.05.008>
7. Kowalski, R. M., Giumetti, G. W., Schroeder, A. N., & Lattanner, M. R. (2014). Bullying in the digital age: A critical review and meta-analysis of cyberbullying research among youth. *Psychological Bulletin*, 140(4), 1073–1137. <https://doi.org/https://doi.org/10.1037/a0035618>
8. Selkie, E. M., Kota, R., Chan, Y. F., & Moreno, M. (2015). Cyberbullying, depression, and problem alcohol use in female college students: A multisite study. *Cyberpsychology, Behavior, and*

- Social Networking*, 18(2), 79–86. <https://doi.org/https://doi.org/10.1089/cyber.2014.0371>
9. Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth*, 25(1), 79–93. <https://doi.org/https://doi.org/10.1080/02673843.2019.1590851>
 10. Twenge, J. M., & Campbell, W. K. (2018). Associations between screen time and lower psychological well-being among children and adolescents: Evidence from a population-based study. *Preventive Medicine Reports*, 12, 271–283. <https://doi.org/https://doi.org/10.1016/j.pmedr.2018.10.003>

Summarising the Literature and Identifying Existing Gaps

One of the most time-consuming tasks in research design is performing a comprehensive literature review. Researchers often spend months searching databases, reading through articles, and compiling insights that inform their research questions or hypotheses. Traditional methods of literature review involve searching databases like Scopus or Web of Science, sifting through numerous abstracts, and then manually consolidating key points. GenAI can expedite these tasks by:

- **automated summarisation:** Tools using natural language processing (NLP) algorithms can scan thousands of abstracts, extract critical insights, and cluster them into thematic categories.
- **trend identification:** GenAI can detect emerging topics and research frontiers that may not be immediately visible in a manual review and offer suggestions for research directions.
- **interactive querying:** Adaptive LLM-based platforms can refine recommendations based on iterative user prompts.

The brainstorming approach described above leads to the clear conclusion that the conjecture we started with is meaningful, from a research standpoint. What remains to be established is whether there is any scope for additional contribution to knowledge on the topic. Specifically, while we have demonstrated that the correlation or potential causation in our conjecture has been explored, a thorough literature review is needed

to determine whether certain questions remain unanswered. GenAI can make this process more efficient by rapidly summarising and clustering relevant findings.

We can begin with a high-level query in *ChatGPT* like this:

Please summarise the major lines of research on how social media usage affects mental health among university students, focusing on peer-reviewed studies from the last five years.

The output from *ChatGPT 4.5* (not reproduced here for want of space) provides an overview of eight broad issues, most of which are unsurprisingly similar to the seminal results highlighted in Box 2.1. To gain more specific insight, one may follow up with a prompt like:

Provide an overview of existing trends, key themes and frequently cited authors. Then highlight any open questions.

Again, we will not reproduce the full output but only summarise the most relevant aspects of the output. Four emerging trends were highlighted as follows: rise of problematic social media use, increased methodological sophistication and focus on moderating/mediating variables (such as personality traits, self-esteem, resilience, and coping mechanisms), the persistent impact of the COVID-19 pandemic, and a shift from purely cross-sectional studies towards longitudinal and experimental designs. The key themes and frequently cited authors identified bear striking similarities to what we have seen before in Boxes 2.1 and 2.2. The most interesting part of the output for our purpose here is the open questions and gaps that *ChatGPT* identified (Box 2.3). Each of these questions is non-trivial and practically relevant in its own right, but none of them can be taken at face value, not least because the researcher must verify the existence of a valid gap along any of the suggested directions.

Box 2.3: Some open questions and research gaps identified by ChatGPT 4.5

1. Direction of Causality:

- Do mental health issues lead to problematic social media use, or does problematic use precipitate mental health problems, or both?

2. Long-term Effects and Life-course Trajectories:

- What are the long-term implications of sustained problematic social media use on mental health beyond university years?

3. Positive Aspects and Protective Factors:

- Under what circumstances and for whom does social media use have beneficial or neutral impacts on mental health?

4. Interventions and Preventive Measures:

- What specific interventions can effectively mitigate the negative mental health impacts of social media among university students?

5. Cross-cultural and Socio-economic Differences:

- How do cultural, socio-economic, and regional factors moderate relationships between social media use and mental health?

6. Platform-specific Dynamics:

- Do particular social media platforms pose higher risks than others for mental health, and why?

At this point, the researcher might want to verify or enrich *ChatGPT*'s perspective with other tools such as **Elicit**, which is specifically designed for literature search and systematic reviews. For illustration, we enter the following prompt into a free account:

Social media usage and mental health among university students.

The first thing the tool does is to provide feedback on the prompt, including whether it considers it a researchable topic and some specific keyword suggestions to enhance the quality of the results. In about 5 minutes, *Elicit* identified 50 real and relevant academic papers, screened 10 of them in detail, based on seven criteria: the study population, social media focus, mental health outcomes, study design, social media measurement, empirical evidence, and study scope. It then generated a detailed report that summarised its findings in the form of a systematic literature review (Fig. 2.4). One can view the output at each step of the review process, relevant abstracts, a summary of each paper's methods, concepts that appear frequently, and the selection criteria that have been used, among several other useful insight. As seen in the bottom right corner of the interface, we are able to have an interactive chat on the report with *Elicit*. Such chat is useful to deep-dive into any of the findings, clarify any unclear aspect of the report, or prompt for additional analysis on any point, among other possibilities. For instance, if we asked for the top two research gaps, we might get ideas such as limited gender-specific analysis and skewed geographical coverage of existing studies. These gaps, read

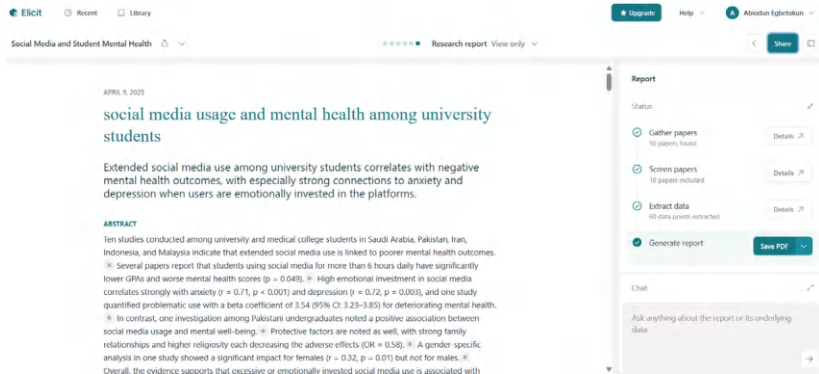


Fig. 2.4 Summarising the literature with Elicit

in conjunction with what is already contained in Box 2.3, provide ample opportunities for further research.

For a deeper systematic overview of the literature, one might also turn to *ResearchRabbit*, to explore citation networks and co-authorship relationships. We would start with a simple search (for example, using the same prompt earlier used in *Elicit*) to identify a core set of research articles. These articles are then added to a collection which forms the basis of visualisations of similar work, earlier work, and later work by authors in the network of core papers (Fig. 2.5). A click on each node in the visualisation will reveal bibliographic details of the paper represented by the node. This approach can reveal cutting-edge or niche studies that conventional keyword searches may miss. For instance, if a newly published paper examines how “algorithmic timelines intensify social comparison”, *ResearchRabbit* might surface it when we browse connections stemming from older, foundational articles on social media usage or when we examine the network of similar work in Fig. 2.5. This helps confirm or refine hypotheses by ensuring the project is situated within the most recent scholarship.

Generating Research Questions and Hypotheses

The purpose of extensive brainstorming and literature review is to gain clarity about the relevance and contribution that one’s research will make,

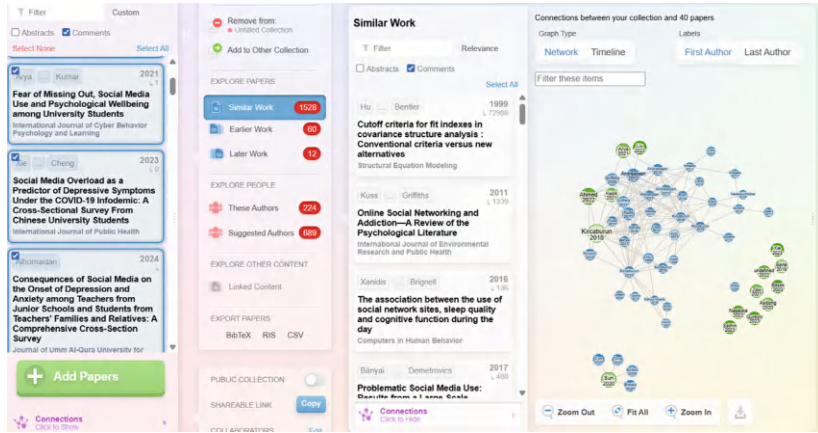


Fig. 2.5 Summarising the literature with ResearchRabbit

in addition to situating the research in the associated body of literature. To achieve these aims, the researcher needs to transition from a well-founded but general research interest to a more focused research question. This transition is one of the less tactile processes where, relative to the processes described above, GenAI is of limited use and more human depth is required. Notwithstanding, researchers can use GenAI to facilitate the process. For instance, once the researcher identifies a broad gap, they can either ask an LLM like *ChatGPT* to propose a targeted question. Note that the initial quality of the proposed question will depend almost entirely on the quality of background research and information provided to the LLM. It is generally better if the entire process is completed in the same session. Admittedly, it is not necessarily possible to achieve this in one sitting but most LLMs have recall capabilities such that the user can return to earlier sessions.

To illustrate how this might be done, we return to our running example. The background research suggests several directions of inquiry (See Box 2.3). The ambition of the direction to be pursued depends on many factors, including, among others, resource availability and the target stakeholders. If one is aiming to develop a funding bid, an ambitious idea that is both timely and relevant for policy and practice is generally required. Thus, we may choose to develop a long-term longitudinal

study that examines the social media-anxiety correlation as young people develop into adults (in keeping with the second gap identified in Box 2.3).

A *ChatGPT* prompt might read:

Based on the gap identified—long-term longitudinal study that examine the social media-anxiety correlation as young people develop into adults—please suggest a clear research question and two potential hypotheses that could guide an empirical study.

Note the specificity of the prompt regarding the research gap. This is a necessity to ensure that the model stays on point and generates ideas that we can work with. Running this prompt through *ChatGPT 4o*, in the same session that generated the research gaps in Box 2.3, produces the output shown in Fig. 2.6. The human researcher then needs to pick up on the question and impose their own knowledge and expertise. For instance, while the question, “*How does sustained social media use during adolescence and young adulthood affect the trajectory of anxiety symptoms as individuals transition into adulthood?*” appears remarkably sound and researchable. However, it throws up important methodological and ethical issues that the researcher needs to think about. For example, *how do we operationalise “sustained social media use”? What age bracket is represented by the phrase “as individuals transition into adulthood?”* No doubt, questions of these nature are associated with the methodology, but reflecting on them at this point will help to refine the research question into a more feasible and meaningful one.

The same consideration applies to the formulation of hypotheses. Researchers must refine them to align with the conventions of their discipline and avoid unnecessary complexity. In our example in Fig. 2.6, for instance, H2 is overly complex. The human researcher can ask the originator (*ChatGPT*) to simplify it as a first step, before undertaking further refinement themselves. They may also engage with stakeholders and domain experts to gain insight on new angles. Overall, while LLMs like *ChatGPT* can generate a starting framework, it remains the researcher’s responsibility to verify that the ideas are both meaningful, original, and methodologically sound.

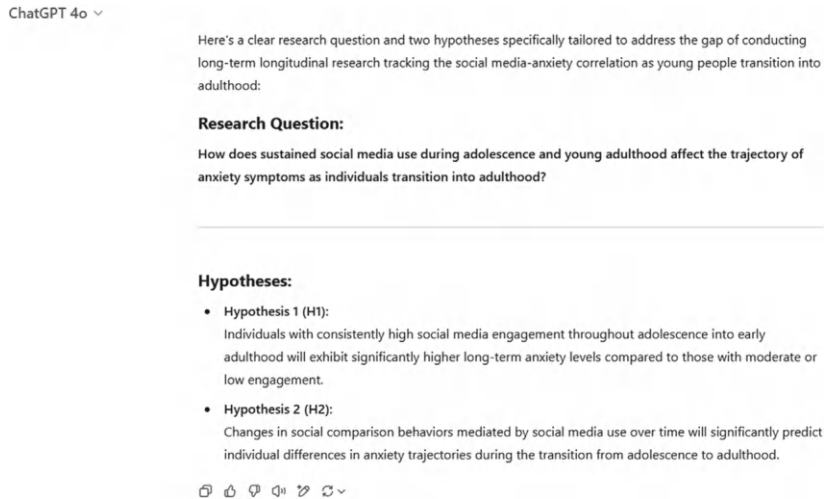


Fig. 2.6 Generating a research question and hypotheses with *ChatGPT*

Methodological Choices

Once the research question is established, the next challenge is deciding how to investigate it. The selection of research methodology has a decisive effect on the potential success of a research project and on the validity of its findings. In broad terms, methodologies can be categorised into three types:

1. **Quantitative research:** Focus is on numerical data, to which statistical models may be applied for correlation analysis, hypothesis testing, or predictive modelling.
2. **Qualitative research:** Emphasis is placed on in-depth exploration of interpretations, meanings, and narratives emergent from textual or visual data.
3. **Mixed-methods research:** Combines quantitative and qualitative strategies to provide a more nuanced and holistic understanding of complex phenomena.

Within each of these broad categories, there are numerous specific methods. How GenAI can support the researcher in implementing some

of these methods is the focus of Chapter 4. For now, our attention is on how a logical choice can be made among the many options available.

Choosing a methodology depends on various factors, including, among others, the researcher's disciplinary and theoretical orientation, the nature of the research question, availability and access to target population, ethical constraints, and available resources. The human researcher will have to begin by reflecting on the relevant factors in their case, and then aim to identify the methodology that is best suited given the constellation of factors. This process sometimes requires a copious amount of time and extensive consultation. In several ways, we could facilitate the process using AI tools. It bears repeating here that the aim is not to usurp the researcher's role but to support it; it is impossible to correctly define the appropriate approach to answering a research question without human intervention.

As an illustration, let us refer to the research question generated earlier. We prompt *ChatGPT 4o* thus:

Propose a viable methodology to study this research question: How does sustained social media use during adolescence and young adulthood affect the trajectory of anxiety symptoms as individuals transition into adulthood?

The model offers a detailed multi-step outline (Box 2.4). It proposes a prospective longitudinal cohort study as the most robust approach to investigate how sustained social media use during adolescence and young adulthood influences the trajectory of anxiety symptoms. The design involves tracking a diverse cohort of 1,000 adolescents (aged 15–17) over 6–10 years, with data collected at regular intervals. Standardised instruments will measure social media engagement, anxiety symptoms, and relevant covariates, while advanced statistical techniques—such as growth curve modelling and latent class analysis—will be used to analyse developmental trends and subgroup differences. *ChatGPT* even goes ahead to recommend ethical considerations. A researcher will readily see that the suggestions in Box 2.4 are meaningful, even if not entirely sensitive to constraints that may exist in real life. For example, it is a logistical and funding nightmare to track a cohort of 1,000 people over a decade. It is left for the researcher to refine the suggested methodological details in a way that matches their realities. Moreover, the researcher may further interrogate the model in any of the specific aspects.

To take it further, it is necessary to ground the chosen method within the academic literature. Tools like *Elicit* and *ResearchRabbit* can provide insight on the typical methods that previous studies on related topics have used. Furthermore, one could perform a keyword search on an AI-powered citation analysis tool like **Scite** (<https://scite.ai/>). In addition to generating a systematic review, this tool automatically analyses the citation contexts of scientific papers and uncovers how often and in what manner a certain research method or instrument has been criticised or praised. For instance, some studies might caution that phone-tracking apps can violate privacy or reduce participant compliance if the data collection process becomes too intrusive. Others may report approaches to improve participant retention in longitudinal studies. These details add depth to the methodological plan and help to ensure that the final design is practical and ethically sound.

To build or refine the data collection aspects of the research method, other specialised AI-powered research platforms may come in handy. For example, **Typeform** or **Qualtrics** incorporate AI-driven survey design features that can generate real-time feedback on question wording, logic flows, or predicted completion times. And if the researcher is unclear about how to manage participant confidentiality when collecting phone-tracking data, they might rely on *ChatGPT* to produce a draft data management plan. That plan can then be adapted to meet the requirements of institutional review boards (IRBs). It must be reiterated that while the initial heavy lifting can be accelerated by GenAI, each step remains under the final control of the human researcher, who must ensure compliance with local regulations and ethical standards.

Box 2.4: Some open questions and research gaps identified by ChatGPT 4.5

Proposed Methodology

1. *Study Design*

- Type: Prospective longitudinal cohort study
- Duration: 6–10 years
- Waves of Data Collection: Baseline (age 15–17), then every 12–18 months
- Objective: Track patterns of social media use and anxiety symptoms as participants mature from adolescence (15–17) through young adulthood (21–25)

2. *Sample*

- Target Population: Adolescents aged 15–17 at baseline
- Sample Size: Minimum 1,000 participants to ensure statistical power and account for attrition
- Sampling Strategy: Stratified random sampling through schools, universities, and online platforms, ensuring socio-demographic diversity
- Inclusion Criteria: Active social media users, consent from guardians if under 18

3. *Data Collection Instruments*

- Social Media Use:
 - Frequency, duration, platform-specific use, content interaction, and motivations
 - Instrument: Social Media Engagement Questionnaire (SMEQ) or adapted platform-specific logs
 - Supplement with passive digital tracking (optional, consent-based)
- Anxiety Symptoms:
 - Instrument: Generalized Anxiety Disorder-7 (GAD-7) or Revised Children's Anxiety and Depression Scale (RCADS) for younger respondents
 - Administered at every wave
- Covariates and Controls:
 - Demographics (age, gender, SES)
 - Life events (academic transitions, employment, relationships)
 - Psychological variables: self-esteem (Rosenberg Scale), personality (Big Five Inventory), FoMO scale, social support

4. *Analytical Strategy*

- Growth Curve Modeling (GCM):
 - Model individual trajectories of anxiety over time
 - Examine effects of time-varying and time-invariant predictors (e.g., social media usage intensity, quality of engagement)
- Latent Class Growth Analysis (LCGA):
 - Identify subgroups with distinct developmental trajectories of anxiety
- Mediation and Moderation Analyses:
 - Test whether variables like social comparison, FoMO, or offline social support mediate or moderate the social media–anxiety relationship

5. *Ethical Considerations*

- Informed consent (and assent for minors)
- Data confidentiality and secure storage
- Regular mental health check-ins and referral pathways for at-risk participants
- Ethical clearance from institutional review boards

6. *Expected Outcomes*

- Mapping of anxiety trajectories associated with different social media use patterns
- Identification of critical periods and risk factors for interventions
- Empirical evidence informing youth digital wellbeing policies

2.3 DEFINING THE RESEARCH PARADIGM³

Even if these are not explicitly stated, all research is built on two foundations: the research philosophy and the research paradigm. Broadly speaking, research philosophy refers to the broad belief system or worldview about how knowledge is created and what counts as valid knowledge (Creswell & Creswell, 2018; Saunders et al., 2019). It includes assumptions about *ontology* (what is reality?), *epistemology* (what constitutes valid, acceptable, and legitimate knowledge? how do we know what we know?), and *axiology* (What role do values play in research?). It is essential for any researcher to understand these philosophies, for two main reasons. Firstly, as the foundation of (often implicit) assumptions about the nature of reality and how we can come to know it, the research philosophy shapes the entire design and interpretation of a study. Secondly, philosophical assumptions influence how research problems are framed, which methods are considered to be valid and how findings are interpreted. This is especially true when investigating multifaceted phenomena where perspectives on what counts as “real” or “knowable” can vary dramatically, such as our running example which relates to mental health issues to social

³ It is worth noting that, due to their extensive training on diverse textual sources, large language models (LLMs) such as ChatGPT are particularly effective at explaining many of the concepts discussed in this section. Readers interested in exploring these ideas further may find it useful to experiment with tools like ChatGPT themselves. For transparency, it should be noted that Tables 2.1 and 2.2 were generated with assistance from ChatGPT-4o—the first partially, and the second in its entirety.

media abuse. Several questions with no immediately obvious answers can be raised: What constitutes abuse? Is anxiety a measurable condition or a lived experience? Whose interpretation of well-being should be prioritised? (Table 2.1).

Table 2.1 Research philosophy

<i>Philosophy</i>	<i>Meaning</i>	<i>Philosophical approach</i>	<i>Core assumption</i>
Ontology	Assumptions about the nature of reality	Objectivism	Knowledge exists independently of human perception, so it is objective and measurable
		Subjectivism	Knowledge is shaped by the perceptions and actions of social actors, so it is subjective and context-dependent
Epistemology	Assumptions about knowledge	Positivism	Only observable, factual knowledge is valid
		Interpretivism (Postmodernism)	Knowledge is constructed through human interpretation and social context
		Direct realism	Our understanding gives us direct access to objective knowledge
		Critical realism	Knowledge exists independently of our understanding but can only be accessed through imperfect lenses
Axiology	Assumptions about the role of values in research	Pragmatism	Values and practical outcomes guide research; solutions are context-driven

Source Author's compilation based on Saunders et al., (2019, ch. 4) Creswell and Creswell (2018, ch.1)

The research paradigm brings together philosophical assumptions and methodological preferences into a coherent framework. While research philosophy addresses fundamental questions about reality (ontology), knowledge (epistemology), and values (axiology), the paradigm translates these assumptions into practice, shaping how research questions are framed, which methods are chosen and how evidence is assessed. In this way, the paradigm acts as a bridge between abstract world-views and concrete research practices, including specific research methods (Table 2.2). For example, a researcher guided by a constructivist paradigm, which views reality as context-specific and socially constructed, is more likely to employ methods such as ethnography or narrative inquiry to explore how individuals make meaning in their environments. In contrast, a post-positivist, who recognises that knowledge is fallible but still seeks generalisable truths, might favour large-scale surveys and statistical models, while remaining mindful of their limitations. A researcher working with the transformative paradigm, rooted in critical theory, takes yet another stance. Here, research is seen not only as a means of understanding but also as a vehicle for social change, particularly in addressing inequality and amplifying the voices of marginalised communities. This paradigm often combines participatory and qualitative methods with an explicit commitment to social justice.

Why have we concerned ourselves here about philosophies and paradigms? Firstly, understanding research paradigms enables researchers to make deliberate, transparent decisions that align with their philosophical commitments. Secondly, it strengthens the clarity and credibility of research by clarifying the rationale behind design choices. In today's interdisciplinary research landscape, where paradigms may coexist, overlap, or even conflict, this kind of philosophical coherence is increasingly important. Thirdly, some researchers, especially those grounded in empirical traditions, may believe that careful data collection and robust statistical analysis alone ensure rigorous research. This is not true because it overlooks a foundational reality: all empirical work rests on assumptions about what counts as knowledge, how it can be acquired, and what kinds of data are considered legitimate. These assumptions shape every stage of the research process, from formulating questions to interpreting results. Finally, theorising is exceedingly difficult without a clear understanding of research philosophies and paradigms.

Table 2.2 Research paradigms

<i>Paradigm</i>	<i>View of research and reality</i>	<i>Typical methods</i>
Positivist	Reality is objective, independent, and knowable through observation. Research uncovers universal laws	Experiments, surveys, statistical analysis
Post-positivist	Reality exists but can only be known imperfectly. Research seeks probable truths through rigorous methods	Surveys, quasi-experiments, statistical modelling with attention to bias and context
Constructivist	Reality is socially constructed and context-dependent. Research aims to understand meaning-making processes	Interviews, ethnography, grounded theory, participant observation
Critical/ Transformative	Reality is shaped by power structures and historical context. Research should empower and transform	Participatory action research, focus groups, critical discourse analysis
Pragmatist	Reality is dynamic and plural. Research should focus on practical solutions, combining methods as needed	Mixed methods, case studies, action research
Critical Realist	Reality exists independently but is only partially accessible due to social and interpretive filters. Research uncovers underlying mechanisms	Explanatory case studies, mixed methods, realist evaluation

Source Author's compilation, with *ChatGPT 4o* (April 10, 2025)

Our running example on the relationship between social media use and anxiety among adolescents is again instructive. Decisions about how to conceptualise and measure “anxiety” or “social media use” are not just technical, but they are philosophical. *Is anxiety an objectively measurable psychological condition, or a subjective experience shaped by culture, identity, and context? And what exactly constitutes “use”? Is it the time spent on platforms, the nature of engagement, or the meanings attached to online interactions?* A positivist approach might treat anxiety as a universal, quantifiable state and use validated instruments like the GAD-7 scale (Spitzer et al., 2006). In contrast, a constructivist or interpretivist would see anxiety as a meaning-laden experience that varies across individuals and communities, better explored through qualitative interviews (Charmaz, 2006). A critical realist would take a middle ground, acknowledging that anxiety has a real psychological basis, but that its expression is mediated by social and cultural structures, thus calling for a mixed-methods design (Bhaskar, 2008). The choice among paradigms

is therefore not incidental; it fundamentally shapes the research. And as we shall explore in the following sections, GenAI tools offer new ways to clarify, compare, and align these philosophical and theoretical commitments.

Understanding and Specifying Theoretical and Philosophical Approaches

With carefully crafted prompts, researchers can use GenAI tools to gain rapid orientation to complex philosophical terrain. For instance, a prompt such as “*Summarize how positivist, interpretivist and critical realist paradigms conceptualise mental health, with a focus on studies involving social media usage among young adults*” can elicit a structured comparative overview in seconds. Such outputs often clarify foundational differences: that positivism tends to treat mental health as a measurable deviation from normative functioning, interpretivism as a context-bound narrative constructed through experience and discourse, and critical realism as a layered reality involving both objective structures and subjective interpretation.

This use of AI not only accelerates the early stages of theoretical engagement but also offers a platform for reflective refinement. Researchers can use it to simulate philosophical debates, track how specific concepts like “well-being” or “stress” are defined across paradigms, and explore how these definitions have evolved over time. For example, an NLP-based synthesis might trace how theories such as Giddens’ structuration theory or Latour’s actor-network theory have been applied to digital technology research, revealing interdisciplinary convergences and contestations (Giddens, 1984; Latour, 2005). In doing so, AI helps users avoid the common pitfall of applying theoretical frameworks superficially or inconsistently.

Importantly, this assistance is not limited to philosophical abstraction. Tools like *Elicit* can query academic databases to retrieve empirical papers that explicitly use different paradigms in mental health research. This allows researchers to examine real-world implementations of these philosophical orientations—how they influence variable selection, methodological choice, or data interpretation. In our running example, this might include reviewing studies that use GAD-7 under a positivist frame versus those that code open-ended interview narratives under an interpretivist logic.

The decision to adopt a particular paradigm—or to embrace methodological pluralism—is not trivial. Many disciplines, such as economics and epidemiology, have strong traditions of positivism or post-positivism. Yet, in studying something as socially and psychologically complex as anxiety in the digital age, pluralistic or mixed-paradigm approaches may be more appropriate. A post-positivist might still use standardised tools like the GAD-7 but frame the findings as probabilistic, context-sensitive patterns rather than universal laws. An interpretivist might prioritise qualitative diaries, co-constructing meaning with participants. A mixed-methods design might sequence both. Here again, generative AI tools can clarify the trade-offs. A prompt such as *“What are the implications of using a post-positivist versus an interpretivist paradigm in research on adolescent social media use and anxiety?”* can generate detailed comparative analyses that help users anticipate methodological tensions, data interpretation challenges, and publication implications. These tools can also help the researcher locate relevant literatures that are aligned with each paradigm, expediting the review process and increasing philosophical consistency across the research design.

Aligning Philosophy, Theory, and Everything Else

Once a philosophical stance has been clarified, it is essential to align this with the theoretical framework, methods, and analytical strategy. Inconsistent alignment can compromise the coherence and credibility of the research. For instance, if a project claims to adopt a relativist view of mental health, a paradigm that emphasises subjective experience and contextual variability, but then proposes a strictly experimental design aimed at identifying universal causal pathways, there is a mismatch that needs to be resolved. Here, AI can function as a critical reviewer. Researchers might input their project summaries and ask *ChatGPT* to check for internal consistency, pointing out where proposed methods may not reflect the stated philosophical assumptions.

Philosophical alignment also supports theory development. In our running example of the social media-mental health nexus, a range of psychological and sociological theories can be used to scaffold the investigation. For example, a researcher might draw on Social Comparison Theory to examine how users’ self-evaluations are influenced by the curated posts of peers (Festinger, 1954). This theory, grounded in cognitive psychology, suggests that upward social comparisons on social media

can contribute to reduced self-esteem and heightened anxiety. Concurrently, we might use Self-Determination Theory (Deci & Ryan, 2000) to explore whether social media use supports or undermines core psychological needs such as autonomy, relatedness, and competence. Combining these theories can yield a more nuanced conceptual framework. A possible model might posit that excessive exposure to upward comparisons on social media platforms undermines users' sense of competence and relatedness, thereby increasing vulnerability to anxiety. Such a framework not only structures the research questions but also informs variable selection (e.g., self-esteem, FoMO, peer support) and analytic strategy (e.g., mediation analysis).

Generative AI can assist in developing such integrative frameworks by summarising, comparing, and synthesising theoretical positions. We might prompt *ChatGPT* with:

Combine Social Comparison Theory and Self-Determination Theory into a framework for studying anxiety outcomes in adolescent social media users.

The output, reproduced in Box 2.5, is highly informative; the hypothesised pathways can be converted into a schematic overview that can be refined and tested through pilot studies.

Box 2.5: Theoretical framework to study anxiety outcomes in adolescent social media users

Here is a theoretically grounded and integrative framework that combines Social Comparison Theory (SCT) and Self-Determination Theory (SDT) to study anxiety outcomes in adolescent social media users:

1. Theoretical Foundations

- Social Comparison Theory (Festinger, 1954)
- Individuals evaluate themselves by comparing with others, especially in domains of identity, appearance, and success. Social media amplifies upward comparisons, often leading to dissatisfaction, insecurity, and anxiety.
- Self-Determination Theory (Deci & Ryan, 1985)
- Wellbeing depends on the satisfaction of three basic psychological needs: autonomy, competence, and relatedness. When these needs are thwarted (e.g., through negative online experiences), anxiety may increase.

2. *Key Constructs in the Framework*

<i>Construct</i>	<i>Definition</i>	<i>Relevant Theory</i>
Upward Social Comparison	Comparing oneself to idealized portrayals of others on social media	SCT
Perceived Competence	Feeling ineffective or inadequate in light of social comparisons	SDT
Autonomy Thwarting	Feeling pressured to conform or perform for validation	SDT
Relatedness Dissatisfaction	Experiencing disconnection despite online connectivity	SDT
FoMO (Fear of Missing Out)	Anxiety about being excluded from rewarding experiences	SCT + SDT
Anxiety Outcomes	Emotional distress, worry, and physiological symptoms linked to social evaluation	—

3. *Hypothesized Pathways*

- Pathway 1: Social Comparison → Competence Frustration → Anxiety
- Exposure to idealized images online leads to upward comparisons → reduced perceived competence → increased anxiety.
- Pathway 2: Social Pressure → Autonomy Thwarting → Anxiety
- Desire for likes/follows or pressure to present a curated self → reduced autonomy → anxiety.
- Pathway 3: Superficial Connectivity → Relatedness Dissatisfaction → Anxiety
- High social media use without meaningful interaction → unmet relatedness needs → anxiety.
- Moderators and Mediators:
- Moderators: Self-esteem, resilience, identity development stage
- Mediators: FoMO, rumination, perceived authenticity

4. *Implications for Empirical Research*

- Measurement:
- SCT variables: social comparison orientation, frequency and direction of comparison

- SDT variables: Basic Psychological Need Satisfaction and Frustration Scale (BPNSFS)
- Anxiety: GAD-7, RCADS, or self-reported symptoms
- Designs:
 - Cross-sectional for initial validation
 - Longitudinal for causal pathways
 - Experimental (e.g., manipulated exposure to curated vs. authentic profiles)

5. *Contribution of the Framework*

- Offers a multi-theoretical lens to explain how and why social media use leads to anxiety in adolescents.
- Integrates cognitive-evaluative processes (SCT) with motivational and emotional needs (SDT).
- Provides specific, testable mechanisms to inform intervention strategies that promote healthy social media use.

At a more philosophical level, the multi-theory approach illustrated here can support methodological pluralism. Rather than confining a study to the strictures of a single paradigm, researchers might choose to mix qualitative and quantitative methods and draw on the strengths of each to address different dimensions of the research problem. For instance, while standardised surveys can track the evolution of anxiety symptoms across a large sample over time, in-depth interviews might show how these experiences are articulated, managed, and understood by individuals from diverse backgrounds. AI tools can support this pluralism by helping researchers locate exemplar studies, identify compatible data collection instruments, and evaluate the philosophical coherence of the overall design.

2.4 CONCLUSION

To conclude this chapter, it is important to present some reflections not just on the capabilities but also the potential challenges of AI use in research. GenAI tools now allow researchers to design studies with greater speed and conceptual depth than ever before. Through the illustrative case of how social media use may impact mental health among university

students, this chapter has demonstrated the value of tools like *ChatGPT*, *Elicit*, and *ResearchRabbit*, among others, in supporting various stages of the research process. These tools function as tireless research assistants available around the clock and continuously expanding their informational reach.

While they offer powerful capabilities for supporting research, it is essential to recognise that no AI system can substitute for the nuanced judgement, creativity, and ethical accountability that define good scholarship. The potential risks associated with AI use, including algorithmic bias, misinformation, researcher deskilling, privacy violations, and even plagiarism, highlight why the final responsibility for research design must always rest with the human researcher. Rather than relinquishing decision-making to automated systems, scholars are better served by viewing GenAI as a catalyst: one that streamlines repetitive tasks, suggests alternative perspectives, and flags under-explored angles, thereby freeing researchers to focus on interpretive, methodological, and ethical scrutiny where it matters most.

As these tools continue to evolve, they are likely to incorporate even more advanced features—such as real-time analysis of pilot data, automated prompts for ethical compliance, or interactive “theory-building” modules that dynamically link conceptual models with relevant literature. While such developments hold great promise, they must be approached with cautious optimism. Meaningful intellectual and methodological breakthroughs typically emerge not from automation alone, but from the delicate interplay between computational efficiency and the human capacity for critical thinking, skepticism, and empathy. Only by remaining mindful of this interplay can researchers harness the strengths of GenAI to produce work that is both rigorously designed and responsive to the deeper ethical and philosophical dimensions of knowledge creation.

At the same time, it is crucial to acknowledge that generative AI tools are not neutral. Their outputs reflect the data on which they are trained. These data often centre dominant epistemologies and theoretical paradigms while side-lining alternative or emerging perspectives. For example, when prompted about mental health, a large language model may default to frameworks grounded in logical empiricism or behavioural psychology, potentially overlooking feminist, postcolonial or, depending on the context, autochthonous perspectives (Harding, 2006). These limitations are not simply theoretical; they carry the real risk of

reproducing epistemic injustice by reinforcing the marginalisation of non-dominant ways of knowing. Consequently, researchers must approach AI-generated content with a high degree of reflexivity. Outputs from tools like *ChatGPT* should be treated as starting points for inquiry—not definitive answers. Researchers should return to primary texts to ensure that philosophical arguments are not oversimplified or distorted in the name of coherence. This is particularly critical when working with ethically sensitive topics where misrepresentation or reductionism can have far-reaching consequences. Furthermore, researchers should be conscious of how their own positionality, disciplinary backgrounds, and institutional contexts shape their interpretation of AI-generated insights.

AI systems can also inadvertently present theoretical debates in misleading ways. In their effort to synthesise complex material efficiently, they may gloss over internal contradictions, unresolved tensions, or critical perspectives. A user might receive a tidy summary that frames paradigms as complementary or interchangeable, when in fact they may rest on incompatible assumptions. For this reason, engagement with philosophical frameworks must extend beyond AI output to include close reading, scholarly dialogue, and, where necessary, consultation with subject-matter experts.

Finally, we wish to note that theoretical and philosophical alignment, as presented in this chapter, is not merely a technical exercise; it has profound implications for how research translates into policy, practice, and public understanding. Returning one last time to our central example—examining the relationship between social media use and anxiety among youth—the paradigm one adopts will directly influence the kind of interventions one proposes. If the research is rooted in a strictly positivist approach, solutions may focus on behavioural control, such as limiting screen time or monitoring online activity. However, if the research is informed by constructivist or critical perspectives, more nuanced responses may emerge, targeting identity development, social support, digital literacy, or even the design of social media algorithms that mediate user experiences. In this way, aligning one's philosophical, theoretical, and methodological choices becomes not only a matter of internal coherence but also of external relevance. As demonstrated throughout this chapter, generative AI—when used critically and reflectively—can support this alignment. It can help researchers clarify their assumptions, connect their theoretical frameworks, and communicate their contributions more effectively. Yet its utility depends on how it is used. As with

any tool, it is the researcher's discernment, integrity, and purpose that ultimately determine the quality and impact of the work.

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Gen AI-Enabled Data Generation and Simulation in Social Sciences

3.1 INTRODUCTION—AI AND THE CHALLENGES OF DATA IN EMPIRICAL RESEARCH

In the knowledge economy, data serves as the cornerstone of evidence-based inquiry across a wide spectrum of disciplines. Whether in the social sciences, computing, healthcare, education, management, or even law, the ability to curate, access, and analyse high-quality data directly influences the depth, validity, and societal relevance of research outputs. The proliferation of digital technologies has indeed expanded access to large-scale datasets and advanced computational tools, allowing researchers to model, interpret, and engage with complex social and technical phenomena with unprecedented precision (Guo et al., 2024).

However, a persistent and often under-discussed problem is the challenge researchers face in acquiring the *right* data—particularly when the subject matter is ethically sensitive or when significant gaps exist between the unit of analysis and the chosen approach to data collection. These challenges are even more pronounced when the populations under study are either unreachable or hesitant to share authentic perspectives. In some cases, respondents may offer what could be described as “asymmetrical data”—information shaped more by what they believe researchers want to hear than by their actual lived experiences (Owoseni, 2023).

I recall a series of consultancy projects I undertook several years ago in Nigeria, which aimed to investigate how microbusiness owners in the

informal sector perceive digital transformation. The research ran into notable communication complications. Prior studies had already hinted that respondents in this demographic, particularly microbusiness owners, often perceive academic research as a form of extractive exercise, one that advances researchers' careers but does little to impact their own livelihoods. As a result, many participants provided answers they assumed would please the researchers, rather than offering genuine insights into their perceptions and realities. The lack of meaningful data combined with the ethical imperative to avoid exploitative research practices may ultimately influence the richness and reliability of the findings.

In such instances, the potential of Gen AI to simulate research environments, model participant behaviours, or generate plausible data narratives becomes interesting conversation and particularly compelling. The ability to synthetically construct representative samples, pre-test instruments, and forecast respondent dynamics could have greatly enhanced the preparation and design phase of the study. This is not to suggest that AI should replace human participants, but rather that it can serve as a valuable companion in contexts where data access is constrained or ethically complex.

Even in fields like computing and the natural sciences—where data acquisition might seem more straightforward, similar challenges exist, particularly when researching under-resourced regions or designing inclusive systems that reflect diverse user needs. These cross-sectoral challenges highlight a broader issue: the persistent concern around data quality, inclusivity, and contextual relevance, especially when research engages with nuanced realities that are culturally embedded, politically sensitive, or socially marginalised.

Can AI help to address these concerns? Can synthetic data serve as a methodological bridge where real-world data is limited or inaccessible? These are the central questions that this chapter seeks to explore. Despite global advances in data science, researchers focusing on sensitive and underrepresented populations, such as ethnic minorities in the Global South, often encounter a triad of challenges: data scarcity, bias, and inaccessibility. Many official datasets either omit or inadequately represent these populations, arguably, resulting in structural blind spots and epistemic injustices. Furthermore, ethical constraints and logistical limitations frequently impede the collection of primary data, especially in low-resource settings or communities with heightened vulnerability. These data constraints not only hinder empirical investigations but also risk

reinforcing stereotypes, marginalising lived experiences. Researchers are thus faced with the urgent task of developing innovative, context-sensitive methods for generating (collecting, extracting, simulating) meaningful and inclusive data that may drive transformative research. (Goyal & Mahmoud, 2024; Guo et al., 2024).

This chapter explores the role of Generative AI (Gen AI) in enabling data generation and simulation, with particular emphasis on its application in researching sensitive and underrepresented populations. It begins by contextualising the use of synthetic data in research, tracing its evolution, and distinguishing between traditional and AI-enabled approaches. The chapter then presents mechanisms, use cases, and examples of how Gen AI—in this case through tools like ChatGPT—can be used to generate synthetic research participants and datasets. This includes applications in research sampling and the co-creation of research instruments such as surveys and interview guides.

Through practical illustrations, the chapter highlights both the affordances and limitations of Gen AI in social science research. The discussion then extends to interdisciplinary contexts, outlining broader implications for fields beyond the social sciences. The chapter closes with a critical discussion on the ethical considerations of using AI tools as data simulators in social science research. It addresses key concerns around bias, validity, governance, and transparency. Finally, the chapter reflects on emerging directions, future research opportunities, and the epistemological implications of incorporating synthetic data into responsible and inclusive research practice.

3.2 THE LANDSCAPE OF SYNTHETIC DATA IN EMPIRICAL RESEARCH

Synthetic data refers to artificially generated information that replicates the structure, properties, and statistical patterns of real-world data. Unlike field datasets—derived from actual individuals and anonymised by removing personally identifiable information—synthetic data is entirely fabricated using algorithms and computational models, including large language models (LLMs) such as ChatGPT, Gemini, and Copilot. (Goyal & Mahmoud, 2024).

Despite its artificial nature, synthetic data can be highly representative, as will be demonstrated shortly, and serves as a valuable proxy for real-world observations in a range of research contexts.

Simulation, in this context, involves creating scenarios or environments in which synthetic data is generated to reflect plausible social, behavioural, or physical processes. It enables researchers to model interactions, test hypotheses, and observe outcomes in controlled yet dynamic settings. In essence, simulations powered by synthetic data facilitate “what-if” experiments, allow for iteration in research design, and help uncover emergent patterns without requiring immediate real-world access.

The use of synthetic data in research is not entirely new. Early applications emerged in fields such as epidemiology, finance, and systems modelling, where real-world data was often too sensitive, costly, or difficult to obtain. Over time, synthetic datasets have been used to augment machine learning training data, validate software systems, and simulate the effects of policy interventions.

In the social sciences, however, the adoption of synthetic data has been more cautious, primarily due to concerns around authenticity, validity, and ethical implications. Nonetheless, the rise of computational social science and the integration of AI into research methodologies have gradually expanded the potential for synthetic data use. Recent advancements in generative modelling—particularly through Generative AI (Gen AI)—have significantly improved the realism and complexity of synthetic datasets, making them increasingly viable for exploratory and early-stage research.

Gen AI is emerging as a promising frontier in addressing many of the traditional limitations of synthetic data. By leveraging models such as Generative Adversarial Networks (GANs), Large Language Models (LLMs), and diffusion architectures, Gen AI can produce high-fidelity synthetic data that closely mimics real-world patterns. These capabilities allow researchers to generate representative datasets, simulate participant profiles, and prototype research instruments without directly engaging human subjects in the initial stages.

For studies involving marginalised communities or sensitive topics, Gen AI offers a powerful way to model hypothetical scenarios, test conceptual frameworks, and surface implicit assumptions—while minimising ethical and logistical barriers. Importantly, the use of Gen AI for synthetic data generation is not intended to replace traditional data collection methods. Rather, it serves to complement them by providing a methodological bridge—enabling researchers to ideate, refine, and de-risk research designs before deploying them in real-world settings. This is particularly

useful in feasibility studies, early-phase investigations, or ethically complex contexts.

Traditionally, synthetic data generation relied on statistical modelling and rule-based systems, where researchers would define parameters and probability distributions based on known data characteristics to generate artificial samples. While these approaches have been valuable, they are often limited in their ability to model the high-dimensional, non-linear relationships that characterise many social and behavioural phenomena. The emergence of Gen AI helps to overcome these limitations by introducing more flexible, data-driven generation methods that improve realism and scalability.

3.3 MECHANISMS OF SYNTHETIC DATA GENERATION

The mechanisms through which Generative AI (GenAI) models generate synthetic data vary depending on the data modality—text, images, structured data, or audio—but they typically follow a generalised pipeline composed of four key phases:

Step 1. Training Phase

In this phase, GenAI models are trained on large-scale datasets, such as textual corpora, image libraries, survey responses, or structured tabular data. Through this exposure, the model learns to identify and replicate underlying statistical patterns, semantic relationships, and context-dependent features present in the data.

Step 2. Prompting or Conditioning

At the point of use, researchers provide an input prompt or a set of conditioning parameters that guide the model's output. This input serves as a directive for generating data within a defined scope or context. For example, a researcher might instruct a large language model (LLM) to:

Simulate a 35-year-old female entrepreneur in Nairobi responding to a digital literacy questionnaire.

The prompt helps ensure that the generated content reflects the desired demographic, thematic focus, or behavioural context.

Step 3. Generation Phase

Based on the prompt, the model produces synthetic data that aligns with the specified parameters. This content can take various forms, including:

- Demographic-specific survey responses
- Simulated interviews or diary-style narrative entries
- Persona-driven behavioural data for modelling
- Structured datasets suitable for statistical or machine learning analysis

The versatility of GenAI allows for fine-tuned generation across qualitative and quantitative formats.

Step 4. Evaluation and Refinement

Once generated, the synthetic data should be reviewed for realism, internal coherence, and alignment with the research objectives. Some platforms offer controls to adjust generation settings such as creativity, tone, factuality, or diversity. In more advanced settings, researchers may iteratively refine outputs through prompt engineering or model parameter adjustments.

In technically advanced environments, researchers may develop or fine-tune custom GenAI models to generate synthetic data within highly specific domains or conditions. However, for broader accessibility—especially for researchers with limited technical expertise—off-the-shelf models can be effectively used. Freely available tools (e.g., ChatGPT) or subscription-based services (e.g., GPT-4o) offer sufficient capabilities for many academic research scenarios. In such cases, the pipeline may be reduced to Steps 2 and 3 (Prompting and Generation), especially when using pre-trained models.

Additionally, certain pre-trained models and platforms are purpose-built for specific domains, offering out-of-the-box capabilities that align with research needs. The following table provides a comparative overview of selected GenAI tools and their relevance to research contexts:

These AI tools itemised in Table 3.1 support various phases of the research lifecycle, from early-stage idea exploration and prototype development to data augmentation and visual presentation. Their flexibility

enables integration with both qualitative and quantitative methodologies, making them valuable companions for interdisciplinary and applied research.

As synthetic data generation becomes more accessible, researchers are increasingly empowered to create rich, scalable, and ethically sound datasets—especially where real data is scarce, sensitive, or ethically restricted.

Table 3.1 Gen AI research data simulation tools (*Source* Author)

<i>Tool</i>	<i>Type</i>	<i>Key features</i>	<i>Use cases in research</i>
ChatGPT (OpenAI)	Large Language Model (LLM)	Natural language generation, persona simulation, dialogue generation	Simulating interviews, generating survey responses, drafting tools
Synthea	Structured Data Synthesiser	Generates synthetic healthcare records based on clinical logic	Public health, epidemiology, medical training in low-resource settings
DALL·E / Stable Diffusion	Image Generators	Text-to-image generation with stylistic control	Visual stimuli creation, ethnographic representation, cultural studies
Gretel.ai	Tabular Data Synthesiser	Privacy-preserving structured data synthesis	Demographic and administrative data simulation
Forefront/Claude	Conversational AI	Multi-turn, context-aware dialogue simulation	Focus group emulation, simulated respondent interaction

3.4 USE CASE: EXPLORING AFRO-CARIBBEAN IMMIGRANT MICROBUSINESSES IN THE EAST MIDLANDS, UK

This use case draws on a research project I was involved in approximately a year ago, which focused on Afro-Caribbean immigrant micro-enterprises operating in the East Midlands region of the UK. The study explored how these businesses manage and operate through interactions with customers, partners, advisors, mentors, and competitors, with the overarching aim of identifying cultural symbolism and relational values that could inform the design of more inclusive digital platforms.

The context for the study is grounded in the recognition that, while the UK offers a variety of digital platform opportunities for minority-owned businesses, the adoption and effective integration of such platforms among Afro-Caribbean micro-enterprises often remain limited. This limitation can be attributed, in part, to the misalignment between platform design and the existing and emergent needs, especially the culturally embedded, and often tacit, expectations, of these business owners.

The primary objective of the project, therefore, was to critically examine the ways in which Afro-Caribbean microbusinesses interact with key stakeholders in their business ecosystems—including customers, business partners, advisors, mentors, and even competitors—in order to uncover culturally symbolic practices that a digital platform could potentially recognise, nurture, and support.

One of the challenges we faced during the project was gaining meaningful access to, and engagement with, the target group of microbusiness owners. This difficulty in field access became a significant point of reflection. As I considered how best to frame this chapter, I found it particularly compelling to revisit this scenario as a case in point, especially as we now have prior empirical insights into how these businesses operate.

Given our familiarity with the research terrain and an understanding of the real-world outcomes, it presents an interesting opportunity to explore how synthetically generated AI data might compare to lived experiences and previously gathered empirical findings. This comparative approach offers a lens through which to evaluate the fidelity and cultural sensitivity of generative AI in simulating nuanced, community-rooted practices.

Prompts and AI-Generated Synthetic Data

The next sections will introduce the specific prompts and interactions used in a ChatGPT-4o session designed to simulate responses aligned with the original research context.

My Prompt:

I would like to use you as a data simulator for research that focuses on African Caribbean immigrant businesses in the East Midlands area of UK. below is the synopsis of the research: The UK presents several digital platform possibilities for Minority Businesses—nonetheless, for better adoption and integration, digital platforms need to be designed or reviewed based on the existing and emergent needs of Afro-Caribbean micro-enterprises, including the cultural and often tacit requirements. Against this backdrop, the project aims to: Critically examine how Afro-Caribbean businesses manage/operate their businesses through interactions with customers, partners, advisors, mentors, and competitors; to identify cultural symbolism elements that a digital platform can nurture and support.

ChatGPT:

Excellent—I'd be glad to assist as a data simulator for this research. To ensure the simulation aligns closely with your objectives, here are a few questions to help calibrate the data generation:

1. **Business Profiles:** What types of micro-enterprises are you focusing on? (e.g., retail, food services, hair and beauty, logistics, etc.)
2. **Data Parameters:** What specific types of data do you want simulated? For example:
 - Demographic details (e.g. age, gender, length of residence in UK)
 - Business operations (e.g. use of digital tools, customer interaction methods)
 - Cultural expressions (e.g. language, symbols, values)
 - Platform preferences or digital challenges
3. **Scale and Format:**
 - How many cases/business profiles would you like?
 - Would you prefer qualitative-style case narratives, structured survey-style data, or both?

4. Theoretical or Conceptual Anchors:

- Are you using any particular frameworks to guide your analysis (e.g., affordance theory, cultural symbolism, digital adoption models)?

Once I have this, I can generate realistic and contextually appropriate synthetic data that can be used for testing hypotheses, designing platform features, or supporting proposal development.

Would you like to start with a few illustrative business profiles?

My Prompt:

Thank you, I will upload an image that contains 4 personas of the target participants I need you to simulate, you can then use the information to generate up to 20 business profiles

ChatGPT:

Perfect—please go ahead and upload the image with the four personas. Once I review it, I'll generate 20 synthetic business profiles that align with the personas and your research focus. Looking forward to the upload!

My Prompt:

Here I the image (upload)

Johnson Nwachukwu  Background • Born in Nigeria, grew up in the UK • Business Type: Software consultancy • Started in 2010, grew to 10 employees • Rebranded to Digital First Solutions Scenario • Originally started their family business in their home country. • They have since expanded to open branches in other countries. • He has experience with accounting 'cloud' platforms • Can speak to the cloud IT infrastructure space	Motivations • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" Pain points • "Accounting is a complex part of financial management" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me"	Ahmed Hassan  Background • Born in Egypt, grew up in the UK • Business Type: Import/Export • Started in 2015, grew to 5 employees • Rebranded to Digital First Solutions Scenario • A business owner, who recently moved to the UK (less than 2 years) • He came into the UK through work visa • He is working alongside running his new business	Motivations • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" Pain points • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me"
Sarah Williams  Background • Born in the UK, grew up in the UK • Business Type: Import/Export • Started in 2010, grew to 10 employees • Rebranded to Digital First Solutions Scenario • A business owner, who has been in the UK for years but did not start a business until recently • She has experience with accounting 'cloud' platforms • She has been working for about 4 years in marketing	Motivations • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" Pain points • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me"	Michelle Thompson  Background • Born in the UK, grew up in the UK • Business Type: Import/Export • Started in 2010, grew to 10 employees • Rebranded to Digital First Solutions Scenario • A business owner, who relocated to the UK 10 years ago as a professional • She has experience with accounting 'cloud' platforms • She has been working for about 4 years in marketing	Motivations • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" Pain points • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me" • "I wanted to build a business that was scalable and could grow without me"

ChatGPT:

Thanks, I've reviewed the image — it outlines four key personas representing diverse Afro-Caribbean micro-enterprise owners in the East Midlands. Based on these, I'll now simulate **20 diverse business profiles** using the personas as templates, varying their characteristics (e.g., business type, motivations, challenges) while preserving cultural and contextual realism.

I'll generate the profiles in a structured table format with the following fields: Name, Country of Origin, Years in the UK, Business Type, Business Age, Entry Route to UK, Motivations, Pain Points, Digital Platform Use, Cultural Elements or Symbolism Observed. Please hold on while I prepare the table.

Here are 20 simulated Afro-Caribbean micro-enterprise profiles based on the personas you provided (See Table 3.2) The dataset includes realistic variations in business type, experience, motivations, and digital practices, while embedding cultural symbolism elements relevant to your research goals (Table 3.3). Let me know if you'd like:

- A narrative/qualitative format for a subset
- Visualisations or summary statistics
- Refinement to include Ubuntu constructs or platform design preferences

Happy to help further with analysis, publication support, or proposal development

My Prompt:

Thank you, now, I would need you to simulate 4 focus group sessions of 5 participants each from the pool of enterprises you generated. before I provide the focus group questions, first create the 4 groups

ChatGPT:

The 20 simulated entrepreneurs have now been grouped into 4 focus groups, each with 5 participants. These groups represent a realistic mix of business types, backgrounds, motivations, and

Table 3.2 ChatGPT simulated sampling and demographic data

Name	Country of origin	Years in UK	Business type	Business age (yrs)	Entry route to UK	Motivations	Pain points	Digital platform use	Cultural elements or symbolism
David Mensah	Ghana	12	Mobile Catering	10	Student Visa	Affordable marketing tools, Build a legacy	Lack of digital skills, Limited access to business capital	Uses Xero/QuickBooks	Displays national symbols in shop or website
Abena Clarke	Trinidad and Tobago	7	Caribbean Grocery	5	Dependent Visa	Access government grants, Financial transparency	Time management challenges, Limited access to business capital	Uses WhatsApp and Instagram for customer engagement	Uses culturally resonant language and slogans
Chinedu Okoro	Zimbabwe	11	IT Consulting	10	Student Visa	Balance business and family, Explore growth opportunities	Expensive software, Limited access to business capital	Uses WhatsApp and Instagram for customer engagement	Displays national symbols in shop or website
Janice Bailey	Ghana	2	Bridal Wears	1	Family Reunification	Streamline operations, Access government grants	Limited access to business capital, Expensive software	No digital tools currently used	Displays national symbols in shop or website

(continued)

Table 3.2 (continued)

<i>Name</i>	<i>Country of origin</i>	<i>Years in UK</i>	<i>Business type</i>	<i>Business age (yrs)</i>	<i>Entry route to UK</i>	<i>Motivations</i>	<i>Pain points</i>	<i>Digital platform use</i>	<i>Cultural elements or symbolism</i>
Kwame Addai	Ghana	14	Mobile Catering	3	Asylum	Support community values, Access government grants	Limited access to business capital, Time management challenges	Relies on spreadsheets and mobile banking apps	Uses culturally resonant language and slogans
Lorna Brown	Barbados	2	IT Consulting	0	Skilled Worker Route	Financial transparency, Support community values	Limited access to business capital, Lack of accounting knowledge	Experimenting with Canva and Shopify	Prioritises community support
Tariq Ellis	Nigeria	7	IT Consulting	4	Asylum	Build a legacy, Explore growth opportunities	Lack of accounting knowledge, Lack of digital skills	No digital tools currently used	Runs promotions on cultural holidays
Blessing Osci	Trinidad and Tobago	11	Arts & Crafts	8	Student Visa	Build a legacy, Financial transparency	Expensive software, Lack of digital skills	Uses WhatsApp and Instagram for customer engagement	Prefers storytelling and oral communication
Marlon James	Zimbabwe	10	Food Importation	2	Student Visa	Affordable marketing tools, Balance business and family	Difficulty with financial tracking, Limited customer reach online	No digital tools currently used	Prefers storytelling and oral communication

<i>Name</i>	<i>Country of origin</i>	<i>Years in UK</i>	<i>Business type</i>	<i>Business age (yrs)</i>	<i>Entry route to UK</i>	<i>Motivations</i>	<i>Pain points</i>	<i>Digital platform use</i>	<i>Cultural elements or symbolism</i>
Ebony Grant	Ghana	1	Mobile Catering	0	Student Visa	Support community values, Establish a strong foundation	Difficulty with financial tracking, Time management challenges	No digital tools currently used	Prioritises community support
Solomon Kure	Barbados	8	Arts & Crafts	3	Work Visa	Affordable marketing tools, Support community values	Limited customer reach online, Uncertainty about regulations	No digital tools currently used	Prefers storytelling and oral communication
Nadine Thomas	Jamaica	12	Hair Salon	2	Skilled Worker Route	Financial transparency, Balance business and family	Limited customer reach online, Uncertainty about regulations	Uses WhatsApp and Instagram for customer engagement	Trusts word-of-mouth referrals
Franklyn Ncube	Barbados	1	Caribbean Grocery	0	Skilled Worker Route	Support community values, Establish a strong foundation	Uncertainty about regulations, Difficulty with financial tracking	Uses Xero/QuickBooks	Uses culturally resonant language and slogans

(continued)

Table 3.2 (continued)

<i>Name</i>	<i>Country of origin</i>	<i>Years in UK</i>	<i>Business type</i>	<i>Business age (yrs)</i>	<i>Entry route to UK</i>	<i>Motivations</i>	<i>Pain points</i>	<i>Digital platform use</i>	<i>Cultural elements or symbolism</i>
Amara Dube	Zimbabwe	2	IT Consulting	0	Dependent Visa	Streamline operations, Affordable marketing tools	Limited access to business capital, Lack of digital skills	No digital tools currently used	Trusts word-of-mouth referrals
Dean McKenzie	Jamaica	4	Bridal Wears	4	Skilled Worker Route	Explore growth opportunities, Balance business and family	Limited access to business capital, Difficulty with financial tracking	Uses Xero/QuickBooks	Prefers storytelling and oral communication
Ruth Annor	Nigeria	12	Food Importation	0	Skilled Worker Route	Establish a strong foundation, Support community values	Difficulty with financial tracking, Lack of digital skills	Experimenting with Canva and Shopify	Runs promotions on cultural holidays
Jermaine Walters	Trinidad and Tobago	14	Food Importation	8	Skilled Worker Route	Streamline operations, Build a legacy	Lack of digital skills, Limited access to business capital	No digital tools currently used	Prefers storytelling and oral communication

<i>Name</i>	<i>Country of origin</i>	<i>Years in UK</i>	<i>Business type</i>	<i>Business age (yrs)</i>	<i>Entry route to UK</i>	<i>Motivations</i>	<i>Pain points</i>	<i>Digital platform use</i>	<i>Cultural elements or symbolism</i>
Nkechi Bello	Trinidad and Tobago	14	Bridal Wears	2	Family Reunification	Support community values, Balance business and family	Lack of digital skills, Time management challenges	Experimenting with Canva and Shopify	Prioritises community support
Trevor Boateng	Zimbabwe	8	Bridal Wears	5	Skilled Worker Route	Establish a strong foundation, financial transparency	Expensive software, Difficulty with financial tracking	Uses WhatsApp and Instagram for customer engagement	Displays national symbols in shop or website
Charmaine Reid	Nigeria	9	Mobile Catering	1	Dependent Visa	Support community values, Balance business and family	Expensive software, Limited access to business capital	Uses Xero/QuickBooks	Prioritises community support

Table 3.3 ChatGPT simulated focus group outcomes

<i>Focus Group</i>	<i>Participants</i>	<i>Q1_Relationship_Building</i>	<i>Q2_Cultural_Influence</i>	<i>Q3_Mentorship</i>	<i>Q4_Digital_Platform_Ideas</i>
Group 1	David Mensah, Nkechi Bello, Ruth Annor, Abena Clarke, Marlon James	Participants emphasised trust, face-to-face interactions, and informal communication via WhatsApp. There is a strong reliance on word-of-mouth and personal recommendations. Respect and loyalty are central	Cultural heritage plays a major role; participants shared how traditions, faith, and community events shape business decisions. Oral storytelling and using culturally resonant names or decor are common	Mentorship often comes from elders in the community or previous business owners. Some participants noted informal coffee chats and church groups as key support channels. Storytelling was highlighted as a form of guidance	They suggested platforms that support voice notes, local languages, culturally themed templates, and easy group chats. A sense of community and trust was noted as key to adoption of features like testimonials, elder spotlights, or a local business map were mentioned
Group 2	Lorna Brown, Nadine Thomas, Janice Bailey, Trevor Boateng, Jermaine Walters	Participants emphasised trust, face-to-face interactions, and informal communication via WhatsApp. There is a strong reliance on word-of-mouth and personal recommendations. Respect and loyalty are central	Cultural heritage plays a major role; participants shared how traditions, faith, and community events shape business decisions. Oral storytelling and using culturally resonant names or decor are common	Mentorship often comes from elders in the community or previous business owners. Some participants noted informal coffee chats and church groups as key support channels. Storytelling was highlighted as a form of guidance	They suggested platforms that support voice notes, local languages, culturally themed templates, and easy group chats. A sense of community and trust was noted as key to adoption of features like testimonials, elder spotlights, or a local business map were mentioned

digital engagement levels, which should support rich and diverse discussions.

Feel free to go ahead and provide the focus group questions—I'll simulate detailed session transcripts or summaries based on those next.

My Prompt:

Great, these are the question and the motivations for each question:

1. *"Can you describe how you typically build and maintain relationships with your customers, partners, or other businesses in your community?" Purpose: To explore the relational practices and values (e.g., trust, respect, reciprocity) that underpin business interactions. Follow-up prompts: What matters most to you in these relationships? Are there unspoken norms or expectations?*
2. *"What role do cultural values or shared heritage play in how you run your business or make decisions?" Purpose: To identify specific cultural constructs, symbolic language, or traditions (e.g., oral storytelling, communal support) that influence business conduct. Follow-up prompts: How do these values shape how you engage with others or resolve conflicts?*
3. *"Can you share examples of how mentors, advisors, or elders have supported your business journey?" Purpose: To surface the cultural significance of mentorship, knowledge transfer, or intergenerational guidance, which could inform platform features like mentorship matching or storytelling archives. Follow-up prompts: How do you usually seek advice or mentorship? What makes it valuable to you?*
4. *"In what ways do you think a digital platform could reflect or support your way of doing business, particularly in staying connected with your community or collaborators?" Purpose: To elicit user-driven ideas about the role of digital platforms in expressing cultural identity, facilitating communication, and supporting symbolic practices. Follow-up prompts: What would make such a platform feel familiar, trustworthy, or 'ours'?*

My Prompt:

Could you provide a full raw (transcribed text) of the focus group session for group 1 and how the session unfolded synthetically? Make it rich and real in real, the conversations may not be that straight forward, it may have follow up question, tweaks, twists. And reactions

ChatGPT:

Absolutely—you're right. Real focus groups are layered, conversational, and include moments of clarification, overlap, emotion, and even hesitation or humour. Below is a much richer, more organic simulated transcript of Focus Group 1, reflecting real-world group dynamics, facilitator techniques, cultural nuances, and interpersonal dialogue.

Simulated Focus Group 1 Transcript

Topic: Exploring Culture, Relationships, and Digital Platforms in Afro-Caribbean Micro-Enterprises

Participants:

- David Mensah—Mobile Catering (Ghana)
- Nkechi Bello—Bridal Wears (Trinidad and Tobago)
- Ruth Annor—Food Importation (Nigeria)
- Abena Clarke—Caribbean Grocery (Trinidad and Tobago)
- Marlon James—Food Importation (Zimbabwe)

Facilitator: Dr. Ayo

Opening Remarks

Dr. Ayo: Thank you all for coming. Today is not a “formal” research session — think of it as us sitting down in a circle to talk about your businesses, your values, your culture, and how digital platforms could better serve what you do. This is your space. So please, speak freely, bounce off each other, and share as you're led. Okay?

(All nod, some chuckles)

Marlon: As long as we're not filling forms, I'm good!

David (laughs): I left my forms at the truck!

Q1. Building and Maintaining Relationships

Dr. Ayo: Let's begin here—how do you usually build and maintain relationships in your business? With your customers, partners, maybe even competitors?

David: For me, it's just being present. You see them every day. School mums, taxi drivers, teachers—I know what time they pass by my van. I don't even need posters. I cook, I greet, I joke, they come back.

Abena (nodding): Same with my shop. I know which elders want soft yam, who prefers Grace over Dunn's River. I write their names and preferences in a little book. It's old-school, but it works.

Dr. Ayo: So, personalised service?

Abena: Exactly. It's not just selling—it's serving.

Ruth: Hmm, I agree. Sometimes it's not even what you're selling—it's how you make them feel. One woman told me, "I come to you because you remind me of Lagos." That touched me.

Nkechi: Yes oh! In my bridal business, it's even deeper. Some women come just to talk. One bride cried on my shoulder because her mum couldn't attend the wedding. That's not a "client"—that's a sister.

Marlon: In Zim, we say "hukama igasva hunozadzi swa nekudya"—kinship is incomplete until we share a meal. I always keep a seat behind the counter. People sit, sip something, chat. That's my CRM system.

Dr. Ayo: That's beautiful. What do you all think matters most in these relationships?

David: Trust. They trust I won't give them yesterday's stew. *(Laughter)*

Nkechi: Also... dignity. No matter who they are—young, old, rich or broke—treat them with dignity. That keeps them coming.

Q2. Cultural Values and Heritage

Dr. Ayo: Let's explore that more—how does your culture or heritage show up in your business or how you make decisions?

Ruth: Big time. I named my business "Ajoke's Basket" after my grandmother. And I cook recipes the way she taught me. No shortcuts.

Abena: Same here. I play soca music in the shop. My niece once said, “It smells like home in here.” I almost cried. We’re not just trading—we’re curating belonging.

David: Sometimes I wear kente when I serve on weekends. People ask why. I tell them, “This stew came from Kumasi, so I must honour it properly!”

Marlon (grinning): I’ve got mbira music playing sometimes. And when someone haggles too hard, I quote a proverb—“The lazy man blames the wind for not catching the chicken.” Then we both laugh.

Nkechi: I love that. In bridal, I include African and Caribbean traditions in fittings—wrapping fabrics, dancing a bit, praying. One couple brought their whole family. It was like a village gathering in my studio.

Dr. Ayo: How do these values guide you when there’s conflict or tension?

Abena: Hmm. You don’t rush to react. You cool off. You maybe call an elder. My dad taught me: “Let your silence speak first.”

David: And sometimes I deliver stew for free the next day. That solves most things.

Q3. Mentors and Elders

Dr. Ayo: Can you share any moments when a mentor or elder helped you in business?

Nkechi: Ah! My Auntie Bev. After my first boutique collapsed, she sat me down every Saturday. No judgment. Just “let’s learn and try again.” She’s why I’m still standing.

Marlon: Mine is Mr. Banda, who ran a bakery before he retired. He drops by now and then and says, “Don’t just count your coins. Count your customers.”

Ruth: You know what’s funny? Some of my best advice comes from church sisters. One told me, “Put the customer’s face in your prayer list.” I did. Sales doubled.

David: We learn in layers. Sometimes it’s not direct advice. Just stories. One uncle told me about how he built his chop bar on trust—letting customers pay later. That shaped how I handle debt.

Dr. Ayo: How do you usually seek this kind of guidance?

Abena: WhatsApp groups. Voice notes. Sometimes just showing up at aunty's porch with biscuits.

David: We don't "book a session"—we live it.

Q4. Digital Platforms for Culture and Connection

Dr. Ayo: Okay, shifting gears. What would a digital platform look like if it truly reflected your way of doing business?

Nkechi: Let me send voice notes instead of typing, please! Especially when I'm with a bride or cooking rice.

Ruth: And make it visual—show people's faces, tell stories. Not just "Add to cart." Maybe "Meet the Maker."

Abena: If I could get a platform that lets me post weekly specials, showcase elder-approved recipes, and chat with my customers easily—I'm in.

David: Give me a "market square" feel—where people can browse, talk, recommend, even gossip a bit.

Marlon: Trust is big. If someone vouches for you on the platform—like an elder, or a long-time customer—that should mean something. Call it "Community Verified" or something.

Dr. Ayo: What would make it feel like "ours"?

Ruth: Don't make it too formal. Use Afro-Caribbean colours, familiar phrases. Even little things—like "Ahoy there!" or "Yuh good?"—go a long way.

Nkechi: Also, don't hide the humans behind the tech. Show the people. Make it a community, not a tool.

Closing

Dr. Ayo: Wow. You've given gold today—in stories, values, dreams. I'm honoured. Any final thoughts?

David (smiling): Don't forget our invite when you build the platform.

Nkechi: We'll bless it with oil and ginger beer!

Would you like a structured thematic analysis of this transcript (e.g., using Braun & Clarke's framework), or a version ready for inclusion in a research paper or presentation?

Reflections on the Generated Research Data

The use of ChatGPT to simulate research data within the defined context of Afro-Caribbean micro-enterprises in the East Midlands yielded a number of noteworthy insights. The process combined case study design with conversational AI interaction to produce a synthetic dataset that, while artificial, often appeared strikingly realistic and contextually appropriate.

The conversational generation loop produced heterogeneity that conventional pseudo-sampling techniques tend to blur. By prompting ChatGPT with personas, we could inject rare but policy-relevant attributes and then let the model propagate plausible downstream variables, such as cash-flow volatility or migration/settlement status. Recent empirical studies show that large language model probes can yield multi-granular synthetic records whose internal correlations track real datasets within acceptable tolerance bands, provided the prompts are sufficiently scoped and iterated (Molenaar, 2022; Watermeyer et al., 2024).

Moreover, the cases highlight the need to treat ChatGPT output as scaffolding—a rapid-prototyping tool to explore variable interactions and refine demographic attributes of units of analysis. When the data is interpreted in this complementary role, the synthetic dataset proved invaluable for accelerating methodological design, sharpening the methods and tools that are context-appropriate for this research, without compromising confidentiality or waiting for bespoke micro-data to be located.

Persona-Based Business Profiles

The initial generation of 20 business profiles from the four illustrated personas produced results that were, on the surface, convincingly real. Each profile integrated a combination of demographics, motivations, business types, and operational challenges. However, closer scrutiny reveals subtle inconsistencies that highlight the synthetic nature of the dataset. For example, the name Charmaine Reid is more culturally aligned with Trinidad and Tobago, whereas Nkechi Bello clearly reflects Nigerian naming conventions. While such mismatches may appear trivial, they can undermine the perceived authenticity of the data, especially for culturally attuned readers or researchers with regional expertise.

Aside from these inconsistencies, the dataset largely holds up when considering other demographic variables such as business age, digital

adoption levels, and types of enterprises. The profiles offer useful diversity and reflect plausible entrepreneurial trajectories.

Focus Group Composition and Summary Themes

The allocation of these simulated participants into four focus groups was seamless and helped create a structured environment for deeper qualitative engagement. The resulting summaries presented in Table 3.2 were well-organised and covered key thematic areas relevant to the research questions. However, a critical limitation is evident in that the same base narrative was replicated across all four focus groups, with only participant names differing. This lack of variation reveals the constraints of automated synthesis unless explicitly prompted to diversify outputs.

The intentional choice to simulate focus group discussions, rather than individual interviews or survey responses, introduces a layer of complexity. Focus groups inherently involve dynamic interpersonal interactions, turn-taking, overlapping dialogue, and emergent insights that can be difficult to replicate artificially. Therefore, evaluating how well ChatGPT can approximate this complexity offers a more rigorous test of synthetic data generation.

Simulated Focus Group Narratives

When tasked with simulating a full-length, realistic focus group transcript, ChatGPT produced a text that was both compelling and commendable.

- **Narrative Plausibility:** The conversation flowed in a coherent and logical manner, with participants offering diverse yet thematically aligned responses. For the average reader, the data may not immediately appear synthetic. However, experienced researchers or those familiar with AI-generated content may detect patterns and structures that suggest a non-human origin. That said, the narrative resonated strongly with real-world feedback gathered in prior studies, including reflections on trust, cultural identity, oral storytelling, and informal mentoring within Afro-Caribbean business communities. One minor gap in the synthetic discussion was the omission of certain culturally grounded practices previously surfaced in empirical studies, such

as the preference for hiring family members or fellow community members, or the adaptation of traditional business norms into modern platforms.

- **A Tool for Mental Simulation:** Despite its limitations, the simulated focus group provides a rich mental model for researchers—especially those designing protocols or preparing to enter the field. It offers a vivid, low-risk environment in which researchers can anticipate participant reactions, refine their questions, and even imagine how group dynamics might evolve.
- **Support for Thematic Analysis:** The transcript serves as a valuable sample for practicing thematic analysis. It can help researchers experiment with coding structures, test the applicability of qualitative methods (e.g., Braun & Clarke’s six-phase approach), and anticipate what themes may emerge in real settings. It also enables a discussion about which coding techniques (e.g., inductive, deductive, semantic, or latent) may be most appropriate.
- **Ethics, Realism, and Research Accessibility:** Perhaps most importantly, the use of synthetic data generation significantly reduces ethical risks associated with research involving human participants. While the data is not ‘real’ in the conventional sense, it represents a valid approximation of lived experiences—particularly in contexts where financial, logistical, or ethical constraints limit access to real-world participants. Moreso, researchers can make significant progress with research design without the “bottleneck” of ethics approval, as a matter of fact, one could argue that these types of simulation make it possible for researchers to put forward a more nuance and context specific ethic application following a realistic mental simulation of the research process with AI.

This opens the door to a more expansive interpretation of in situ or lab-like research, extending qualitative experimentation beyond physical field sites. Generative AI tools such as ChatGPT have democratised access to complex research simulation, offering low-cost, scalable solutions for early-career researchers, practitioners in the Global South, and under-resourced institutions.

Looking ahead, the evolution of generative AI—including features such as ChatGPT Voice—could enable even more naturalistic simulation

of data collection. For instance, researchers could conduct voice-based synthetic interviews, where prompts are delivered verbally, and the model responds conversationally in real time. These interactions could be transcribed automatically, enabling researchers to collect realistic training datasets or conduct dry runs of fieldwork protocols. This approach could be particularly useful for piloting surveys, practicing qualitative interviews, or training novice researchers in participant engagement techniques.

3.5 CO-CREATING RESEARCH INSTRUMENT WITH AI

Creating research instruments is one of the sensitive and important aspects of the research process—not only because it is a creative act, but also because it is pivotal to the overall success and credibility of the research. A well-crafted instrument does more than just collect data; it serves as a central piece that integrates multiple dimensions of the study. It reflects the research philosophy, the framing of the research question, the aims and objectives, as well as the unit of analysis. It is also sensitive to contextual factors such as cultural nuances, linguistic preferences, and demographic characteristics. For example, the way a survey is worded for participants in the informal business sector—particularly those who may be semi-literate or have limited formal education—must be significantly different from how it would be designed for participants in the formal sector. This difference is not merely linguistic, but conceptual, as it involves aligning with how participants understand and experience the phenomena under study.

These delicacies point to the need for research instruments to be iterative and co-creative in nature. The best instruments are often designed with participants or stakeholders, not just for them. This process, while invaluable, can be time-consuming and resource intensive. However, the use of GenAI potentially presents an exciting opportunity to shorten this cycle while enriching the design process. GenAI can act as a co-creator—suggesting new formats, rewording statements, and helping to frame questions in ways that are contextually relevant and participant-friendly. I recall a moment from about eight years ago, during an interpretive study I conducted on the dynamic capabilities of microbusinesses using mobile apps in a developing country. I was developing an interview guide to explore three specific dimensions of dynamic capabilities: absorptive, adaptive, and innovative capacities. Designing the instrument required several rounds of revision to ensure that the questions resonated with

the participants and reflected their lived experience. Looking back now, I can imagine how different that process might have been if I had access to GenAI as a creative partner. The tool could have helped me generate variations of interview questions, simulate how participants might interpret them, and refine the language for better clarity and relevance.

In the next section, we will demonstrate how GenAI can be used to co-create research instruments, particularly in the following areas:

- Converting conceptual intentions into clearly structured Likert-scale items
- Repurposing existing research questions to suit specific target audiences without losing the original intent of the instrument

Through this exploration, we aim to showcase the practical utility of AI not as a replacement for the researcher's judgement, but as a **collaborative tool** that supports creativity, reflexivity, and contextual sensitivity in instrument design.

3.6 USE CASE: CO-CREATING RESEARCH INSTRUMENT WITH AI

This case study illustrates an interaction with ChatGPT-4o to develop a survey instrument designed to explore how the concept of digital transformation is understood by a diverse range of participants from both the public sector and small to medium-sized enterprises (SMEs).

My Prompt:

I wanted to create a questionnaire that extract what digital transformation means to a variety of participants across SMEs and public sector, how would you suggest I go about developing the questionnaire given that the concept of digital transformation could mean different things to different people, I need to be sure the respondents understand the question.

ChatGPT:

That's a very important and thoughtful consideration, Adebowale—especially since *digital transformation* is a fluid and context-sensitive concept that can mean anything from digitising a single process to reimagining an entire business model or service delivery system.

Your objective—understanding what digital transformation means *to different participants*—requires a careful design that both *accommodates variation* and *ensures conceptual clarity*.

Here’s a step-by-step approach I’d recommend for developing your questionnaire:

1. Clarify Your Conceptual Focus Before Designing Questions

Since digital transformation (DT) can include everything from adopting cloud services, using mobile apps, automating workflows, to shifting organisational culture—begin by identifying:

- Core constructs you want to explore (e.g., technology adoption, process innovation, service redesign, mindset shift, leadership).
- The dimensions of DT that matter across SMEs and the public sector. These may differ, and your questionnaire should be able to capture those differences.

2. Begin with a Framing Statement or Definition

Before asking questions, provide a simple, neutral framing statement to anchor respondents’ understanding, such as:

In this questionnaire, we use the term ‘digital transformation’ to refer broadly to changes in how businesses or organisations operate, deliver services, or interact with stakeholders using digital technologies. This can range from adopting new tools or platforms to rethinking internal processes or customer experiences.

This allows respondents to self-interpret within a guided boundary.

3. Use a Mixed Approach: Structured + Open-Ended Items

a. Start with Open-Ended Exploration

Capture participants' own interpretations before leading them with your categories:

- *"In your own words, what does digital transformation mean to you or your organisation?"*
- *"Can you describe any recent changes you've made that you would consider part of digital transformation?"*

This allows for inductive insight and gives you a baseline for their mental models.

b. Follow with Scaled/Structured Items

Use Likert-scale or matrix-style items to test common dimensions, such as:

To what extent do you agree with the following statements? (1–Strongly Disagree to 5–Strongly Agree)

- "Digital transformation in my organisation primarily involves upgrading technology infrastructure."
- "Digital transformation is more about mindset and culture change than just technology."
- "We use digital tools to improve service delivery/customer experience."
- "We rely on data-driven decision-making as part of our transformation efforts."

This helps you identify patterns across respondents.

4. Tailor Items to Sector-Specific Realities

Use branching or differentiated question sets:

- For SMEs, you might ask about e-commerce, payment systems, social media, CRM tools.
- For the public sector, ask about service automation, digital citizen engagement, or data governance.

Use inclusive language like:

Which of the following best reflects how your organisation has engaged with digital transformation?

Options can include both tech-focused and process/culture-focused changes.

5. Include Contextual and Demographic Anchors

Gather information on:

- Sector (public, private, non-profit)
- Organisational size
- Digital maturity level (self-assessed)
- Job role/function

This will help you analyse variation in interpretations of DT based on position, sector, or size.

6. Pilot the Instrument and Use Think-Aloud Interviews

Before full deployment, conduct a pilot phase with a few representatives from each stakeholder group.

- Use think-aloud protocols where participants verbalise what they think each question means.
- Revise wording for clarity, accessibility, and relevance.

Optional: Use GenAI to Support Iteration

You can use tools like ChatGPT to:

- Reword complex items in more accessible terms.
- Simulate responses from different sectors to test comprehension.
- Translate questions into sector-specific vocabulary.

Would you like help drafting the initial questionnaire with a combination of open-ended and structured items for both SMEs and public sector actors? I can help you build a prototype.

My Prompt:

Yes please...

ChatGPT:

Great! Here's a draft questionnaire designed to explore what *digital transformation* means to participants across SMEs and the public sector. It includes a framing statement, open-ended questions, Likert-scale items, and sector-specific sections, while remaining adaptable to varied levels of digital maturity.

Understanding Digital Transformation: A Cross-Sector Questionnaire

Framing Statement: This questionnaire aims to understand how individuals and organisations define and experience digital transformation. We understand that digital transformation can mean different things to different people. For this questionnaire, we use the term "digital transformation" to refer broadly to changes in how organisations operate, deliver services, or interact with customers, citizens, or stakeholders using digital technologies. These changes may involve adopting digital tools, improving processes, or rethinking how value is delivered.

Section A: General Understanding

1. In your own words, what does digital transformation mean to you or your organisation?
(Open-ended)
2. Can you describe one or two specific changes in your organisation that you would consider part of digital transformation?
(Open-ended)

Section B: Perceptions and Priorities

3. To what extent do you agree with the following statements about digital transformation in your organisation?

(Scale: 1—Strongly Disagree, 5—Strongly Agree)

Statement	1	2	3	4	5
a. Digital transformation is mostly about adopting new technologies					
b. Digital transformation requires a change in mindset and organisational culture					
c. We use digital tools to improve communication with customers/citizens					
d. Our leadership actively supports digital innovation.					
e. We have a clear digital strategy guiding our transformation efforts					
f. Digital transformation is relevant to the long-term sustainability of our organisation					

Section C: Sector-Specific Application

If you work in an SME:

4. Which of the following digital tools or practices has your business adopted in the last 2–3 years? (*Select all that apply*)
 - Online payment systems (e.g., Stripe, PayPal, Square)
 - E-commerce platforms (e.g., Shopify, Etsy, WooCommerce)
 - Social media for marketing or customer engagement

- Mobile apps for business operations
- Cloud-based accounting or inventory tools
- Digital customer service (e.g., WhatsApp, live chat)
- Data analytics tools
- We have not adopted any of the above

5. What challenges, if any, have you faced in adopting digital tools?

(Open-ended)

If you work in the public sector:

6. Which of the following digital transformation initiatives has your organisation implemented? *(Select all that apply)*

- Online service delivery for citizens
- Digital communication channels (e.g., chatbots, mobile apps)
- Data analytics for decision-making
- Automation of internal processes (e.g., HR, procurement)
- Use of cloud infrastructure
- Digital upskilling of staff
- We have not implemented any of the above

7. What barriers or enablers have shaped your organisation's digital transformation journey?

(Open-ended)

Section D: Self-Assessment and Future Outlook

8. How would you describe your organisation's current stage of digital transformation?

- We are just beginning to explore digital options
- We have adopted some digital tools, but change is limited

- We are undergoing moderate digital transformation
- We are actively transforming how we work and deliver value
- We consider ourselves digitally mature or advanced

9. In your view, what does successful digital transformation look like?

(Open-ended)

10. What support would help you or your organisation move forward with digital transformation?

(Open-ended)

Optional Add-ons:

- Demographic info: (sector, size of org, job role, years of experience)
- Consent and data privacy disclaimer
- Option to provide contact for follow-up interviews or workshops

The interaction with ChatGPT in this instance, much like the previous use case, took less than five minutes, which was quite remarkable considering the amount of work it accomplished in such a short time. Reflecting on my experience from about five years ago, I recall that developing the initial version of a similar questionnaire took me well over an hour just to structure and formulate the right questions. In contrast, ChatGPT provided a working draft almost instantly, offering a clear structure and language that significantly accelerated the process.

Of course, the output generated by ChatGPT is not intended to be a fully polished, ready-to-field instrument. Rather, it serves as an excellent starting point, one that helped to crystallise my thinking and allowed me to assess how well the suggestions aligned with other aspects of my research design, such as the underlying theoretical framework, research objectives, and philosophical orientation.

The real value of this process lies in its iterative and co-creative nature. I was able to take the initial suggestions and engage in further interactions with the AI to refine specific items, adjust terminology, and consider alternative phrasings. Moreover, the tool's ability to simulate responses from a target audience, essentially acting as a proxy respondent, provided another layer of insight by highlighting potential areas of ambiguity or misinterpretation.

In this way, GenAI does not replace the researcher's judgement but augments it. It allows for rapid prototyping, encourages reflective thinking, and makes the process of instrument design more efficient and, arguably, more enjoyable.

3.7 ETHICAL CONSIDERATIONS AND EPISTEMIC IMPLICATIONS

As this chapter has explored the integration of GenAI into the co-creation of research instruments and synthetic data generation, it is imperative to critically reflect on the ethical and epistemological implications of such practices. While the use of GenAI may reduce direct risks to human participants—especially in the early stages of instrument design or exploratory inquiry—it raises important questions around authenticity, transparency, and the epistemic status of AI-generated content.

At the heart of these reflections lies a fundamental query: *What constitutes "data" in research today?* When synthetic narratives, simulated responses, or AI-assisted survey questions inform our research design or analysis, are we merely working with proxies for human experience, or are we engaging with a new category of knowledge artefacts that carry their own epistemic weight?

These questions are not just philosophical; they have immediate, practical consequences for how we design, conduct, and report our research. As synthetic research practices become increasingly common, particularly in digital and computational social sciences—there is a growing need for ethical frameworks that extend beyond traditional notions of informed consent and participant risk. These frameworks must engage with the ontological status of AI-generated content, recognising it as neither neutral nor self-explanatory.

Data Validity and Reliability

One of the central concerns when using GenAI in research is how to assess the validity and reliability of AI-generated outputs. While AI can simulate plausible responses based on vast training data, it lacks lived experience and cultural situatedness. This raises questions such as:

- Can AI-generated data be considered “valid” in the same way as data derived from human participants?
- What are the risks of over-reliance on synthetic participants in shaping our understanding of social phenomena?

Although GenAI may help in prototyping instruments or simulating edge cases, there remains a risk that over-dependence on such tools could introduce distortions or obscure the very complexities that qualitative research often seeks to capture.

Bias, Fairness, and Representation

GenAI tools are not free from bias. They are trained on large datasets that may reflect historical and systemic inequalities. As a result, AI-generated content can unintentionally reproduce dominant narratives or reinforce exclusions, especially in contexts involving marginalised or underrepresented communities.

Ensuring fairness and representativeness in simulated responses is particularly challenging. Researchers must remain alert to the possibility that the AI may reinforce normative assumptions rather than challenge them, especially when used without sufficient critical oversight or contextual grounding.

Regulation and Governance

Current ethical guidelines for research are primarily built around human subjects and do not yet adequately address the governance of synthetic content or AI co-authorship. There are gaps in how institutional review boards, funding bodies, and journals treat the role of GenAI in research design and data generation.

There is a need for clear guidelines and standards for the responsible use of GenAI in academic research. These should include principles around transparency, attribution, reproducibility, and accountability, ensuring that researchers disclose the use of AI tools and critically evaluate their impact on research outcomes.

Informed Consent and Transparency

Even in studies where no direct human participation occurs, transparency remains essential. Researchers should clearly communicate the use of synthetic data or AI-generated instruments in publications, reports, and presentations. This includes:

- Clarifying the role of GenAI in shaping research tools or simulating data.
- Distinguishing between synthetic and real data sources.
- Ensuring that readers and reviewers understand the methodological and epistemic implications.

Such transparency not only supports academic integrity but also allows for more nuanced debates around what counts as legitimate knowledge in the age of AI.

It is important to note that, while GenAI offers powerful affordances for innovation in research instrument design and early-stage data simulation, it also challenges us to rethink foundational assumptions about knowledge production. As we embrace these new tools, we must do so with critical reflexivity, ethical rigour, and an openness to reshaping our epistemological frameworks to accommodate both the promise and complexity of AI-enhanced research practices.

3.8 CONCLUSION AND SUMMARY OF KEY POINTS

This chapter has examined the emerging role of Generative AI (GenAI) as a co-creator in the design and development of research instruments within social science research. Through reflective narrative, use cases, and a detailed case study, we have demonstrated how GenAI tools—such as ChatGPT-4o—can support researchers in drafting, refining, and tailoring surveys, interview guides, and questionnaires. This capacity becomes

particularly valuable in studies where cultural sensitivity, language accessibility, and iterative co-design are not just desirable but essential.

We have shown that GenAI can:

- Accelerate the instrument development cycle by generating structured and context-aware drafts.
- Serve as a cognitive partner in translating complex theoretical constructs into accessible research questions.
- Simulate the perspectives of target audiences, enabling reflexive evaluation of clarity, tone, and alignment.
- Adapt language and framing to suit specific cultural, sectoral, or demographic contexts.
- Foster an iterative and participatory approach to instrument design—especially when complemented by human judgement and community feedback.

While the technology is still evolving, these applications demonstrate a new frontier for digital research methods—one where human expertise and artificial intelligence can co-produce meaningful and contextually attuned instruments.

The Promise and Perils of GenAI in Social Science Research

The promise of GenAI in the social sciences lies in its potential to democratise access to advanced research design, reduce the time and labour associated with instrument development, and expand our methodological imagination. For researchers working across cultural boundaries or under time/resource constraints, GenAI offers a responsive and adaptive tool that can enrich the quality of the research process.

However, the integration of GenAI into research also comes with notable perils. These include:

- The risk of over-reliance on AI-generated content without sufficient critical review or contextual grounding.
- The possibility of bias replication, where the model subtly encodes dominant assumptions or frameworks that may marginalise alternative perspectives.

- Ethical concerns around transparency, authorship, and intellectual integrity—particularly when using AI to simulate human responses or generate content that feeds into published outputs.

Furthermore, GenAI operates within a technical and epistemological frame that does not inherently understand the situated, power-laden, and relational nature of social inquiry. Its outputs must therefore be interrogated, not just accepted.

Final Reflections: Ethical, Practical, and Epistemological Implications

The use of GenAI in co-creating research instruments invites a deeper reflection on the ethical, practical, and epistemological dimensions of our craft as researchers.

Ethically, we must ask: Who owns the intellectual contributions generated by AI? How do we acknowledge co-creation without conflating machine outputs with human insight? And how can we ensure that AI supports inclusive research rather than reinforcing digital divides?

Practically, GenAI can be a powerful complement to traditional research workflows, especially when used with transparency, iteration, and community involvement. It should not be treated as a shortcut to bypass the necessary complexities of design, but rather as a tool to deepen our engagement with those complexities.

Epistemologically, this chapter raises questions about what it means to know and to design in the digital age. GenAI challenges us to reconsider the boundaries between researcher and research assistant, between theory and application, between the human and the artificial. It compels us to think not only about what our instruments capture, but about also how they are produced, and whose logics shape their construction. The co-creation of research instruments and generation of synthetic research data with GenAI hold great promise, when guided by critical reflection, methodological rigour, and a commitment to participatory ethics. As researchers, we are called not just to adopt new tools, but to shape them in ways that uphold the values of our disciplines and the dignity of those we study.

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Generative AI Use Cases for Data Processing and Analysis

4.1 INTRODUCTION

Data processing and analysis represent the bedrock of empirical research in almost every academic and industrial domain. From large-scale social science surveys and biological datasets to real-time financial transactions and satellite imagery, researchers face the constant challenge of sifting through vast and complex information to derive meaningful insights. Traditional data analysis workflows typically involve substantial human effort—data cleaning, transformations, exploratory analyses, visualisations, and advanced modelling. Although these workflows remain indispensable, recent breakthroughs in Generative Artificial Intelligence (GenAI) have introduced new pathways to streamline data-centric tasks, reduce errors, and significantly enhance productivity.

GenAI models—exemplified by large language models like GPT-4, LLaMA, and Claude—can generate human-like text, identify patterns in unstructured data, and even produce synthetic datasets for training or simulation. They also help automate the process of data ingestion, cleaning, and preliminary exploration. For instance, a researcher might prompt a specialised GPT model to organise messy financial transaction records into a standardised format, detect outliers or fraudulent cases, and generate quick reports on suspicious patterns. These tasks, once considered mundane or highly time-intensive, can now be completed with minimal human intervention.

Yet, the utility of GenAI in data processing goes beyond simple automation. With the integration of advanced machine learning models, researchers can uncover subtle trends or anomalies that might elude even seasoned data scientists. The pattern-recognition power of deep neural networks enables sophisticated clustering and classification, while improved generative techniques facilitate data augmentation and predictive modelling. NLP-based GenAI, moreover, is able to handle unstructured textual data such as interview transcripts, user reviews, or policy documents—tasks that historically required large teams of coders or painstaking manual annotation.

Still, despite these remarkable capabilities, GenAI tools are not without limitations or risks. Critics highlight potential pitfalls involving algorithmic bias, lack of transparency, hallucinated outputs, and concerns related to privacy and intellectual property (Bender et al., 2021; Rudin, 2019). Researchers who rely solely on black-box models may inadvertently incorporate errors or hidden biases into their analyses. Consequently, the role of the human data scientist or domain expert remains pivotal. Rather than replacing human acumen, GenAI complements it by handling laborious tasks at scale, thus freeing researchers to focus on interpretation, methodological rigour, and ethical considerations.

This chapter explores how GenAI techniques enhance the end-to-end pipeline of data processing and analysis. We begin with a brief historical context for AI-driven data analysis, followed by a closer examination of how AI automates data cleaning, preprocessing, statistical analysis, and visualisation. We then delve into more advanced topics, such as predictive analytics and natural language processing (NLP) for unstructured data. Furthermore, the chapter addresses challenges related to algorithmic bias, reproducibility, and privacy, providing best practices for handling sensitive data. Ultimately, we aim to offer researchers and practitioners a comprehensive understanding of how they can leverage GenAI methods to work with large and complex datasets more efficiently—while still upholding the highest standards of scientific integrity and ethical practice.

It is important to note that, at the time of writing, most advanced features (including detailed data analysis) in GenAI tools require a paid subscription. For instance, the Advanced Data Analysis feature is only available by default in ChatGPT Plus, the entry-level paid version of ChatGPT. However, even without a subscription, free-tier users still have access to impressive data analysis capabilities. For example, they can prompt ChatGPT to generate Python or R scripts for data cleaning,

transformation, and visualisation, or ask it to explain the output of a regression model in plain language. These features alone can significantly enhance productivity and accessibility, particularly for researchers with limited technical expertise or resources.

4.2 THE EVOLUTION OF AI IN DATA PROCESSING AND ANALYSIS

Although discussions about AI date back to the mid-twentieth century, the notion of using AI to automate data processing tasks has accelerated dramatically in the last decade. Early statistical packages (e.g., SPSS, SAS) offered point-and-click functionalities for basic data cleaning and regression analyses. However, these primarily required explicit instructions from users. The evolution from simple rule-based systems to machine learning (ML) introduced algorithms capable of making inferences from data without being rigidly programmed (Jordan & Mitchell, 2015). This shift allowed researchers to automate tasks like classification, clustering, and anomaly detection in increasingly large and complex datasets.

With the surge of big data, advanced architectures—most notably deep neural networks—have made it feasible to analyse images, text, and complex relational data at scale (LeCun et al., 2015). Generative models like Generative Adversarial Networks (GANs) (Goodfellow et al., 2014) and Variational Autoencoders (VAEs) (Kingma & Welling, 2014) emerged next, making synthetic data creation, advanced imputation, and data augmentation not only possible but also highly effective. The term “Generative AI” has since come to encapsulate a broad class of algorithms capable of producing new outputs—whether text, images, or entire synthetic datasets—that mimic patterns learned from input data (Bommasani et al., 2022).

Today, large language models based on transformer architectures—e.g., GPT (Brown et al., 2020), BERT (Devlin et al., 2019), T5 (Raffel et al., 2020)—are rapidly reshaping how we process and interpret data. These models can be fine-tuned on domain-specific corpora, thus providing contextual insights and performing sophisticated tasks such as summarisation, entity extraction, sentiment analysis, and more. When integrated with command-line or web-based data analytics platforms, they can automatically generate code that performs data cleaning or advanced statistical modelling in R, Python, or SQL. While such

automation augments the researcher's capabilities, it also raises methodological and ethical questions. How do we ensure that AI-generated methods align with the conceptual frameworks of a given discipline? How do we preserve transparency when workflows are partially hidden within black-box algorithms?

Despite ongoing debates, the net effect is that generative and machine-learning-based approaches to data analysis are democratising advanced analytics. Scholars can tackle bigger questions, integrate multiple data sources, and identify patterns that would be infeasible to detect with purely manual approaches. Nevertheless, vigilance about interpretability, reproducibility, and data quality must keep pace with these transformations.

4.3 CREATING DUMMY DATASETS

One particularly useful feature of ChatGPT is its ability to generate simulated datasets on request. This capability is especially valuable in teaching and training contexts, where access to real-world data may be limited due to privacy concerns, proprietary restrictions, or simply the lack of suitable examples. For instance, educators and learners can easily produce realistic data for classroom demonstrations, coding practice, or methodological exercises. Users can prompt ChatGPT to create a dataset with specific variables, data types, or relationships for the purpose of designing assignments around particular analytical techniques. Beyond teaching, synthetic data is also useful for sharing code, workflows, or reproducible research protocols when the original dataset cannot be made public. For example, a researcher developing a script to clean and analyse survey data may want to demonstrate their process without exposing confidential participant information. In such cases, a dummy dataset generated by ChatGPT can closely mimic the structure and statistical properties of the original, making it possible to publish tutorials, share methods with collaborators, or seek technical support—without compromising data security.

Consider the following prompt:

I have data on the age, household size, household monthly income and sexual orientation of 300 respondents. This data cannot be shared due to privacy reasons, but I need a similar dataset for teaching. Simulate my dataset with the following characteristics: average age is 32, maximum household size is 5, median monthly income is £5,000. Create a.csv file.

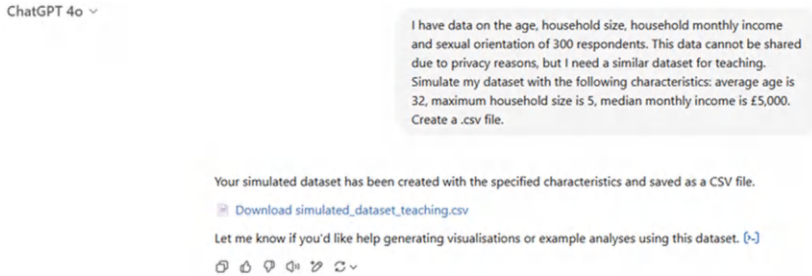


Fig. 4.1 Simulating a dataset in ChatGPT

In response, ChatGPT will readily create a downloadable simulated dataset in a matter of seconds (Fig. 4.1). The more hands-on user may choose to request a Python code which they can tweak and run in any Python environment as desired. To check what ChatGPT has produced, we may explore the distribution of the variables, say, age of the respondents (Fig. 4.2) or the summary statistics—average age in the simulated dataset is 31.46 years, maximum household size is 5, and median income is £5036.5. These statistics show that ChatGPT adhered to the distributional assumptions that we provided in the prompt.

4.4 DATA CLEANING AND PREPROCESSING

Data cleaning is often cited as the most time-consuming phase of any empirical project. Missing records, inconsistent formats, duplicate entries, and outliers can severely affect the validity of subsequent analyses (Van den Broeck et al., 2005). Traditional data cleaning workflows involve methodical checks for errors, manual standardisation of strings or numbers, and labour-intensive transformations of variables. Because mistakes at this stage can propagate throughout the rest of the project, ensuring data integrity is paramount. In this section, we will explore some of the capabilities of GenAI, particularly ChatGPT, to automate key aspects of getting data ready for analysis.

One of the most recent and arguably the most useful feature of ChatGPT for empirical work is Advanced Data Analysis. It allows researchers to upload and interact with data files directly in the ChatGPT interface, enabling the model to write, execute, and debug code in real time. This functionality is particularly valuable for data cleaning and

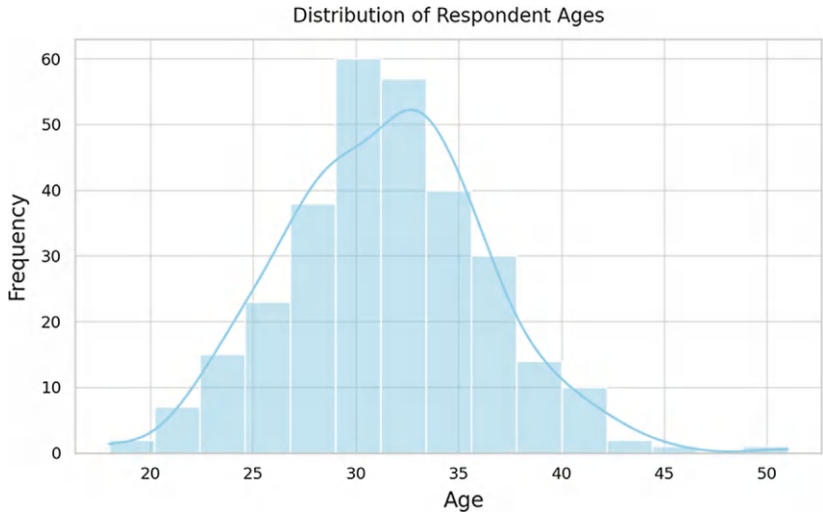


Fig. 4.2 Age distribution in the simulated dataset by ChatGPT

preprocessing. Users can upload raw datasets—such as.csv or.txt files containing survey responses or log data—and instruct ChatGPT to detect and handle missing values, standardise formats, convert data types, or flag outliers. Advanced Data Analysis supports a range of file formats and processes these primarily using Python. It is therefore ideal for automating common tasks like reformatting inconsistent date strings, merging data from multiple sources, or renaming columns according to standardised conventions.

Suppose a researcher wishes to study the link between human capital and economic growth. One way to measure economic growth is per capita real gross domestic product (GDP) and human capital is often measured by the educational attainment of a country’s population. For illustration, we can consider the share of the population aged at least 25 years that completed lower secondary school. We can obtain the relevant data in CSV format, which ChatGPT seems to prefer, from the World Bank.¹ The aim of the data cleaning and preprocessing task is to generate a panel dataset that could be analysed. Figure 4.3 gives an idea of what the raw

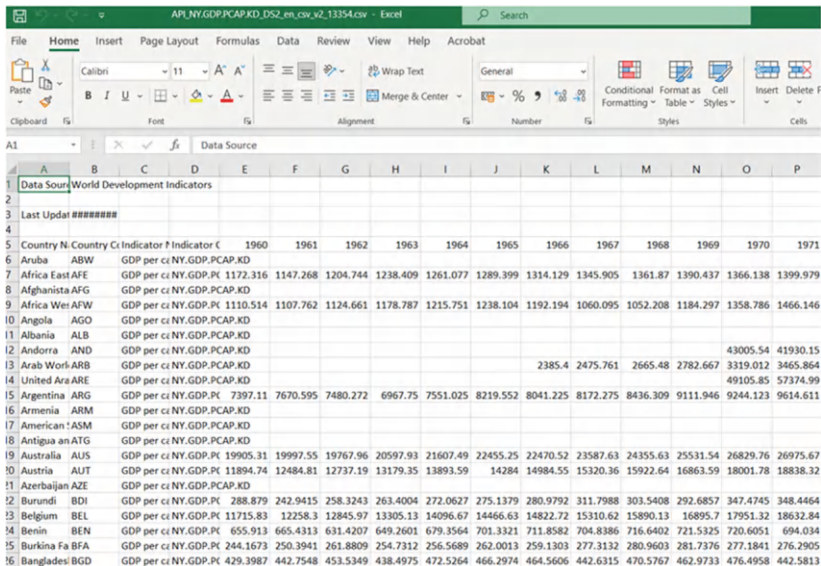
¹ <https://data.worldbank.org/>

per capita GDP dataset looks like in Excel (the education data is similarly structured).

To start, we may simply upload the files to ChatGPT and instruct:

Tell me about the data in these spreadsheets

In return, we get a comprehensive and clear description of the datasets (Box 4.1). Not only does the model correctly describe the two datasets, but it also provides one specific example in each case which we can verify. Next, we want clean panel data files where any year or country for which there is no data has been removed. In the current data structure, there is one row per country and one column per year. The panel structure should have one column each for country, year, and variable. The following prompt accomplishes the task in one go and generates downloadable CSV files:



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	Data Source	World Development Indicators														
2																
3	Last Updated	#####														
4																
5	Country N	Country C	Indicator F	Indicator C	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970	1971
6	Aruba	ABW	GDP per c	NY.GDP.PCAP.KD												
7	Africa East	AFE	GDP per c	NY.GDP.PCAP.KD	1172.316	1147.268	1204.744	1238.409	1261.077	1289.399	1314.129	1345.905	1361.87	1390.437	1366.138	1399.979
8	Afghanistan	AFG	GDP per c	NY.GDP.PCAP.KD												
9	Africa West	AFW	GDP per c	NY.GDP.PCAP.KD	1110.514	1107.762	1124.661	1178.787	1215.751	1238.104	1192.194	1060.095	1052.208	1184.297	1358.786	1466.146
10	Angola	AGO	GDP per c	NY.GDP.PCAP.KD												
11	Albania	ALB	GDP per c	NY.GDP.PCAP.KD												
12	Andorra	AND	GDP per c	NY.GDP.PCAP.KD												
13	Arab World	ARB	GDP per c	NY.GDP.PCAP.KD							2385.4	2475.761	2665.48	2782.667	43005.54	41930.15
14	United Arab	ARE	GDP per c	NY.GDP.PCAP.KD												
15	Argentina	ARG	GDP per c	NY.GDP.PCAP.KD	7397.11	7670.595	7480.272	6967.75	7551.025	8219.552	8041.225	8172.275	8436.309	9111.946	9244.123	9614.611
16	Armenia	ARM	GDP per c	NY.GDP.PCAP.KD												
17	American	ASM	GDP per c	NY.GDP.PCAP.KD												
18	Antigua and	ATG	GDP per c	NY.GDP.PCAP.KD												
19	Australia	AUS	GDP per c	NY.GDP.PCAP.KD	19905.31	19997.55	19767.96	20597.93	21607.49	22455.25	22470.52	23587.63	24355.63	25531.54	26829.76	26975.67
20	Austria	AUT	GDP per c	NY.GDP.PCAP.KD	11894.74	12484.81	12737.19	13179.35	13893.59	14284	14984.55	15320.36	15922.64	16863.59	18001.78	18838.32
21	Azerbaijan	AZE	GDP per c	NY.GDP.PCAP.KD												
22	Burundi	BDI	GDP per c	NY.GDP.PCAP.KD	288.879	242.945	258.3243	263.4004	272.0627	275.1379	280.9792	311.7988	303.5408	292.6857	347.4745	348.4464
23	Belgium	BEL	GDP per c	NY.GDP.PCAP.KD	11715.83	12258.3	12845.97	13305.13	14096.67	14466.63	14822.72	15310.62	15890.13	16895.7	17951.32	18632.84
24	Benin	BEN	GDP per c	NY.GDP.PCAP.KD	655.913	665.4313	631.4207	649.2601	679.3564	701.3321	711.8582	704.8386	716.6402	721.5325	720.6051	694.034
25	Burkina Faso	BFA	GDP per c	NY.GDP.PCAP.KD	244.1673	250.3941	261.8809	254.7312	256.5689	262.0013	259.1303	277.3132	280.9603	281.7376	277.1841	276.2905
26	Bangladesh	BGD	GDP per c	NY.GDP.PCAP.KD	429.3987	442.7548	453.5349	438.4975	472.5264	466.2974	464.5606	442.6315	470.5767	462.9733	476.4958	442.5813

Fig. 4.3 Snippet of the raw per capita GDP dataset

Clean the data files by removing any years or countries that contain all null values. Then transpose the data to form a panel structure with columns for country, year and indicator.

The resulting panel datasets (Fig. 4.4) are consistent with the raw data (Fig. 4.3) and this whole cleaning exercise took less than five minutes, including the time to download the data from the source. Admittedly, the duration of the process depends on several factors such as internet speed and how long it takes to locate the raw data. Yet, the efficiency gains of the AI-mediated process will always be significant because the manual cleaning process cannot possibly be completed as quickly. In most real-life situations, this extent of cleaning sometimes takes hours to complete, depending on the size of the starting datasets, the number of variables, and the initial cleanness of the raw data.

It is important to regularly verify the accuracy of the outputs received from GenAI tools because, despite being advanced, they are still capable of producing errors. A useful approach is to ask the model to explain or describe its reasoning during the task. This can compel the model to reassess and clarify its logic. Users may also exert some oversight by clicking on the “view analysis” icon at the end of the ChatGPT output to reveal further detail about how the result was generated. Once we are

	A	B	C	D	E	F
1	Country Name	Country Code	Indicator	Year	Value	
2	Africa East	AFE	GDP per capita	1960	1172.316	
3	Africa West	AFW	GDP per capita	1960	1110.514	
4	Argentina	ARG	GDP per capita	1960	7397.11	
5	Australia	AUS	GDP per capita	1960	19905.31	
6	Austria	AUT	GDP per capita	1960	11894.74	
7	Burundi	BDI	GDP per capita	1960	288.879	
8	Belgium	BEL	GDP per capita	1960	11715.83	
9	Benin	BEN	GDP per capita	1960	655.913	
10	Burkina Faso	BFA	GDP per capita	1960	244.1673	
11	Bangladesh	BGD	GDP per capita	1960	429.3987	
12	Bahamas	BHS	GDP per capita	1960	18789.51	
13	Belize	BLZ	GDP per capita	1960	1554.737	
14	Bermuda	BMU	GDP per capita	1960	39906.02	
15	Bolivia	BOL	GDP per capita	1960	1276.966	

	A	B	C	D	E
1	Country Name	Country Code	Indicator	Year	Value
2	Argentina	ARG	Education: Years	1970	19.3
3	Belgium	BEL	Education: Years	1970	33.87
4	Belize	BLZ	Education: Years	1970	9.26
5	Bermuda	BMU	Education: Years	1970	54.2
6	Brazil	BRA	Education: Years	1970	11.52
7	Barbados	BRB	Education: Years	1970	65.3
8	Canada	CAN	Education: Years	1970	60.2
9	Chile	CHL	Education: Years	1970	30.4
10	Cayman Islands	CYM	Education: Years	1970	18.1
11	Dominica	DMA	Education: Years	1970	6.3
12	Dominican Republic	DOM	Education: Years	1970	14
13	Spain	ESP	Education: Years	1970	9.41
14	Ghana	GHA	Education: Years	1970	16.5
15	Grenada	GRD	Education: Years	1970	6.77

Fig. 4.4 Snippet of the clean per capita GDP and educational attainment datasets

satisfied with the output in each file, we can readily prompt ChatGPT to do many different things:

- i. combine both files into one
- ii. remove regional aggregates
- iii. limit the range of years, say, to the most recent 20 years
- iv. transform the GDP variable by dividing all values by a thousand so that it is scaled similarly to the educational attainment variable
- v. retain only four columns—country, year, and the two indicators with their units in parentheses

Box 4.1: Dataset description

Thanks for uploading the datasets. Here's an overview of what each spreadsheet contains:

■ Education Data (File: `API_SE.SEC.CUAT.LO.ZS`)

- **Indicator:** *Educational attainment, at least completed lower secondary, population 25+ (%)*
- **Description:** This dataset shows the percentage of the population aged 25 and older who have completed at least lower secondary education.
- **Coverage:** Over 200 countries and regions
- **Years:** 1960 to 2023 (though many countries have missing data for earlier years)
- **Format:** Each row is a country; columns represent years.
- **Example:** In 2021, Afghanistan reported that 11.63% of its 25+ population had completed lower secondary education.

🕒 GDP Data (File: `API_NY.GDP.PCAP.KD`)

- **Indicator:** *GDP per capita (constant 2015 US\$)*
- **Description:** This dataset tracks GDP per capita, adjusted for inflation (constant 2015 USD), reflecting real income per person.
- **Coverage:** Same global span with data from 1960 to 2023.
- **Format:** Also structured with one row per country and columns for each year.
- **Example:** Afghanistan's GDP per capita in 2021 was \$408.63, while Aruba's was \$27,469.

Would you like to compare these two indicators over time for selected countries, or generate summary tables or visualizations?

Advanced Data Cleaning Affordances

There are several additional use cases for AI tools in data cleaning and preprocessing. While space does not allow for a comprehensive demonstration of each, the principles illustrated in the example above should equip the reader to explore the following advanced capabilities with confidence. Note that the advanced capabilities described in this section

require a certain level of programming skills, access to APIs, or ability to build custom GPTs.

Detecting Anomalies

Generative AI tools, particularly those employing transformer-based text processing, have become very proficient at recognising and correcting anomalies in datasets, something that is exceedingly useful when dealing with big data (Chalapathy and Chawla, 2019). As a simple example, a GPT-based system can parse a CSV or JSON file, detect irregularities such as malformed dates, and propose standardised conversions (e.g., “MM/DD/YYYY” to “YYYY-MM-DD”). When integrated with a domain-specific knowledge base, the system can also suggest plausible values for missing data, using context gleaned from the rest of the dataset. Consider, for instance, a small business dealing with large customer datasets. Simple attributes like transaction IDs and dates can cause major bottlenecks in data processing that could be quickly overcome by parsing the data through an AI platform like ChatGPT and issuing a prompt like this, depending on the exact situation:

Review the attached dataset of 10,000 customer transactions. Identify and correct any inconsistent date formats, standardise the date to ‘YYYY-MM-DD,’ and flag rows with missing transaction IDs for manual review.

Upon execution, the tool can generate a detailed report outlining how many errors were found and how they were corrected.

Dealing with Missing Data

Missing data can degrade the performance of most data-driven decision-making processes, including, among others, predictive models and inferential analyses. Traditional methods like mean imputation or listwise deletion are simple but could introduce bias. AI-based techniques, particularly those using generative models, can learn from the patterns in the observed data to impute plausible values for missing entries. For numeric data, methods such as *Multiple Imputation by Chained Equations (MICE)* can be automated using Python libraries (e.g., fancyimpute) or R packages. Furthermore, generative models can create “synthetic” samples that capture the joint distribution of the dataset more accurately

than simpler approaches (Zhang et al., 2021). This generative imputation approach is especially helpful in fields like clinical research, where incomplete patient records are frequent. After training on representative data, a GenAI system can propose imputed values for missing lab results based on correlations with other known variables such as age, gender, and comorbidities. The advantage is a fuller dataset that remains faithful to the underlying relationships among variables. Of course, domain experts must still examine the plausibility of AI-imputed data and apply these techniques ethically, especially when dealing with sensitive patient information (Shen et al., 2020).

Detecting Outliers

Outliers may reflect measurement errors or genuinely unusual events that warrant further investigation. Standard statistical approaches like z-scores, interquartile range (IQR), and robust Mahalanobis distance are well-established. However, these methods can be less effective in high-dimensional data or complex distributions. GenAI can help in this area by learning the “typical” data distribution. Any data point that significantly deviates from this learned distribution can be flagged for human review. For example, if a retailer’s transaction logs typically have daily sales volumes between £100 and £5,000 for a given store, a model might quickly detect a sudden spike to £100,000 or a sudden dip to £20 as an anomaly which may indicate an error or fraudulent activity. Users must however exert oversight to discern whether a flagged point is a genuine anomaly or a novel pattern that the model failed to anticipate.

Transforming Data

Sometimes, situations demand that raw variables be transformed raw variables into more informative representations. This often requires domain knowledge, for the researcher to identify the right transformations. GenAI can support even those without specialised expertise by suggesting suitable transformations based on established best practices, or by generating new features from textual descriptions. For instance, an AI tool might suggest a log transformation for heavily skewed data or propose discretising a continuous variable when certain threshold-based patterns are known to be relevant. These suggestions may be reviewed, modified, or directly integrated by the user. In a marketing dataset, for instance, a

model trained on user behaviour data could suggest creating time-lagged variables to capture delayed purchase effects. While the final decision rests with the human researcher who understands the context, objectives, and potential confounding factors, the use of GenAI can expedite the data transformation process significantly.

Extracting Data from Images and Text

LLMs are particularly strong in terms of their ability to extract structured data from images and unstructured text. This includes not only qualitative information but also numerical data, such as stock prices mentioned in news articles or dosage details from pharmaceutical databases. When prompted with, “*Provide examples of the kinds of numbers you can extract from text?*”, ChatGPT 4o listed phone numbers, postcodes, identification numbers, credit card numbers, bank account or sort codes, dates, times, prices, percentages, and others. A similar list is obtained if the prompt is modified to include images. It is especially handy, for those involved in qualitative research where interview and focus group notes or data may be handwritten, to take photos, upload to ChatGPT, and ask for an extraction. This kind of information extraction can be automated at scale through API access and is often feasible using smaller, more cost-effective models than GPT-4 (Korinek, [2023](#)).

4.5 DATA ANALYSIS AND VISUALISATION

Automating Data Analysis and Visualisation

After data cleaning and preprocessing, researchers typically conduct exploratory data analysis by examining the distribution of their data in order to identify key patterns, spot potential outliers, and make an informed choice of appropriate statistical techniques for subsequent analyses. This is followed by formal statistical tests of many different types, depending on the research objectives. Today, specialised statistical tools have simplified these processes. However, the expertise required to deploy specialised software is unequally distributed; early-career researchers and those in low-resource contexts often grapple with basic challenges such as what types of summaries and visuals to generate, and what are the most appropriate modelling techniques based on the data structure and

distribution. The last task—choosing the right statistical test—is a non-trivial one.² It is the point where many researchers not only struggle but also fall into the cherry-picking trap, that is, randomly running different types of analyses and reporting only the ones that seem desirable (in terms of significant results or conformance to the researcher’s expectations). GenAI can lower the entry barrier by enabling researchers to engage in complex analytical tasks using natural language prompts rather than advanced programming or statistical knowledge. With the right instructions, LLMs can suggest appropriate summary statistics, recommend or generate suitable visualisations, and explain the rationale behind different modelling choices. These capabilities not only accelerate the learning curve for less-experienced researchers but also support greater equity in access to high-quality analytical tools.

Returning to the example developed in Sect. 4.4, we now wish to use the clean dataset to explore the link between human capital and economic growth. A good starting point is to explore the distribution of the data. After uploading the dataset to ChatGPT 4o, a practical prompt is:

Summarise this data. Put the results in a table and include all the standard summary statistics that would normally be reported in a research article. Put the variables in columns and the stats in rows. Export the table in Word format.

The unedited output is reproduced in Table 4.1. The table is decent, requiring only minor editing. Without being specific about the variables of interest, the model also reported summary statistics for “year”, which is not useful other than to see if there is an outlier. Also, decimals appear everywhere and the number of observations is essentially repeated in “count” and “Non-missing Observations”. The minimum recorded value for the share of individuals aged 25 and older who have completed at least lower secondary education is zero. This is an unusual observation, and a user might simply ask ChatGPT to investigate the reason. Upon examination, it turns out that the dataset contains only a single country-year instance with a value of zero: Iran in 2017. How to handle this anomaly is ultimately a decision for the researcher. The purpose of this example, however, is to demonstrate how ChatGPT can support the data

² See, for instance, <https://risingscholars.net/en/news/details/1233/> for a discussion of how to choose the right statistical tests.

Table 4.1 Summary statistics

<i>Statistic</i>	<i>Year</i>	<i>Completed Lower Secondary Education (%) of population 25+</i>	<i>GDP per Capita (Constant 2015 US\$, thousands)</i>
<i>count</i>	1773.0	1773.0	1773.0
<i>mean</i>	2014.82	67.44	18.31
<i>std</i>	5.06	26.18	21.75
<i>min</i>	2004.0	0.0	0.27
<i>10%</i>	2007.0	29.36	1.3
<i>25%</i>	2011.0	47.43	3.51
<i>50%</i>	2015.0	71.88	8.41
<i>75%</i>	2019.0	91.39	26.9
<i>90%</i>	2021.0	97.95	49.24
<i>max</i>	2023.0	100.0	173.12
<i>Non-Missing Observations</i>	1773.0	1773.0	1773.0

analysis process by quickly exploring data and identifying and explaining such irregularities.

We may further explore the data by visualising the distribution:

Generate an appropriate visualisation for the variables that help to identify their distributions and highlight any potential issues.

The resulting histograms (Fig. 4.5) clearly show that both variables are skewed and will not lend themselves to statistical approaches that assume normality unless they are transformed in some way, say, by taking logarithms. The curious user may ask ChatGPT for a detailed explanation of the histograms and their implications for analysis. It is sufficient for our purposes here to ask ChatGPT to:

Suggest an analysis to examine the link between the two variables. The research question is about how human capital is associated with economic growth.

The output in Box 4.2 cannot replace human expertise and instruction, especially if this has been generated by a beginner in empirical analysis. We must emphasise here again the importance of human agency. The quality of the results depends on how clearly the task is specified and on the user’s ability to evaluate the outputs critically. The AI model can carry

out complex routines accurately. And even if it makes clear and coherent suggestions, it does not make independent judgements about data quality, the appropriateness of models, or the implications of statistical assumptions. For this reason, while tools like ChatGPT can significantly enhance the efficiency of research, they must be used in partnership with human expertise to ensure that the analysis remains rigorous, transparent, and meaningful. The content of Box 4.2 offers an outstanding starting point as a resource to study data analysis, either by oneself or under the instruction of someone else. We may, for instance, prompt for a step-by-step guide on how to implement any of the steps, ask for recommended texts to read, or use the output to seek further instruction.

That said, most readers with some level of expertise in panel data analysis will readily see that the output is of very good quality and can be taken to the data using a specialised software of choice. If we prefer, we may ask ChatGPT to run any of the analyses, knowing that this will be done using Python, a versatile coding language that has strong data analysis capabilities. Say we ask for the panel data analysis suggested in number 5 in Box 4.2, with a visualisation of the results that includes explanatory notes, the output in Fig. 4.6 is what we receive. The scatter points represent country-year observations, and the red line shows the fitted linear relationship. This output demonstrates the strengths of using GenAI tools for empirical research. The analysis is technically sound because it draws on best practices such as fixed effects modelling, clustering of standard errors, and appropriate variable transformation. The visualisation is not only informative but also readable and ready for inclusion in research or teaching materials. The explanatory notes offer context and interpretive guidance which help our substantive understanding.

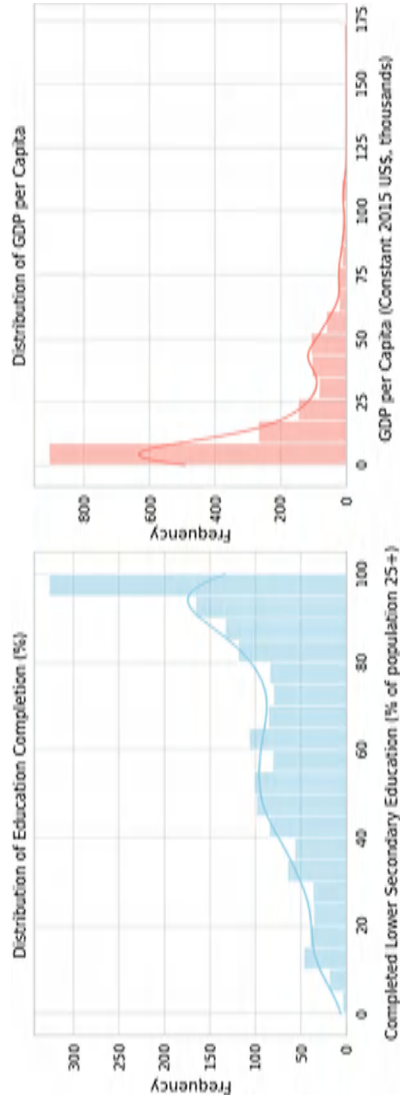


Fig. 4.5 Histograms showing data distribution

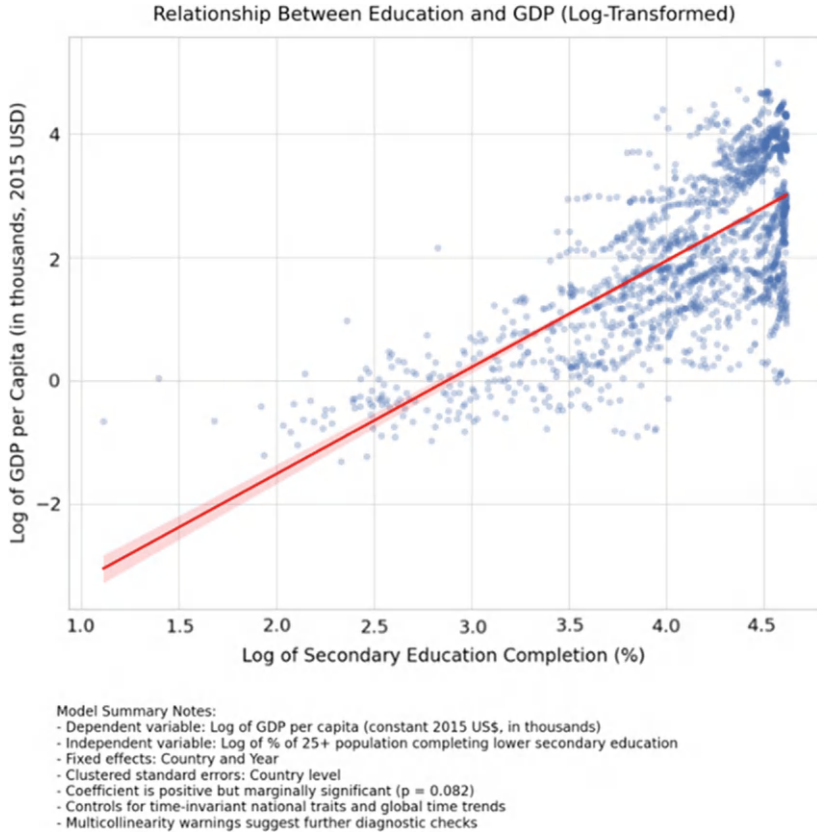


Fig. 4.6 Results of regression analysis by ChatGPT

Box 4.2: Data analysis plan generated by ChatGPT

☒ Suggested Analysis Approach

1. Descriptive and Exploratory Analysis

- Begin with **scatter plots** to visually inspect the relationship between the two variables across countries and over time.
- Compute **correlation coefficients** (e.g. Pearson or Spearman) to assess the strength and direction of association.
- Consider grouping countries by income level or region to identify patterns that may be context-specific.

2. Log Transformation

- Both variables are right-skewed, so apply a **log transformation** to reduce skewness and make the relationship more linear:
 - $\log(\text{GDP per capita})$
 - $\log(\text{Secondary Education \%}) + 1$ (to avoid $\log(0)$ if necessary)

3. Cross-Sectional Regression Analysis

- Estimate a basic **ordinary least squares (OLS)** regression:

$$\log(\text{GDP per capita})_{it} = \alpha + \beta \log(\text{Education}_{it}) + \epsilon_{it}$$
 where i denotes country and t year.
- This tests whether countries with higher educational attainment tend to have higher GDP per capita.

4. Panel Data Modelling (Fixed or Random Effects)

- Since you have a panel dataset (countries over time), a more rigorous approach is a **panel regression**:

$$\log(\text{GDP per capita})_{it} = \alpha_i + \beta \log(\text{Education}_{it}) + \gamma_t + \epsilon_{it}$$
 where:
 - α_i : country fixed effects (control for time-invariant characteristics)
 - γ_t : year fixed effects (control for global shocks/trends)
- This allows for **within-country analysis** over time and improves causal inference compared to pooled models.

5. Robustness Checks

- Use **non-parametric methods** (e.g. LOESS smoothing) to check for non-linear relationships.
- Cluster standard errors by country to adjust for serial correlation.
- Test lagged effects: Does education in year t predict GDP in year $t+5$?

Interpretation

If the coefficient β is positive and statistically significant, this would suggest a positive association between human capital and economic growth. Interpretation should be cautious, especially regarding causality, and supported by theoretical justification and robustness checks.

The exercise above has illustrated how GenAI tools like ChatGPT can generate and execute a structured analysis plan, complete with visualisations, correlation matrices, and clear justifications for chosen statistical methods. These capabilities are particularly valuable when working with large datasets or unfamiliar information. They enable researchers to explore and understand data more efficiently. Beyond the examples demonstrated, GenAI can support a wide range of analytical tasks. In regression and predictive modelling, it can assist with model selection, hyperparameter tuning, and performance evaluation across classical and machine learning methods. Tools like AutoML in platforms such as H2O.ai or AutoGluon (Erickson et al., 2020) automate hyperparameter tuning, cross-validation, and model ensembling, often producing results that match or surpass those crafted by human analysts. For time-series analysis, GenAI can identify trends, lags, and seasonal patterns, and even simulate future scenarios under varying assumptions. Although time-series

models like ARIMA and SARIMA remain popular, AI-based approaches such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) models, and Transformer architectures (e.g., Temporal Fusion Transformers) can capture more nuanced temporal dynamics (Lim et al., 2021). In high-dimensional datasets, GenAI can facilitate clustering and dimensionality reduction, helping uncover latent structures and generate synthetic representations. When exploring high-dimensional datasets (e.g., genomic data, image collections, or text corpora), clustering algorithms (k-means, hierarchical clustering, DBSCAN, etc.) and dimensionality reduction techniques (PCA, t-SNE, UMAP) are valuable for discovering structure (Van der Maaten & Hinton, 2008). These traditional methods remain relevant but AI-driven enhancements can automatically tune hyperparameters (e.g., the optimal number of clusters) or adapt embeddings to preserve semantic relationships more effectively. Again, while these affordances enhance analytical productivity, they also raise important considerations around interpretability, methodological transparency, and human oversight. The true value of GenAI lies not in replacing expert judgement, but in augmenting it—making advanced analytical techniques more accessible, interpretable, and responsive to research needs.

Advanced Data Analysis Affordances

As researchers move beyond basic data analysis, they often encounter more complex tasks such as building predictive models or working with large volumes of unstructured text. GenAI tools are increasingly capable of supporting these advanced analytical needs. The following two sections explore how GenAI can assist with predictive analytics and natural language processing. The sections describe how advanced GenAI capabilities offer practical ways to handle structured and unstructured data.

Predictive Analytics

Generative AI is becoming a powerful tool in the world of predictive analytics. It can support the entire process of building predictive models—from collecting and cleaning data to training the model and explaining the results. With carefully written prompts, users can ask AI systems to carry out complex tasks automatically. For example, we might instruct

ChatGPT to *“use a machine learning model to predict when a machine will fail, clean the data, split it for training and testing, and report the results.”* The model can then generate both the code and the output needed. This will not only save time, but it will also ease the debugging and modification process because the code can be tested almost an unlimited number of times.

More advanced uses of AI include deep learning—models that are particularly good at working with images, sounds, or large amounts of text. These models can be customised to suit specific problems without needing a huge amount of data. For instance, a healthcare researcher could take an existing model trained on general medical texts and teach it to classify a smaller set of clinical notes. AI can also help create synthetic examples (like altered images or adjusted sensor readings) to boost small datasets. Another growing area is reinforcement learning, where AI systems improve over time based on feedback—often from humans. This is useful for systems that need to adapt quickly, like recommendation engines or real-time analysis tools. In research, an AI assistant could learn to adjust its settings to improve accuracy for smaller or more difficult groups of data. While these techniques are helpful, researchers must be cautious: synthetic data may introduce unwanted patterns or bias that affect the reliability of results.

Natural Language Processing for Unstructured Data

Much of the information researchers need is stored in text: things like interview transcripts, policy documents, news articles, or social media posts. Traditionally, turning this kind of unstructured data into something useful took a lot of manual work, including reading, tagging, and summarising. Now, AI tools powered by natural language processing (NLP) can handle many of these tasks quickly and accurately. They can sort, summarise, and even analyse the tone of large volumes of text in ways that were not possible before. These tools are especially good at picking out key information from text. For example, named entity recognition helps identify names of people, places, or organisations in a document. Topic modelling can show what general themes are present in a large collection of texts, such as public concerns over time or shifts in media coverage. Summarisation tools allow researchers to condense hundreds of pages of text into a few clear paragraphs, saving time while still capturing the core message. However, even though these summaries are often very

good, researchers should still check them carefully, as AI can occasionally make mistakes or introduce bias.

Sentiment analysis is another area where AI is making a big difference. It can detect shifts in public mood, track how people feel about a new policy, or study how customers respond to a product. Unlike older methods, which often relied on keyword matching, new AI models can understand more complex and subtle forms of language. Some (e.g., SpaCy, an open-source NLP library in Python) can even uncover relationships between different people or organisations mentioned in a text, helping researchers map networks or understand influence. As these tools continue to improve, they open up new ways to explore and make sense of unstructured data. For example, a researcher analysing corporate reports and media articles can use AI-powered relationship extraction tools to identify and link named entities such as company executives, board members, and firms. Suppose the AI detects that “Jane Doe” appears frequently in connection with both Company A and Organisation B, and that these entities are also mentioned alongside key terms like “investment” or “acquisition”. This allows the researcher to infer a potential strategic relationship or shared interests.

4.6 CONCLUDING REMARKS: IMPORTANT CONSIDERATIONS FOR AI-MEDIATED DATA ANALYSIS

Before closing this chapter, some important caveats bear repeating. Firstly, researchers should be aware that neural networks, the underlying architecture of most Generative AI tools, often function as “black boxes”. It is difficult for researchers to understand how final predictions or classifications are arrived at (Rudin, 2019). In contexts like healthcare, finance, or criminal justice, this lack of interpretability can have severe ethical and legal ramifications. Even in less regulated contexts, hidden biases can distort scientific findings, hamper reproducibility, or undermine the trust of stakeholders. Secondly, GenAI models and other forms of AI inherit biases from their training data. Gender, racial, or ideological biases in large corpora can reflect, and potentially magnify, societal prejudices (Bolukbasi et al., 2016). When used in data processing tasks, these biases might lead to skewed data cleaning (e.g., systematically ignoring certain demographic categories) or warped inferences (e.g., labelling benign behaviour as anomalous for specific subgroups). Thirdly, reproducibility is a crucial hallmark of rigorous science; yet AI-driven workflows

often involve numerous hyperparameters, data transformation steps, and random seeds that can be challenging to track.

These challenges are not unsurmountable. As with every technology, balancing between the downsides and the upsides of AI requires a deliberate multi-pronged approach. Researchers can adopt strategies such as rebalancing training datasets, imposing fairness constraints during model development, or using explainable AI techniques to surface potential biases. Coupled with manual audits by domain experts, these strategies help ensure that AI-driven data analyses remain equitable and ethically sound (Barocas et al., 2019). Reproducibility can be enhanced by using version control systems like Git, documenting all pipeline stages with tools such as MLflow, setting seed numbers wherever possible, and providing containerised environments (e.g., Docker images) that replicate the computational conditions of a study. The principle is that other researchers—or even the same research group at a later date—should be able to replicate exactly the same results, given identical inputs and code (Peng, 2011). Most importantly, researchers should systematically question AI suggestions, apply domain expertise to interpret anomalies, and ensure alignment with the conceptual underpinnings of the field. Domain knowledge is especially critical when deciding if an outlier is truly erroneous or a groundbreaking discovery. Likewise, in interpretive social sciences, domain experts can detect nuance and context that an AI might overlook (Nelson, 2022). Instead of seeing AI as a replacement, the most effective analyses emerge from a symbiotic partnership between generative models and human intelligence.

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Towards Methodological Innovation: Co-Creating Research Design with Generative AI

5.1 INTRODUCTION

In academic research, the term methodology represents distinct and critical aspects of the research process. Methodology refers to the philosophical and theoretical framework, the underlying thinking and worldview, that informs a research approach from end to end. It also encompasses the epistemological stance (how we know what we know), the ontological assumptions (what we believe about the nature of reality), and the logical reasoning that guides the selection and justification of specific research strategies. In contrast, methods are the practical tools and procedures, the concrete steps involved in collecting, analysing, and interpreting data. These methods operate within the bounds of the chosen methodology, serving as the means through which knowledge is generated and interpreted (Moon et al., 2019; Scotland, 2012).

Understanding this distinction is crucial when we speak of methodological innovation. Innovation in research methodology requires a rethinking of the assumptions, logics, and frameworks that underpin knowledge-driven inquiry. In this light, methodological innovation involves challenging conventional research design practices and embracing new possibilities for inquiry, particularly in response to emerging technologies such as GenAI. One of the most significant developments shaping contemporary research practices is the advent of GenAI, systems capable of autonomously generating content, simulating reasoning, and

providing adaptive responses across a wide range of inputs and disciplines. While GenAI is already being incorporated into various stages of the research process, for instance, in problem formulation, literature synthesis, data analysis, and writing assistance (Benjamin et al., 2024; Schryen et al., 2025).

Its deeper potential lies in its capacity to act as a co-creator alongside researchers in shaping experimental design. This includes supporting the formulation of hypotheses, the construction of research instruments, and the alignment of these components within coherent methodological frameworks. This chapter argues that GenAI should be considered a co-creative partner, capable of actively contributing to the development of research design itself. To realise this potential, researchers must move beyond viewing AI as a merely instrumental tool and begin to explore how AI systems can provoke critical reflection, generate methodological alternatives, and offer adaptive design suggestions that respond to dynamic and evolving research contexts.

This argument rests on two experiential propositions. First, the complexity of research questions, particularly in interdisciplinary, real-world contexts, demands methodological approaches that are more flexible, iterative, and responsive than those allowed by traditional, human-only-driven models. Second, GenAI tools possess generative capacities that make them suitable collaborators in the early stages of research design, where creativity, co-creation, and scenario building are essential.

To support these propositions, the chapter addresses three key questions:

- What does it mean to “co-create” a research design with a non-human agent?
- This question explores whether and how GenAI may augment, or challenge, the assumptions embedded within conventional research paradigms.
- How do researchers retain agency, ethical responsibility, and methodological rigour
- when working alongside autonomous systems in the design of research methodology?

By engaging these questions, the chapter positions GenAI as a transformative force, an enabling tool in methodological innovation. It does

not advocate for the replacement of human judgement, but rather for the expansion of methodological imagination, one that is open to dialogue with intelligent systems, and grounded in reflexivity, transparency, and critical engagement.

In the sections that follow, we explore co-creation in research, drawing on both real-world and hypothetical examples of GenAI-assisted design, and propose a conceptual framework for responsibly integrating GenAI into research methodology. In the end, this chapter invites readers to reimagine how knowledge is generated, but through research methodologies that are more imaginative, inclusive, and responsive to the evolving research landscape.

5.2 WHAT DOES IT MEAN TO “CO-CREATE” A RESEARCH DESIGN WITH A NON-HUMAN AGENT?

The question at hand, *what does it mean to “co-create” a research design with a non-human agent?* sits at the intersection of technology, epistemology, and research methodology. It calls for a serious examination of whether (and how) GenAI can augment, or even challenge, the foundational assumptions embedded within conventional research paradigms. Conventional in the sense of what researcher are used to, the process of conducting research, the instruments, the approaches, and the ideologies.

In research design, the human researcher is viewed as the sole agent responsible for defining the research problem, creating a scope, selecting methods, and interpreting findings. This model presumes a linear, often hierarchical relationship between the researcher and their tools. Tools are deployed to execute predefined plans; they do not offer conceptual input. However, GenAI introduces a new kind of tool: one that is *suggestive, generative, interactive, and prescriptive arguably*. For instance, GenAI can produce alternative formulations of research questions, simulate experimental scenarios, and assist in constructing methodologies based on prompts and prior inputs.

To speak of “co-creation” in this context is to challenge the researcher-tool binary. Co-creation implies a collaborative, iterative process where both human and non-human agents contribute meaningfully to the formulation and structuring of a research project. This does not mean equating the agency of AI with that of the human researcher, but it does mean recognising that GenAI can function as a cognitive extension or

intellectual partner, capable of shaping both the direction and substance of methodological choices (Pagliari et al., 2022).

5.3 CO-CREATION AS EPISTEMIC DIALOGUE

Co-creating a research design with GenAI requires reconceptualising research as a form of dialogue rather than unilateral construction. In this model, the researcher engages in a back-and-forth process with the AI system, treating its outputs not as definitive answers but as provocations—material to be evaluated, recontextualised, and iterated upon. For instance, when prompted with a general research theme, a GenAI system might return a range of possible research questions. These questions might span disciplinary boundaries, introduce unexpected theoretical linkages, or offer novel methodological combinations that the researcher had not previously considered.

This dialogical co-creation process aligns with constructivist and interpretivist research paradigms, which hold that knowledge is not merely discovered but constructed through interaction. Here, the interaction is not only with data or human subjects but also with an intelligent system trained on vast repositories of prior human knowledge. The researcher becomes a curator of possibilities, filtering and refining the outputs of the AI in light of theoretical, practical, contextual, and ethical considerations.

Bringing a non-human agent like GenAI into research design raises important questions about how we usually think about research. Traditional approaches, especially in fields that follow a positivist tradition, often focus on being objective, neutral, and consistent. But using GenAI can introduce a level of uncertainty, especially because AI systems are known to sometimes make things up (hallucinate) or reflect biases from the data they were trained on. These issues raise valid concerns about how accurate, reliable, and transparent AI-assisted research really is.

That said, it is also true that traditional research is never completely free from bias. Researchers bring their own perspectives, backgrounds, and assumptions into their work. So, in some ways, it becomes a matter of human subjectivity versus machine bias, a fascinating challenge that's worth exploring.

One advantage of using GenAI is that it can make these biases and assumptions more obvious (English et al., 2025). By generating different versions of a research design, GenAI gives researchers new options to consider, options they might not have thought of on their own. These

alternatives can be compared, questioned, and even improved upon. For example, a researcher could ask GenAI to suggest several ways to approach a study, then choose the best one based on ethics, relevance to the topic, and practicality. In this way, GenAI does not just assist; it can help researchers think more deeply and creatively about their methods.

5.4 FROM ASSISTANCE TO COLLABORATION

It is important to distinguish collaboration from mere assistance. Many current uses of GenAI in research remain assistive: summarising articles, analysing dataset, or proofreading texts. Co-creation, by contrast, implies a mutual shaping of ideas, where the AI's outputs actively influence the trajectory of the research design. This shift demands a more critical and reflexive approach to research practice. Researchers must begin to make sense of GenAI dialogue outputs not as passive text but as part of a methodological conversation. This includes questioning the assumptions underlying the AI's suggestions, exploring alternative prompts, and documenting the iterative process of design. This also introduces new skills and responsibilities. Researchers must develop competencies in prompt engineering, ethical interpretation of AI outputs, and transparency in documenting how AI contributed to the research process. These responsibilities are essential to ensure rigour, accountability, and reproducibility.

Ultimately, co-creating with GenAI invites a more pluralistic approach to methodology. Rather than replacing traditional methods, it offers a supplementary layer of creativity and critique. Researchers can use GenAI to prototype multiple research designs, evaluate their merits, and select or adapt accordingly. This iterative experimentation can lead to more robust, innovative, and contextually sensitive research. Early-career researchers, particularly those in under-resourced settings, or individuals exploring interdisciplinary questions may find in GenAI a valuable partner for idea generation and methodological scaffolding. This could help address issues of access and equity in research, although it also raises concerns about digital divides and over-reliance on automated systems.

To co-create a research design with a non-human agent like GenAI is to enter a new methodological terrain, one where the boundaries between tool and collaborator become more blurred. While this raises significant epistemological and ethical questions, it also offers an unprecedented opportunity to reimagine how research is designed and conducted. As

GenAI continues to evolve, so too must our baseline for understanding and evaluating methodological innovation. The goal is not to diminish the role of the human researcher, but to expand the horizon of what is methodologically possible when we invite intelligent systems into the creative core of research design.

5.5 HOW DO RESEARCHERS RETAIN AGENCY WHEN WORKING ALONGSIDE GENAI IN RESEARCH DESIGN?

Researcher agency refers to the capacity of the researcher to act intentionally and make decisions that shape the research process linking the research enquiry with the research outcome in ways that are valid, transparent, repeatable, and rigorous. In my opinion, and from experience, when working with GenAI, researcher (human) agency is not lost but reconfigured. The central piece of agency reconfiguration lies in recognising that while AI can generate outputs, it cannot independently determine research value, context, scope, or purpose. These judgements remain firmly within the human domain.

To retain agency, researchers must:

- Set clear research intentions and scope before engaging with AI systems. It is OK to explore, but the exploration with AI should not be open-ended.
- Critically assess AI-generated outputs, treating them as suggestions rather than prescriptions. This leading to iterative process of prompt reengineering that produces a co-created output.
- Document their own decision-making process to show how human reasoning guided the use or rejection of AI (suggestions) contributions.

This way, the researcher actively *co-create* with the AI, guiding its use within the broader goals of the research. Ai is not sentient, it lacks consciousness, and moral judgement or reasoning. Even when it produces outputs that appear sophisticated, these outputs are generated based on patterns, not understanding. This makes the researcher's interpretive control even more critical in the epistemic process. Maintaining this control involves: contextual interpretation, normative judgement, and theoretical alignment.

In this sense, working with GenAI is similar to collaborating with a highly suggestive but non-sentient co-investigator, one that must be guided, questioned, and, at times, ignored. As GenAI becomes an increasingly common feature in research design, the responsibility for its use remains firmly with the human researcher. Retaining agency means making informed, deliberate decisions about how AI contributes to the research process, while recognising that its contributions can still be valid and worthy of inclusion when appropriately contextualised and critically assessed.

To better understand the dynamics of working with GenAI in the research design process, Fig. 5.1 provides a conceptual framework that visualises the interactive relationship between the human researcher and the AI agent. This framework illustrates how co-creation unfolds through a process of iterative dialogue, underpinned by continuous human oversight and critical reflection.

At the core of the framework is the iterative dialogue between the *Researcher (Human Agent)* and *GenAI (AI Agent)*. This exchange begins with a prompt initiated by the researcher, which is shaped by the research context and the intended scope of inquiry. In response, GenAI generates content: ideas, questions, or design options, which the researcher then evaluates. This back-and-forth interaction can occur multiple times, gradually shaping and refining the research design.

The framework places strong emphasis on researcher control, illustrated by a control layer comprising three key dimensions mentioned in the preceding section:

- **Contextual Interpretation:** Researchers must interpret AI-generated content in light of the specific goals, setting, and theoretical orientation of their study. For example, if GenAI suggests interview questions, the researcher must consider whether they are appropriate or relevant to the unit of analysis being studied.
- **Normative Judgement:** Ethical responsibility lies with the human researcher, who must ensure that AI contributions align with professional, disciplinary, and societal standards. For instance, a researcher might discard suggestions that reinforce stereotypes or reflect biased language.
- **Theoretical Alignment:** Outputs from GenAI must be examined for consistency with the research's theoretical framework. If a study is rooted in a critical paradigm, for example, the use of methods or

language that reflect a positivist stance would require adjustment or rejection.

These layers of interpretation, judgement, and alignment underscore the idea that GenAI operates under the direction and oversight of the human researcher. While the AI system can generate useful material, it lacks the capacity to assess relevance, ethical appropriateness, or theoretical fit on its own.

The framework also highlights the importance of prompt engineering, the act of questioning or instructing GenAI, as a critical methodological skill. The quality and clarity of prompts greatly influence the usefulness of the AI's responses. This skill is quickly becoming essential for researchers who wish to use AI meaningfully in their work. Importantly, the diagram does not suggest that GenAI and human researchers are equal partners in the research process. Instead, it frames co-creation as a scaffolded interaction, where the researcher actively shapes the use of AI to support their intellectual agenda. GenAI is positioned as a non-sentient but responsive collaborator, capable of generating novel content, yet always requiring human interpretation and direction. This conceptual model offers researchers a practical way to understand and manage their engagement with GenAI. It reinforces that co-creation, when done responsibly, can enhance creativity and efficiency without compromising ethical or methodological standards.

The next section provides a case study that puts the framework into practice.

Use Cases

To illustrate the practical application of co-creating research design with GenAI, I draw from two vivid and culturally grounded research ideas I am currently developing. The first project seeks to conduct a deductive thematic analysis of national and pan-African AI policy frameworks through the lens of Ubuntu, a foundational African philosophy centred on communalism, interconnectedness, and human dignity. The second project investigates how market women in informal business sector in urban Lagos (Nigeria) adopt and adapt to digital payment technologies. The research is situated within an interpretivist paradigm, aiming to explore lived experiences, socio-cultural meanings, and the challenges

these women face in navigating digital transformation. The GenAI used for the simulation is ChatGPT version 4o.

5.6 EXPLORING AI POLICY THROUGH THE LENS OF UBUNTU—A CO-CREATIVE RESEARCH DESIGN WITH GENAI

The first study is positioned within an interpretivist paradigm, underpinned by a critical epistemology that values culturally embedded forms of knowledge. Ubuntu, in this context, is not just a value system but a lens for reinterpreting AI ethics and governance from an indigenous African standpoint. This approach seeks to uncover how AI policies reflect or neglect, culturally grounded ethical constructs.

The aim of the research is threefold: to evaluate the extent to which African AI policy frameworks reflect Ubuntu-informed values; to contribute to the broader conversation on decolonising AI governance; and to advance an African-centred approach to technology ethics by embedding indigenous epistemologies in policy analysis. The research focuses on identifying key constructs within Ubuntu (Chigangaidze et al., 2022; Mugumbate et al., 2024), such as *interdependence*, *relational identity*, *restorative justice*, and *collective responsibility*, that can serve as analytical anchors in assessing policy documents.

My Prompt:

I would like to design a methodology for a study positioned within an interpretivist paradigm, underpinned by a critical epistemology that values culturally embedded forms of knowledge. The study seeks to explore how African AI policy frameworks reflect, or fail to reflect, culturally grounded ethical constructs, particularly those informed by Ubuntu philosophy. The aim of the research is threefold: (1) to evaluate the extent to which African AI policy frameworks reflect Ubuntu-informed values; (2) to contribute to the broader conversation on decolonising AI governance; (3) to advance an African-centred approach to technology ethics by embedding indigenous epistemologies into policy analysis.

My thoughts: Please note the detailed context and scope in the prompt).

ChatGPT:

1. Deductive Thematic Analysis

Justification:

Given that the study aims to assess the presence or absence of predefined constructs (e.g., interdependence, relational identity, collective responsibility) within AI policy documents, a deductive thematic analysis is highly appropriate. This method allows the researcher to code data using a set of predetermined themes derived from Ubuntu philosophy, aligning with the study's interpretivist and culturally grounded lens. It also enables critical interpretation of how those themes are represented, misrepresented, or absent in AI policy texts.

2. Critical Discourse Analysis (CDA)

Justification:

To contribute meaningfully to the decolonisation of AI governance, it is important to go beyond surface-level content and examine how power, ideology, and cultural bias are embedded in the language and framing of AI policies. CDA is suitable because it critically analyses texts within their social, political, and historical contexts. This aligns well with your critical epistemology and will allow for a deeper interpretation of how African identities, values, and ethical concerns are positioned (or sidelined) in the discourse of technological governance.

3. Documentary Hermeneutics

Justification:

As the study is based on interpreting policy documents through a culturally sensitive lens, documentary hermeneutics, a method rooted in the interpretation of written texts—provides a strong fit. This approach treats policy documents as socially constructed artefacts, enabling the researcher to interpret not just what is said, but what is assumed, omitted, or implied. This complements the Ubuntu worldview, which values relational and contextual interpretation, and supports an ethical reading of the texts that honours indigenous ways of knowing.

Reflection: When I was designing this research, deductive thematic analysis was the primary-and potentially the only, analytical approach I had in mind. This was largely due to its strong alignment with the

Ubuntu framing that underpins the conceptual foundation of the study. Deductive analysis offered a structured way to explore predefined themes rooted in Ubuntu values, enabling a clear and purposeful engagement with the data. However, the responses generated through Generative AI have opened new possibilities. In some ways, these AI-driven interactions have prompted me to reconsider the design of the research itself. They suggest potential for exploring alternative or complementary analytical approaches, including more inductive or hybrid thematic strategies, which could allow for emergent insights beyond the initial framework. This unexpected development has encouraged a more flexible and adaptive view of research design, one that remains anchored in Ubuntu, but also open to methodological innovation.

My Prompt:

Provide more detailed steps to carry out the second and 3rd approaches

ChatGPT:

Critical Discourse Analysis (CDA)

Goal: To uncover how language in AI policy frameworks reflects or marginalises Ubuntu-informed values, power relations, and cultural ideologies.

Steps for CDA:

Step 1: Select the Textual Corpus

- Identify relevant African AI policy documents at the national and regional levels (e.g., South Africa's AI policy, AU frameworks).
- Ensure documents represent different geographical, linguistic, and political contexts within Africa.

Step 2: Develop Analytical Framework

- Ground the analysis in Fairclough's CDA model or another established CDA framework.
 - Text: Analyse linguistic features (e.g., keywords, metaphors, narrative structures).
 - Discursive Practice: Consider how texts are produced, distributed, and consumed.

Social Practice: Examine the broader socio-political and cultural context of the policy (e.g., postcolonial governance, global AI ethics discourse).

Step 3: Identify Ubuntu-Informed Constructs

- Define specific Ubuntu values (e.g., interdependence, communal responsibility, relational identity) as analytical lenses.
- Create a coding scheme to tag language and concepts that reflect or contradict these values.

Step 4: Analyse the Texts

- Conduct a close reading of the documents using your coding scheme.
- Look for patterns in:
 - Inclusion/exclusion of indigenous ethical terms.
 - Framing of concepts like fairness, inclusion, privacy, etc., in culturally neutral vs. culturally situated ways.
 - Use of global north vs. African epistemological references.

Step 5: Interpret Power Dynamics

- Ask: Whose voices are represented or silenced?
- Analyse the power relationships between state, tech corporations, and communities.
- Critically examine colonial continuities in how AI governance is imagined or legislated.

Step 6: Reflect and Synthesise

- Draw connections between linguistic choices and broader social structures.
- Show how the discourse supports or undermines a decolonial, Ubuntu-informed AI governance agenda.

Documentary Hermeneutics

Goal: To interpret AI policy documents as cultural artefacts, understanding how they reflect deeper meanings, worldviews, and ethical commitments (or their absence).

Steps for Documentary Hermeneutics:

Step 1: Define the Hermeneutic Position

- Clarify your interpretive stance (e.g., African-centred, Ubuntu-informed, critical).
- Acknowledge your positionality—your background, cultural context, and relationship to the subject matter.

Step 2: Select Documents for Interpretation

- Choose 5–10 policy documents, strategies, or white papers across African countries.
- Consider variety (e.g., national, continental, draft vs. finalised, state-led vs. public consultation-driven).

Step 3: Conduct Pre-understanding Review

- Read each document without coding, forming initial impressions of tone, language, emphasis, omissions, etc.
- Take note of what feels intuitive or culturally misaligned from an Ubuntu perspective.

Step 4: Identify Hermeneutic Anchors

- Use Ubuntu constructs as interpretive anchors:
- e.g., Ubuntu (I am because we are), restorative justice, relational autonomy, community stewardship.
- Compare how these values are explicitly stated, implied, or ignored.

Step 5: Layered Interpretation

- Engage in cyclical readings (the hermeneutic circle):
 - Move between individual sections (e.g., policy objectives) and the whole document.
 - Ask: How does the whole inform the parts? How do the parts reinforce or challenge the whole?
- Track silences, contradictions, and ethical tensions in the documents.

Step 6: Contextualise Findings

- Situate findings in the social, historical, and cultural contexts of the policies.
- Consider what influenced the framing, international donors, global AI norms, local activism?

Step 7: Synthesis and Theoretical Framing

- Develop a narrative synthesis of how indigenous values are positioned in AI governance.
- Link back to broader themes: decolonial ethics, policy justice, epistemic inclusion.

Final Thoughts:

- Both approaches require reflexivity, transparency, and documentation of your interpretive choices.
- CDA is more critical and analytical in tone; Documentary Hermeneutics is more philosophical and interpretive.
- You may combine both methods in a multi-layered design: use CDA to map dominant discourses, and hermeneutics to unpack deeper meanings.

My thoughts: I found the outputs from ChatGPT to be revealing. The next stage is to take this initial feedback, refine it using relevant existing literature, and situate a contextually appropriate methodology. In fact, this scaffolding exercise with ChatGPT has been incredibly useful, efficient, and productive. The entire interaction took place in about 10 minutes, a task that would likely have taken several hours if I were working alone or even collaboratively with colleagues. This experience highlights the time-saving and idea-generating potential of co-creating with GenAI, especially in the early stages of research design.

5.7 DIGITAL ADOPTION EXPERIENCES OF FEMALE MICRO-BUSINESS OWNERS IN LAGOS, NIGERIA

The second study explores how market women—micro-business owners in informal economic sector in Lagos adopt and adapt to digital payment technologies such as mobile money, QR codes, and point-of-sale systems. Grounded in an interpretivist paradigm, the research focuses on understanding their lived experiences, the socio-cultural meanings attached to technology use, and the challenges they encounter as they engage with digital transformation in everyday business practices. The goal is to: (1) Understand the barriers and enablers of digital adoption from the perspective of market women; (2) Examine how gender, class, and informality intersect in shaping digital inclusion; and contribute to inclusive digital policy by foregrounding grassroots voices often left out of digital innovation discourses.

My Prompt:

I would like to design a methodology for a study that explores how market women—micro business owners in informal economic sector in Lagos adopt and adapt to digital payment technologies such as mobile money, QR codes, and point-of-sale systems. Grounded in an interpretivist paradigm, the research focuses on understanding their lived experiences, the socio-cultural meanings attached to technology use, and the challenges they encounter as they engage with digital transformation in everyday business practices. The goal is to: 1) Understand the barriers and enablers of digital adoption from the perspective of market women; (2) Examine how gender, class, and informality intersect in shaping digital inclusion; and contribute to inclusive digital policy by foregrounding grassroots voices often left out of digital innovation discourses. suggest 3 methodological approaches

ChatGPT:

This is an important and timely study that requires a methodology sensitive to context, lived experience, and power relations—well aligned with an interpretivist paradigm. Below are three qualitative methodological approaches that would suit your research aims, along with brief justifications for each:

1. Ethnographic Fieldwork (Urban Market Ethnography)

Justification:

Ethnography allows for deep immersion in the daily lives and practices of market women, enabling the researcher to observe how digital tools are adopted or resisted in context. This method is particularly effective for capturing non-verbal cues, informal practices, and the social dynamics that shape technology use within informal economies.

- What you'd do: Spend extended time in selected markets in Lagos, engage in participant observation, informal conversations, and community participation.
- Value: Captures the complexity of lived realities, especially where digital adoption is embedded in social and cultural networks rather than isolated decisions.

2. Semi-Structured Interviews with Life History Elements

Justification:

Semi-structured interviews are flexible and allow participants to express themselves in their own terms. Including life history elements (e.g., asking about personal background, business journey, and evolving views on technology) provides rich insights into how past experiences, gender roles, and class dynamics influence adoption behaviours.

- What you'd do: Interview a diverse group of market women (e.g., across age, education, and type of goods sold), exploring their journeys with digital tools.
- Value: Supports your goal of understanding barriers, enablers, and the intersection of gender, class, and informality.

3. Participatory Action Research (PAR)

Justification:

PAR empowers participants to co-create knowledge and reflect on their experiences as part of the research process. This approach aligns with

your intent to foreground grassroots voices and influence inclusive digital policy. It also encourages solutions-oriented dialogue that can inform real change.

- What you'd do: Facilitate small workshops or group discussions where market women reflect on their digital experiences, identify challenges, and propose practical solutions.
- Value: Shifts the research dynamic from extractive to collaborative, enhancing both ethical engagement and policy relevance.

Bonus Thought:

You could combine elements of all three methods in a multi-method qualitative design:

- Use ethnography for observational depth,
- Interviews for individual voice and narrative,
- And PAR for collaborative reflection and policy input.

Let me know if you'd like help drafting a data collection plan or aligning these methods with specific research questions!

My Prompt:

I want it to be rigorous but not too complicated, so it ok to combine two approaches, could you give me a step-by-step activity in the methodology and the instruments that will be required for data collection?

ChatGPT:

Absolutely! Combining semi-structured interviews with ethnographic fieldwork is a rigorous yet manageable approach for your study, especially within an interpretivist framework. This design will allow you to balance depth of understanding with real-world observation, while keeping the process practical and ethically grounded.

Below is a step-by-step methodological plan with suggested activities and data collection instruments:

Methodological Design: Ethnography + Semi-Structured Interviews

Research Context

- Location: Select two to three busy urban markets in Lagos (e.g., Balogun Market, Mile 12, Oshodi).
- Participants: 15–20 market women (micro-entrepreneurs), sampled across age groups, business types, and levels of digital engagement.

Step-by-Step Activities

Step 1: Field Access and Ethical Preparation

- Activities:
 - Obtain necessary permissions from market associations or local authorities.
 - Introduce yourself and your project to participants through informal conversations.
- Secure ethical approval from your institution (if applicable).
- Prepare informed consent forms in both English and Yoruba (or other relevant local language).
- Instruments:
 - Information sheet and consent form
 - Translator/interpreter if needed
 - Field notebook or digital recorder for notes on access process

Step 2: Participant Observation (Ethnographic Phase)

- Duration: 2–3 weeks of regular visits
- Activities:
 - Observe daily routines and digital payment practices in real time.
 - Note how transactions are made, challenges faced, and interpersonal dynamics (e.g., customer relationships, peer influence).
 - Engage in informal conversations (note tone, trust, resistance, enthusiasm, etc.).
 - Take detailed fieldnotes on interactions, behaviours, artefacts (e.g., signage, mobile devices, POS terminals), and market settings.

- Instruments:
 - Observation guide/checklist
 - Field notebook or mobile note-taking app
 - Voice memo app (for personal reflections, not direct recording unless consented)

Step 3: Semi-Structured Interviews

- Duration: Conduct interviews after initial observation phase (1–2 weeks)
- Activities:
 - Select interviewees based on field observations (aim for diversity in digital usage).
 - Use interview guide with open-ended questions focused on:
 - Digital payment experiences (first use, motivations, fears)
 - Barriers and enablers
 - Role of trust, gender, education, peer influence
 - Suggestions for improvement or support
 - Allow for participant storytelling and adaptation of questions based on flow.
- Instruments:
 - Interview guide (translated as needed)
 - Audio recorder or phone (with consent)
 - Notebook for jotting follow-up questions or context

Step 4: Reflection and Memo Writing

- Activities:
 - After each observation or interview, write reflective memos capturing:
 - Your impressions
 - Emerging themes or contradictions
 - Cultural/contextual insights
 - Adjustments to instruments or approach
- Instruments:
 - Reflexive journal or digital memo log

Step 5: Data Management and Preparation for Analysis

- Activities:
 - Transcribe interviews (verbatim where possible)
 - Translate non-English responses carefully
 - Organise fieldnotes and memos
 - Code data using thematic coding approach (using NVivo, Atlas.ti, or manually)
- Instruments:
 - Transcription templates
 - Coding framework (based on themes like trust, access, learning, resistance, etc.)
 - Qualitative analysis software (optional but useful)

Additional Notes:

- Language and trust matter in this context—consider partnering with a local assistant or translator who understands the market culture.
- Flexibility is key—allow time to adapt your tools and strategies based on what you observe in the field.
- Positionality—keep notes on how your identity and presence might be influencing the data (this will enrich your reflexivity).

My Prompt:

How would you organise and analyse the field data in a way that produces reliable results, you may also suggest theories that may support this study.

ChatGPT:

Great question! Organising and analysing field data in an interpretivist, ethnographically informed study like yours involves a systematic, transparent, and reflexive approach to ensure depth, trustworthiness, and contextual sensitivity. Below is a guide to how you can organise, code, and interpret your field data, followed by relevant theoretical frameworks that can support your analysis.

Organising Your Field Data

1. Data Preparation

Transcribe all audio recordings from interviews verbatim.

Translate where necessary, retaining original expressions or idioms with cultural notes.

Organise your data into folders:

- Interviews (labelled by participant pseudonym and date)
- Fieldnotes (from observations)
- Reflective memos (your positional reflections after each encounter)
- Photographs or artefacts (if included and ethically cleared)
- Create a Master Data Log
- Use a spreadsheet to track:
- Participant codes (to ensure anonymity)
- Interview/observation date
- Location
- Type of data (interview, memo, fieldnote)
- Summary of content or emerging theme
- Key quotes or phrases

Analyzing Your Field Data: Thematic Analysis

Step-by-Step Thematic Analysis (Deductive and Inductive blend):

1. Familiarisation

- Re-read all fieldnotes and transcripts.
- Highlight striking quotes, emotional moments, contradictions, or key patterns.

2. Coding

- Begin with a deductive framework based on your research objectives and Ubuntu-informed values (e.g., trust, community support, gendered constraints, adaptation strategies).
- Then allow inductive themes to emerge from the data (e.g., “agent networks,” “device-sharing,” “fear of fraud”).
- You can use qualitative software like NVivo, Atlas.ti, or even Excel if you prefer a low-tech route.

3. Categorising Themes

- Group your codes into theme families such as:
- Barriers to adoption (e.g., digital literacy, fear of scams)
- Enablers (e.g., peer support, youth assistance)
- Socio-cultural meanings (e.g., mobile phone = independence or status)
- Power and gender dynamics (e.g., male partners' influence, control of money)
- Trust and adaptation (e.g., building relationships with POS agents)

4. Cross-Comparative Analysis

- Compare across participant types (e.g., early adopters vs. late adopters).
- Explore contradictions or divergent experiences within similar demographics.

5. Reflexivity

- Regularly revisit your reflexive memos. Ask:
- How might my presence have influenced this account?
- Am I imposing a theme or genuinely uncovering it?
- What assumptions am I carrying into this interpretation?

Theoretical Frameworks to Support the Study

1. Technology Appropriation Theory

- Focuses on how users make technology their own, beyond intended use.
- Useful to analyse how market women creatively adapt digital payment tools to their unique contexts.

2. Feminist Technology Studies

- Highlights the intersection of gender, power, and access in technology use.
- Helps you critically analyse how gendered roles, agency, and social norms shape women's digital experiences in informal economies.

3. Social Practice Theory

- Looks at practices as combinations of meanings, materials, and competences.
- Ideal for understanding how digital payment becomes embedded (or not) in daily routines.

4. Ubuntu Ethics / African Communitarian Philosophy

- Centres values such as relational identity, community, and mutual responsibility.
- Can inform your analytical lens and interpretation, ensuring the study is epistemologically grounded in local knowledge systems.

Ensuring Rigour (Trustworthiness Criteria)

<i>Trustworthiness</i>	<i>Strategies</i>
Credibility	Prolonged engagement, triangulation (interviews + observation + memos)
Transferability	Rich description of context (thick description)
Dependability	Audit trail (document all steps in your process)
Confirmability	Reflexive journaling, peer debriefing if possible

Would you like a sample coding table or template to get started? Or a visual representation of the analysis process (e.g., flowchart)?

The two case studies presented in this chapter, the policy analysis through the lens of Ubuntu, and the fieldwork with market women in Lagos, demonstrate in practical terms how GenAI can be meaningfully integrated into research design without displacing the researcher's intellectual and ethical authority. Both cases activate the conceptual framework of methodological scaffolding by showing how human researchers, through contextual interpretation, normative judgement, and theoretical alignment, remain at the centre of knowledge production.

In the first case, GenAI served as a conceptual partner in identifying relevant Ubuntu-informed constructs for deductive thematic analysis. While the system offered a breadth of analytical possibilities and comparative frameworks, it was the researcher's cultural and philosophical grounding that shaped the final approach. The outputs were filtered

through a decolonial lens, ensuring the methodology aligned with indigenous epistemologies and ethical commitments. This demonstrates the framework in action: GenAI extended the researcher's thinking, but it was human insight that scaffolded the design.

In the second case, GenAI supported the preparation of fieldwork instruments, such as interview questions and observation guides. The AI facilitated speed and expanded idea generation. However, again, it was the researcher's on-the-ground knowledge and relational sensitivity that adapted these outputs to reflect the linguistic, gendered, and socio-economic nuances of the market context. Without this interpretive work, the AI's contributions risked being generic, misaligned, or ethically inappropriate. Both examples illustrate that methodological innovation is not about handing over control to machines, but about co-creating with intention, reflexivity, and cultural awareness. GenAI becomes part of a dialogical process, not a replacement for human reasoning.

5.8 CONCLUSION

This chapter has explored how GenAI can be engaged not just as a tool, but as a co-creative partner in the design of research methodology. Drawing on a critical, interpretivist paradigm, it has been argued that the real value of GenAI lies not in automation or efficiency alone, but in its capacity to expand methodological imagination, provoke critical dialogue, and open up new possibilities for inquiry, especially when guided by culturally grounded epistemologies. Through both conceptual discussion and a reflective case study, the chapter has shown that working with GenAI demands more than technical proficiency. It calls for a scaffolded research practice in which the human researcher exercises contextual interpretation, normative judgement, and theoretical alignment. These elements are not optional; they are essential to ensure that AI-generated contributions are ethically sound, epistemologically coherent, and methodologically rigorous.

Importantly, this chapter has emphasised that researcher agency remains central. GenAI may generate ideas, but it is the human researcher who must decide what is valid, relevant, and meaningful. In this sense, GenAI becomes a prompt for deeper reflexivity, not a replacement for it. As AI tools continue to evolve and become embedded in research workflows, scholars must develop new literacies, ethical frameworks, and methodological strategies to use these systems responsibly. The future

Framework for methodological scaffolding and co

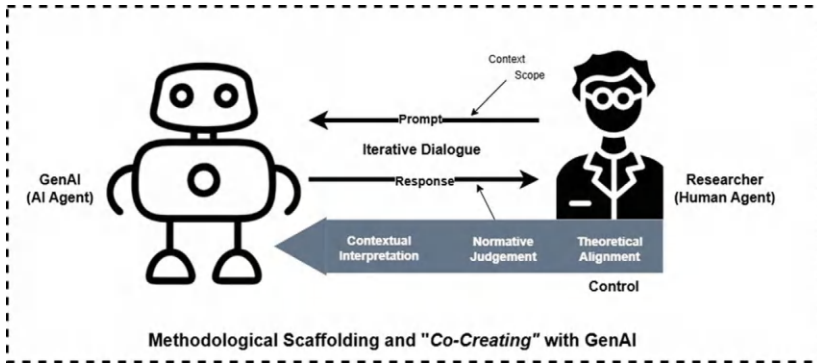


Fig. 5.1 Methodological scaffolding and “co-creating” with GenAI (*Source Authors*)

of research design, then, is not post-human; it is human-led, and AI-augmented. By embracing this hybrid future, we move closer to a more innovative research practice.

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Reviewing Manuscripts for Originality, Significance, and Rigour

6.1 INTRODUCTION

This chapter explores one of the most effective, and arguably non-controversial, ways researchers can co-opt generative AI tools in the research process. It is one word: feedback. Feedback is a cornerstone of the process of knowledge production. As a concept, it is at the heart of the peer review process—informally during the initial stage of manuscript preparation, and more formally after the manuscript has been submitted to a journal or relevant outlet. Multi-author manuscripts provide excellent opportunities for feedback from co-authors. It is even better if the team is interdisciplinary, because they can bring the richness of different disciplinary perspectives and expertise to bear in their feedback and inputs.

However, the most valuable feedback, prior to manuscript submission, is often the feedback researchers get from their peers prior to submission of the manuscript to a journal. Such peer review from critical friends gives the authors the opportunity to get fresh perspectives from researchers external to the project but with relevant expertise in the subject area. In other words, critical friends who are likely to look at the manuscript the way editors and peer reviewers will access it in the formal process down the line. This can be incredibly helpful, and often saves the authors the agony and disappointment of desk rejects, not to mention forestalling time lost through repeated cycles of rejection which, in the case of desk reject, are often without meaningful feedback.

The challenge is that detailed, helpful feedback is not easy to come by. There are many reasons for this, but probably the most significant one is lack of time. It is challenging enough to find colleagues who have direct expertise and experience in the particular topic of the draft manuscript, but finding colleagues with both the expertise and the time required to provide the most meaningful feedback is an even bigger ask—and it is not for lack of willingness. This is where generative AI can be especially effective, that is, if deployed correctly. Against this backdrop, this chapter discusses the example of ROSAR, a custom GPT designed for the purpose of providing feedback on draft manuscript.

6.2 WHAT IS ROSAR?

ROSAR¹—which stands for Review for Originality, Significance, and Rigour—is a structured manuscript evaluation custom GPT developed to help researchers critically assess and improve the quality of their scholarly work. ROSAR aligns with global best practices and metrics for assessing the quality of individual manuscripts. More specifically, it is directly with the *UK Research Excellence Framework (REF)* guidelines, which serve as the national benchmark for assessing the quality of research in UK higher education institutions. These internationally recognised standards are built on three core criteria: *Originality*, *Significance*, and *Rigour* (Johnston, 2014; Thelwall & Holyst, 2023). These criteria form the backbone of ROSAR’s evaluative model.

The three criteria at the heart of ROSAR

1. Originality: This assesses the extent to which a manuscript offers a novel and innovative contribution to knowledge. It encompasses new theoretical insights, original empirical findings, inventive methodologies, and engagement with complex problems. The originality score reflects whether the work has the potential to redefine thinking in a field or open new avenues of scholarly exploration.

¹ To freely download ROSAR, please visit: <https://chatgpt.com/g/g-5xSJGYoVs-rosar>. You will need a free account on ChatGPT.

2. **Significance:** This focuses on the influence or potential influence of the research on scholarly discourse, policy development, or professional practice. A significant manuscript is one that matters—not just in its intellectual construction but in its real-world impact and reach.
3. **Rigour:** This criterion evaluates the scholarly integrity and coherence of the work. It considers whether appropriate methods, sources, analytical approaches, and theories have been applied with precision and intellectual depth.

These three criteria are each scored out of 100 points, making a total of 300 points. The average percentage score is then calculated, which determines the manuscript's provisional Star Rating, following a set conversion system.

ROSAR and research quality metrics

The evaluation system of ROSAR operates in the context of widely recognised journal and research output metrics, but with a critical distinction. In line with the San Francisco Declaration on Research Assessment (DORA), ROSAR prioritises the evaluation of individual research outputs, rather than the prestige or ranking of the journal in which they are published. DORA emphasises that research quality should be assessed based on the content, contribution, and rigour of the work itself, not on publication-based proxies like impact factor or journal reputation.

By contrast, traditional metrics offer contextual-but not definitive—indicators of research quality. These include:

- UK Chartered Association of Business Schools (CABS/ABS) Journal Rankings, which rate academic journals from 1 to 4*
- Australian Business Deans Council (ABDC) Journal Rankings, which categorise journals into A*, A, B, and C
- Bibliometrics such as Journal Impact Factor, H-Index, and Citations per Publication

While these metrics provide useful background and help contextualise journal standards, ROSAR focuses on unpublished, draft manuscripts. Thus, ROSAR's final ratings are grounded firmly in the merit of the individual manuscript, assessed through the three REF-aligned criteria:

originality, significance, and rigour. This approach ensures that researchers receive specific, constructive, and equitable feedback—aligned with international standards of research excellence, but untethered from the constraints of journal prestige and metrics.

How ROSAR Works: Step-by-Step from the Researcher's Perspective

From the moment a researcher uploads their draft, ROSAR guides the evaluation journey in a clear, structured, and interactive manner:

Step 1: Uploading the manuscript: Upon clicking any evaluation prompt (e.g., “Please rate this manuscript on Originality”), the researcher is asked to upload their manuscript. Once uploaded, ROSAR acknowledges the title and provides a brief synopsis before initiating the full evaluation.

Step 2: Evaluation against REF criteria: ROSAR scores the manuscript out of 100 for each of the three REF criteria:

Originality: Does the manuscript show novel insights, creative methodologies, or imaginative interpretations?

Significance: How influential is the research in its field or potential to inform practice?

Rigour: Does the manuscript demonstrate coherence, appropriate use of theories, and robust analytical techniques?

ROSAR leverages a blend of in-system expertise and external benchmarks (such as comparisons to high-ranking journal outputs) to ensure accurate and reliable scoring.

Step 3: Percentage score and star rating allocation: The individual scores for Originality, Significance, and Rigour are summed and averaged to compute a percentage score. This determines the star ratings, as follows:

- 85–100% → ★★★★★ (Four Star)
- 70–84% → ★★★★ (Three Star)
- 55–69% → ★★ (Two Star)
- 40–54% → ★ (One Star)
- Below 40% → Unclassified

Step 4: Feedback on each criterion: For each scored criterion, ROSAR provides ****detailed, specific, and actionable feedback****. Rather than generic remarks, it identifies:

- Weak areas within the manuscript (e.g., undeveloped argument, limited engagement with recent literature).
- Sections needing improvement (e.g., methodology, theoretical grounding).
- Suggestions on what would elevate the work to a higher star category (e.g., deeper contextual framing, more original empirical data, stronger conceptual framework).

Where applicable, ROSAR cross-references these recommendations with insights drawn from comparable outputs in top-tier journals and ranking lists.

Step 5: General Comments and Overall Guidance

Beyond the granular criterion-level comments, ROSAR offers a summary narrative. This includes:

- A general assessment of the manuscript's stage of development.
- A developmental roadmap (e.g., "To reach 3 Star, consider revisiting X section and strengthening engagement with Y literature.")
- Recommendations on potential publication outlets or alignment with journal scopes.

Step 6: Interactive dialogue and ongoing support.

At the end of the evaluation, ROSAR prompts the user: "Would you like specific feedback on any of the three criteria?".

This initiates an ongoing conversation, encouraging the researcher to seek deeper insights and iterate on improvements. ROSAR can also provide feedback on specific sections, and critique development of arguments.

For example:

"Can you help improve the theoretical framework?"

"What changes can I make to boost the Significance score?"

ROSAR is not just a ratings tool—it's a developmental companion. It helps researchers understand what excellence looks like in academic writing, how to move their work towards it, and how to succeed in

a landscape shaped by REF assessments, journal metrics, and institutional expectations. While grounded in evaluation, its ultimate purpose is improvement and empowerment.

At the end of every review, researchers are invited to explore:

- Specific feedback on Originality, Significance, or Rigour
- Practical support in refining sections

6.3 EXPLORING ROSAR IN CONTEXT

Review for Originality

We will now turn our attention to a practical example to illustrate the versatility of generative AI for manuscript evaluation, while also discussing its limitations. In this example, we have used one of ROSAR's conversation starters to evaluate the originality of a working paper being prepared for submission to a journal (Fig. 6.1). For context, this particular manuscript was presented at 2023 edition of the Institute for Small Business and Entrepreneurship. ROSAR's initial response, as trained, was to ask for the paper to be uploaded—just to make sure it does not go into a hallucination mode and start evaluating a bogus paper (Fig. 6.2)! Once uploaded, ROSAR proceeded to provide feedback on the manuscript, based on the criteria of originality (Fig. 6.3). ROSAR's full response to this prompt (indented) is reproduced as follows²:

Thank you for uploading the manuscript. Here's a structured evaluation of **Originality**, following the UK REF 2021 criteria.

■ **Manuscript Title:**

Re-skilling for Post Covid-19 Recovery: Evidence from Minority African and Caribbean Micro-Business Owners in the United Kingdom

🔍 **ORIGINALITY ASSESSMENT (Score: 62/100)**

★ **Strengths:**

² Subsequent full length responses can be accessed in the companion website for this book.

1. Under-Researched Focus Group:

- The study centres on African and Caribbean micro-business owners in the UK—an underserved demographic in both entrepreneurship and crisis management literature.
- This population’s lived experience during COVID-19 is under-explored, and the study does well to highlight specific barriers they face (e.g. lack of financial access, digital readiness).

2. Context-Specific Empirical Work:

- Drawing data from the Project REBOUND intervention adds empirical novelty and gives voice to participant experiences. The use of direct quotes from mentoring participants strengthens this.

3. Practice-Linked Intervention:

- The mentoring and workshop-based intervention, and subsequent analysis, ties research to practice—a novel approach that mixes community engagement with qualitative inquiry.

4. Use of Mixed Embeddedness Framework:

- Applying this framework offers a theoretically grounded way to discuss the intersection of structural barriers, cultural factors, and business opportunity.

△□Areas for Improvement:

1. Limited Theoretical Innovation:

- While the mixed embeddedness framework is appropriate, it is not new to the field. The manuscript could enhance its originality by adapting or extending the framework, or critiquing it in light of the findings.
- Opportunities exist to introduce more novel conceptual angles (e.g. intersectionality, critical race theory, or entrepreneurial resilience models).

2. Predictable Crisis Framing:

- The COVID-19 context is now well-explored in the literature. While the specific group focus helps, the general crisis-recovery framing lacks surprise or disruption to dominant narratives.

3. Case Study Replicability:

- Though rich in qualitative detail, the four case studies are not sufficiently analysed to generate new theory. More interpretative abstraction could make the insights more widely applicable.

4. Over-Reliance on Descriptive Findings:

- The findings often restate what was already known (e.g. minority SMEs are disadvantaged) rather than pushing the boundary of what we know or how we understand these dynamics.
-

Suggestions for Increasing Originality:

- **Extend or Challenge Existing Frameworks:** Introduce a critique or modification to the mixed embeddedness model in light of the COVID-19 context and Black/Caribbean identity.
 - **Develop Typologies or Models:** Use the case material to propose a new typology of recovery pathways or mentoring impact models in crisis contexts.
 - **Innovate Methodologically:** Consider integrating participatory action research or longitudinal elements to deepen the originality of the empirical design.
 - **Theoretical Cross-Pollination:** Engage with literature from sociology, race studies, or digital transformation to enrich the conceptual base.
-

☆ **Originality Score: 62/100**

(*Borderline Two Star, REF scale*)

Would you like feedback on **Significance**, **Rigour**, or overall score next? I can also suggest revisions to strengthen the originality further.

Let me know how you'd like to proceed:

☞ "Please rate this manuscript on Significance"

☞ "Give me feedback on Rigour"

☞ "How can I improve originality specifically in the theory section?"

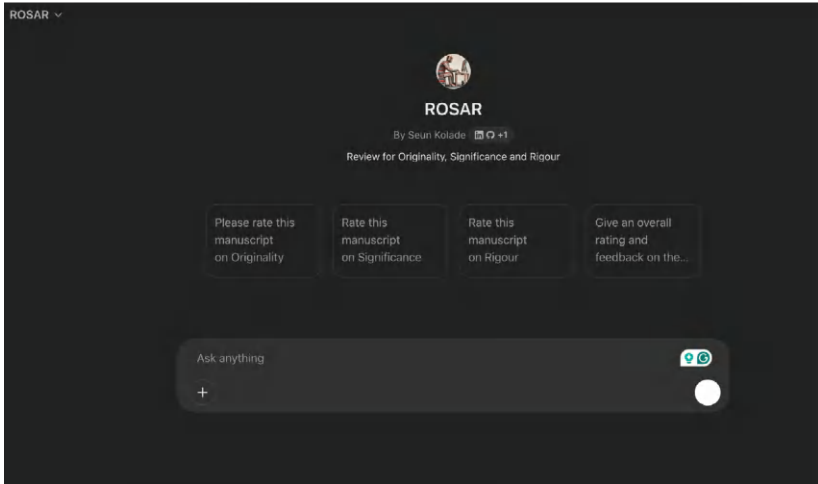


Fig. 6.1 ROSAR landing page

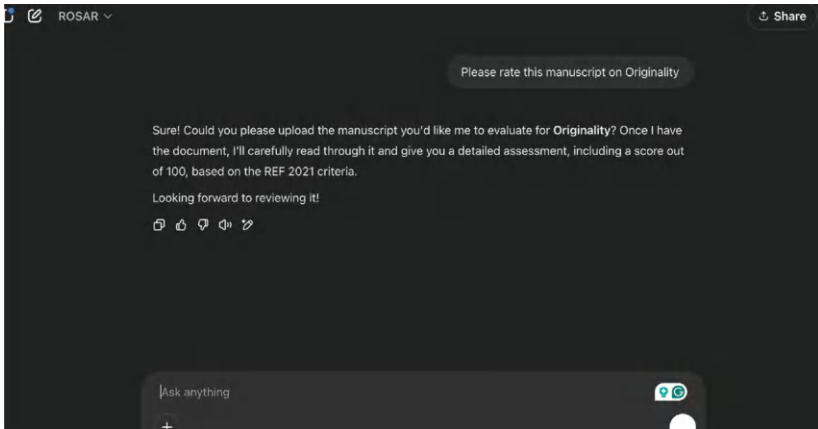


Fig. 6.2 ROSAR originality conversation starter

ROSAR's feedback began with the highlight of the strengths of the manuscript, in terms of its attention on under-researched and under-served demographics, the practice focus that underpinned the workshops

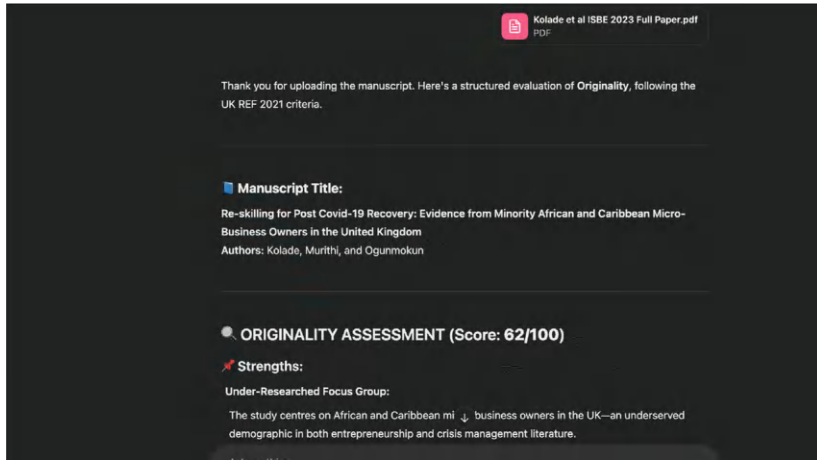


Fig. 6.3 ROSAR's originality feedback

and mentorship sessions, and the appropriate choice of mixed embeddedness framework as the theoretical hook for the paper. Then it went to flag areas of weaknesses for improvement, in which the highlight was the lack of theoretical contribution. This is at once very interesting and significant, because ROSAR had earlier highlighted the choice of mixed embeddedness as appropriate and a key strength of the paper. The key message, in effect, is that appropriateness of the chosen theory is not, in and of itself, equivalent to theoretical contribution. This is a familiar and highly important critique from editors and reviewers, and it is a good thing that ROSAR has flagged it. In addition, ROSAR highlighted other areas of weaknesses, including what it describes as the “predictable crisis framing” of Covid-19, which has now been extensively explored in the literature; the insufficient analysis of the four cases which are otherwise “rich in qualitative details”; and the lack of criticality in the findings and discussion, which ROSAR assesses to be overly “descriptive”.

Let us now turn to ROSAR's suggestions for improvement, particularly in relation to the lack of, or limited, theoretical contribution. ROSAR recommends that the authors should “introduce a critique or modification to the mixed embeddedness model in light of the COVID-19 context and Black/Caribbean identity”. In addition, it suggests that the authors

“engage with literature from sociology, race studies, or digital transformation to enrich the conceptual base”. On the face of it, these are interesting recommendations, but they are too broad to be particularly useful for the authors, beyond the obvious need it has rightly highlighted for the authors to engage more deeply with literature. This example underlines the need for the researcher to have a competent grasp of the relevant literature, and clarity about the direction they want to take the paper. These competence and clarity will enable the authors to probe further and engage more productively with Gen AI assistant.

To further illustrate it, we issued this follow-up prompt: “your feedback on the theoretical contribution is too broad. Can you provide a more specific critique in 150 words? Also (in the same response), and in the light of your assessment of the draft paper, what specific suggestions do you have for articulating the potential contributions to theory?”. ROSAR’s response is as follows:

Certainly—here’s a focused critique of the **theoretical contribution** of your manuscript, followed by specific suggestions for strengthening it:

🔗 **Specific Critique (150 words):**

While the paper rightly applies the **mixed embeddedness framework**, its theoretical contribution remains underdeveloped. The manuscript mostly uses the framework descriptively—to frame barriers and community-level support—without critically interrogating or extending it. It does not challenge assumptions about how structural disadvantage interacts with crises or how embeddedness may evolve in pandemic contexts. Furthermore, the paper does not generate **novel theoretical insights** from the empirical data. For example, while mentorship and re-skilling are shown to be useful, they are not theorised as mechanisms of embedded resilience or as transformative assets within minority entrepreneurship ecosystems. As such, the study risks reinforcing known narratives (e.g., ethnic-minority SMEs are vulnerable) rather than advancing how we conceptualise **resilience**, **adaptive capacity**, or **entrepreneurial agency** in minoritised groups.

💡 **Suggestions for Theoretical Contribution:**

1. **Conceptualise “Embedded Resilience”:** Use your findings to theorise how mentorship and community knowledge-sharing shape *dynamic embeddedness* during crises—beyond static barriers.

2. **Extend Mixed Embeddedness:** Propose a post-crisis adaptation of the framework that incorporates *temporal disruption*, *digital transition*, or *intergenerational differences*.
3. **Propose a Typology:** Develop a typology of business responses (e.g., bounce back, pivot, stagnate) linked to embeddedness dimensions—this offers conceptual clarity.
4. **Link to Crisis Entrepreneurship Literature:** Integrate theories from disaster resilience or crisis entrepreneurship to show cross-pollination and enrich the explanatory power.

Now, this is more useful than the previous feedback on theoretical contributions. At the very least, it provides helpful details on where it thinks the weakness of the theoretical contribution lies. For example, it highlights of clear linkages between the empirical findings on mentorship and re-skilling and the theoretical positioning of the paper on mixed embeddedness. In other words, the empirical findings appear to be disjointed from the theoretical premise of the paper. This is a correct assessment. However, in its “suggestions for theoretical contribution”, ROSAR once again falls short—albeit not for lack of effort. Among others, it suggested a conceptualisation of “embedded resilience” and proposed a “post-crisis’ adaptation and extension of mixed embeddedness. This is a bit confusing, partly because ROSAR appears to assume, wrongly, that mixed embeddedness is a theory that originated in crisis contexts. The rest of the suggestion remains unclear and lacking in detail of how, for example, the theory of mixed embeddedness can be extended to include ideas of “temporal disruption, digital transition, or intergenerational differences”. That is not to say they cannot work within that framework. Instead, it shows that, when it comes to the specific details of intellectual contributions that build creditably on existing ideas, the researcher cannot outsource to generative AI. The intellectual application, the immersion in the extant literature, the Socratic interrogation of ideas, are processes that are at the heart of knowledge production. Researchers must personally embrace the process.

Review for Significance and Rigour

The other conversation starters for significance and rigour would follow similar patterns—of feedback and subsequent opportunities for further probing. We will explore these in the next few paragraphs, but let us return briefly to a reflection on ROSAR’s scores. It awarded a Two Star

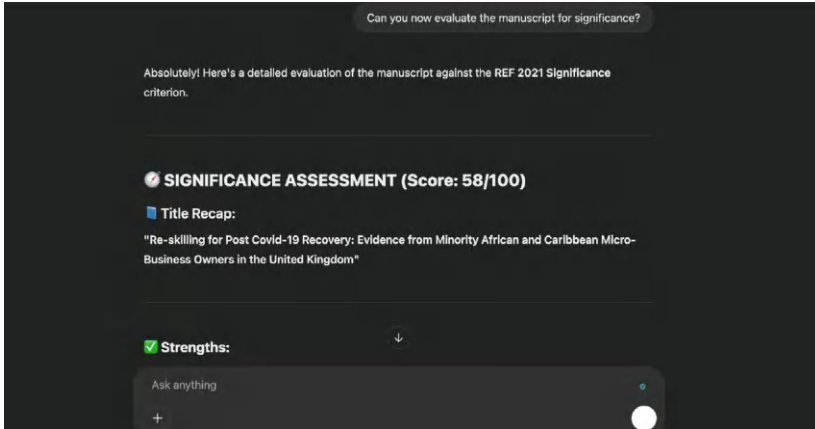


Fig. 6.4 ROSAR's feedback on significance

rating for the exemplar paper we have been looking at. This classification is too generous. If we strictly apply the criteria for the star ratings as outlined in the REF, this paper would very likely be “unclassified”. So it worth saying that, while ROSAR continues to evolve and efforts are made to improve it from users' feedback, it was always the case—and will be for the foreseeable future—that the feedback it provides are more useful than the ratings system. This is in addition to the quality of the researcher's prompts, as discussed in the foregoing. In other words, users should pay closer attention to ROSAR's feedback and what they can get from it—rather than the rating it awards their draft papers.

Coming now to the evaluation for significance. Since this is an ongoing conversation, and we have left ROSAR's landing page, the conversation starters are no longer showing. Instead, we can simply issue a direct prompt for ROSAR to evaluate the draft manuscript for significance (Fig. 6.4).

In response, ROSAR once again provides feedback (see below) on the strengths and weaknesses of the manuscript in relation to significance, followed by suggestions for improvement:

Absolutely! Here's a detailed evaluation of the manuscript against the **REF 2021 Significance** criterion.

☐ **SIGNIFICANCE ASSESSMENT (Score: 58/100)**

 Title Recap:

“Re-skilling for Post Covid-19 Recovery: Evidence from Minority African and Caribbean Micro-Business Owners in the United Kingdom”

☒ **Strengths:**

1. Timely Socio-Economic Relevance:

- The paper addresses the COVID-19 crisis and its aftermath—a topic of global policy and academic relevance.
- The focus on African and Caribbean micro-business owners in the UK aligns with broader inclusion and equity agendas.

2. Policy and Practice Relevance:

- It rightly draws attention to gaps in UK government support during COVID-19 and proposes more culturally informed policy interventions.
- Practical interventions (mentoring, workshops) offer lessons for community development programmes, potentially shaping local economic policy responses.

3. Community Impact Potential:

- The mentorship model embedded in the study demonstrates promising pathways for community-based support.
- The study may inspire replication by NGOs, ethnic business associations, or local authorities.

 ☐ **Limitations That Weaken Significance:**

1. Limited Uptake by Scholarly or Policy Communities (so far):

- The manuscript does not indicate any policy engagement, citations in grey literature, or alignment with government or regional enterprise strategies.

- No evidence is offered of external interest in the project outcomes (e.g., invitations to share insights, adoption by stakeholders).

2. Insufficient Broader Conceptual Framing:

- The findings are framed in localised, context-specific terms, which limits their transferability to other ethnic minority or global south contexts.
- There is little attempt to generalise or abstract implications for broader scholarly debates (e.g. on crisis innovation, minoritised entrepreneurship, or community resilience systems).

3. Lack of Concrete Influence Pathways:

- The paper makes strong claims about its practical value, but lacks mechanisms (e.g., toolkits, partnerships, outreach) for how these insights are or could be translated into action or policy uptake.
-

Suggestions to Strengthen Significance:

1. Strengthen Claims of Societal Impact:

- Include any follow-up engagements, stakeholder dialogues, or workshops with policymakers, local councils, or community groups.
- Add narrative about how the research has shaped or intends to shape real-world interventions.

2. Develop Transferability:

- Identify parallel contexts (e.g. immigrant entrepreneurship in other Western nations) and articulate how findings might generalise or offer comparative insight.

3. Clarify Stakeholder Implications:

- Clearly segment recommendations for *different audiences*—e.g., policymakers, training providers, business mentors, community leaders—showing how each can apply the findings.

4. Publish Supporting Outputs:

- Consider publishing spin-off policy briefs, practitioner-oriented articles, or blog posts that target user communities and improve visibility.

Significance Score: 58/100

(Solid Two Star: Recognised internationally, but with limited reach or transferability in current form)

Would you like to explore how to reframe the **implications section** to appeal more directly to policymakers or practitioners? Or develop a **policy engagement strategy** to increase real-world influence?

You can follow up with:

☞ “Help me make the implications more compelling to policymakers”

☞ “Can you help me translate these findings into a public-facing impact case?”

☞ “Let’s now assess the paper for rigour”

As before, ROSAR provides a numbered system to highlight the areas of strengths and weaknesses, as well as suggestions for improvement. It awards a score of 58%, which is borderline for a Two Star rating (55–69%), but ROSAR incorrectly says it is “solid”—another minor but relevant point about the limitations and value of the rating system. With regard to weaknesses, ROSAR highlights, among others, the lack of alignment between the claims of practical relevance and the evidence to support—what it calls influence pathways. Compared with the section on originality, ROSAR’s suggestions for improvement on significance are more useful and more actionable. This contrast is instructive, as originality is the one aspect of a manuscript evaluation that requires more direct oversight and control from the competent researcher. For significance, ROSAR has more resources in its training data to provide more useful recommendations in the first go.

For rigour, the last of the tripod criteria, we again issue a simple, direct prompt (Fig. 6.5). The following is ROSAR’s response:

Great—here’s a comprehensive evaluation of the manuscript against the **REF 2021 Rigour** criterion.

☐ **RIGOUR ASSESSMENT (Score: 52/100)**

 **Title Recap:**

“Re-skilling for Post Covid-19 Recovery: Evidence from Minority African and Caribbean Micro-Business Owners in the United Kingdom”

☒ **Strengths:**

1. Appropriate Methodological Framework:

- The use of a **qualitative multiple case study** approach is suitable for exploring deeply contextualised, experiential issues in under-researched populations.
- The **Braun and Clarke (2006)** six-step thematic analysis method is explicitly stated and methodologically credible for the dataset.

2. Use of Primary Data:

- Data were drawn from virtual interviews with participants in mentoring/workshop sessions, lending authenticity and insider perspectives.
- Inclusion of verbatim quotes adds to transparency and credibility of interpretations.

3. Participant Selection Criteria:

- Clear rationale provided for selecting four participants based on workshop and mentorship engagement enhances the internal logic of the study design.
-

△□ Limitations That Weaken Rigour:

1. Thin Analytical Depth:

- While thematic coding is described, **analytical abstraction is minimal**. The themes remain largely descriptive and closely tied to participants' surface reflections.
- There is limited cross-case comparison or synthesis—each narrative stands alone, missing opportunities for pattern identification or theoretical deepening.

2. Insufficient Reflexivity:

- The authors do not reflect on their positionality, potential bias, or the dynamics of researcher-participant relationships—critical in qualitative work involving marginalised populations.
- There is no discussion of how themes were validated or challenged across the team—raising concerns about **inter-coder reliability** or analytical triangulation.

3. No Engagement with Negative or Deviant Cases:

- The study does not address contradictions, silences, or minority voices that may have resisted or struggled with the intervention. This **omits nuance** and limits credibility.

4. Unclear Data Saturation & Generalisability:

- With only four cases from 90+ participants, the paper does not discuss whether **data saturation** was reached or what logic governed the number of cases chosen.
- There is no analytical comment on limitations in **external validity** or how the sample reflects wider trends among African and Caribbean SMEs in the UK.

5. Lack of Rigorously Defined Constructs:

- Key concepts such as “resilience,” “recovery,” or even “reskilling” are treated fluidly rather than operationalised or critically examined in the analysis.
-

Suggestions to Improve Rigour:

1. Deepen Cross-Case Thematic Integration:

- Move beyond narrative summaries to generate integrative insights (e.g. similarities and differences in mentorship outcomes or reskilling strategies).

2. Add Reflexivity Statement:

- Include a paragraph reflecting on researcher positionality, biases, and how these may have shaped data collection and interpretation.

3. Clarify Analytic Procedures:

- Specify how codes were developed (inductively or deductively), whether coding was checked by multiple researchers, and how theme validity was ensured.

4. Engage with Counter-Examples:

- Include at least one case where the intervention did not work as intended, or where participant responses diverged from expectations.

5. Define Core Concepts with Precision:

- Anchor key constructs in the literature and state how you interpreted them in your analysis, to avoid analytic drift.

Rigour Score: 52/100

(Mid One Star: Some solid foundations, but lacking in methodological tightness and critical reflexivity)

Would you like help rewriting the **methodology section** to better highlight analytic depth and justify case selection? Or would you like help drafting a **reflexivity paragraph**?

Next steps you could take:

 “Can you help me improve the cross-case analysis?”

 “Draft a reflexivity paragraph for this paper”

 “Give me the overall rating and summary for the paper”

Here, the feedback on weaknesses focuses on the lack of analytical depth, insufficient reflexivity, the omission of nuances, and lack of engagement with negative or deviant cases. There were also comments about data saturation, an important point for a qualitative study; and a feedback on inadequate operationalisation of the constructs. The suggestions for improvement are tailored towards the highlighted weaknesses. Once again, the feedback on rigour is more specific, and more helpful—although the researcher has to prioritise, while drawing on their expertise and competent grasp of key ideas to implement the most relevant recommendations. They can also probe further, including focusing attention on specific sections of the manuscript.

6.4 SUMMARY AND OVERALL FEEDBACK

Like the previous prompts, the overall feedback for the exemplar manuscript is elicited with a simple, direct prompt (Fig. 6.4). In this instance we have simply adopted the prompt recommended by ROSAR at the end of the previous exercise, but you can also issue a similar simple prompt of your own.

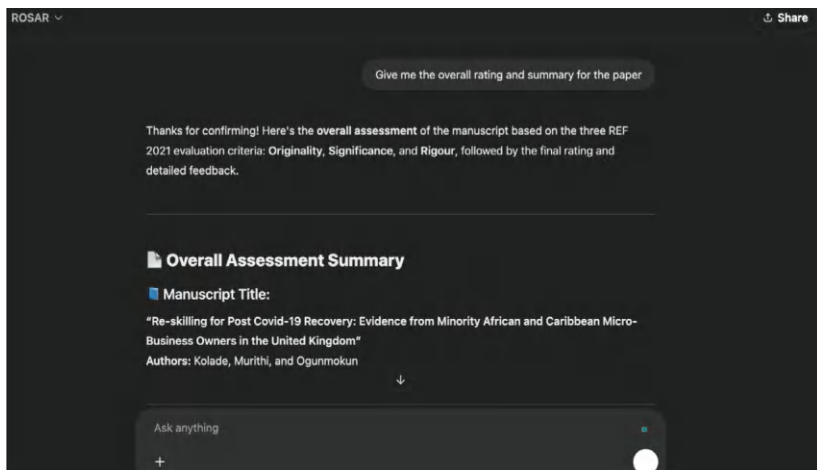


Fig. 6.5 ROSAR's feedback summary

Here, the output (see below) includes a grid summary of the previously listed ratings for originality, significance, and rigour, as well as the average score and average rating—a borderline Two Star (which, as we noted before, is too generous in this instance). More helpfully, it provides an interpretive summary note, and it highlights four key areas to strengthen: development of theoretical contribution; enhancement of significance through engagement; strengthening rigour and reflexivity; and expanding conceptual transferability.

Thanks for confirming! Here's the **overall assessment** of the manuscript based on the three REF 2021 evaluation criteria: **Originality**, **Significance**, and **Rigour**, followed by the final rating and detailed feedback.

■ Overall Assessment Summary.

▣ Manuscript Title:

“Re-skilling for Post Covid-19 Recovery: Evidence from Minority African and Caribbean Micro-Business Owners in the United Kingdom”

Authors: Kolade, Murithi, and Ogunmokun.

🔍 Individual Criteria Scores (Out of 100):

<i>Criterion</i>	<i>Score</i>	<i>Summary</i>
Originality	62	Strong contextual focus and use of under-researched population, but lacks deeper theoretical innovation or challenge to existing frameworks
Significance	58	Relevant topic and meaningful for policy and practice, but lacks evidence of broader academic or societal uptake and generalisability
Rigour	52	Appropriate methodology but limited analytical depth, reflexivity, and methodological justification

▣ Average Percentage Score:

$(62 + 58 + 52) / 3 = 57.3\%$

☆ **Final REF 2021 Rating: TWO STAR (55–69%)**

☒ Interpretation:

This is a **solid Two Star** output—internationally recognised in quality, especially for its contribution to practice and policy in a defined UK context. It offers **useful insights into a marginalised community and meaningful empirical data**, but falls short of REF Three or Four Star standards due to limited conceptual generalisation, underdeveloped theory, and methodological thinness.

✂ ☐ Key Areas to Strengthen:

1. **Develop Theoretical Contribution:**

- Go beyond applying the mixed embeddedness model. Use your data to propose new insights into **resilience, crisis adaptation, or social capital dynamics**.

2. **Enhance Significance Through Engagement:**

- Provide evidence of **impact pathways**—e.g., follow-on activities with community or policy partners, practitioner toolkits, or presentations to stakeholders.

3. **Tighten Rigour and Reflexivity:**

- Improve analytic depth across cases.
- Include a **reflexivity statement**.
- Justify your sampling and coding approach in more detail.

4. **Expand Conceptual Transferability:**

- Position your findings in broader debates about **minority entrepreneurship, informality, or post-pandemic recovery**, especially across different countries or contexts.

☐ Next Steps?

Would you like to:

-  Get help rewriting a section (e.g., theory, methodology, implications)?
-  Develop a stronger theoretical model or framework based on your findings?

- ☞ Create a short **policy brief or impact case** based on this paper?
- ☞ Explore how to improve this to a **Three Star** output in your next revision?

Let me know where you'd like to focus next—I'm here to help sharpen and elevate your work.

The structured assessment provided by ROSAR in Sect. 6.3 demonstrates the value of clear, criteria-driven feedback in strengthening academic manuscripts. By focusing on individual outputs rather than journal metrics, ROSAR supports researchers in improving their work based on content, originality, significance, and rigour. However, as valuable as structured evaluations are, they represent just one dimension of the knowledge production process. In practice, much intellectual development occurs through informal, spontaneous, and collaborative conversations. In the next section, we explore how generative AI can play a creative and supportive role in these interactions, emulating the dynamic exchange of scholarly dialogue

6.5 GENERATIVE AI AS A CREATIVE ASSISTANT IN THE KNOWLEDGE PRODUCTION PROCESS

One of the most exciting aspects of the knowledge production process is the opportunity to engage peers in often informal dialogues and debates about the frontiers of knowledge in a particular discipline. These productive dialogues happen in seminars and fireside chats, and sometimes spontaneously on faculty corridors. Scholars harness these auspicious opportunities to give voice to ideas running in their heads, and have those ideas scrutinised, and sometimes challenges, by critical friends. Sometimes these dialogues involve researchers from other disciplines, or even non-expert members of the public. This meeting point of people is an incredibly fertile melting point of ideas where researchers can gain better clarity about loose ideas they have incubated for a while, but also open their minds to new streams of ideas they have not considered before but has come to view in the light of interdisciplinary interventions of peers. The value cannot be overstated.

Generative AI cannot replace these opportunities for lively and productive human interactions, but it can provide new complementary opportunities with unique flavours of its own. For good measure, while these

human dialogues often come as a result of planned gatherings or spontaneous serendipity, generative AI offers unlimited opportunities for the researcher to engage in creative dialogues that can be enacted and accessed at any time, and for as long as the researcher wants. The colleague on the corridor may have ten minutes to spare, and fireside dialogues can last for an hour. On the other hand, generative AI can be the researcher's creative buddy—silly and limited at times, but always there, always attentive, and in no need of pint of beer or a pot of coffee—as long as the server and the internet connection hold up! Let us explore this further with some illustrative cases.

AI-Enabled Probe of Ideas: The Case of Bricolage and Effectuation

Let us explore two distinct but related theories in entrepreneurship research: bricolage and effectuation. I issued a short prompt, reminding ChatGPT to keep the response short (not custom ROSAR, by the way). Below is the prompt and the output:

Prompt: What, in your view, are the similarities and differences between the theories of bricolage and effectuation in entrepreneurship research? Keep it concise, within 200 words.

Bricolage and **effectuation** are both entrepreneurial theories that focus on resource-constrained environments and adaptive decision-making, but they differ in focus and underlying logic.

Similarities:

Both concepts emphasise **creativity, improvisation, and resourcefulness** in uncertain environments. Entrepreneurs using bricolage or effectuation do not rely on pre-existing plans or optimal resources; instead, they **leverage what is available** and **adapt as they go**. Each theory sees uncertainty not as a barrier, but as a space for innovation and action.

Differences:

Bricolage, rooted in anthropology and adapted for entrepreneurship, focuses on “**making do with what is at hand**.” Entrepreneurs combine existing, often undervalued resources in novel ways to create value. It is fundamentally **resource-centric** and reactive.

Effectuation, developed by Saras Sarasvathy, is **goal-flexible but means-driven**. It highlights how entrepreneurs start with who they are, what they know, and whom they know, and **co-create opportunities** with stakeholders. It includes principles like the **affordable loss** concept and **leveraging contingencies**.

In essence, **bricolage** is about creatively assembling resources in the moment, while **effectuation** is about navigating uncertainty by shaping the future with current means and evolving goals.

For researchers familiar with these theories, ChatGPT has produced a good summary, from where the user can proceed with a dialogic exploration. In the next prompt, I provided the Gen AI tool with the context of a research focusing on entrepreneurial action among displaced populations in Northeast Nigeria, where internally displaced peoples are forging new relationships and mobilising limited resources for entrepreneurial outcome. The prompt, followed by the output below exemplifies the progression of the dialogue from the first prompt.

Prompt: I am undertaking a research about entrepreneurial action in situations of forced displacement in Northeast Nigeria, an area ravaged by terrorist insurgency. These displaced peoples have developed new relationships with previous strangers with whom they now share the same fate in internally displaced peoples' camps. With these new relationships, in form of bridging social capital, they are mobilising limited tangible and intangible resources to achieve entrepreneurial outcomes towards livelihood recovery, which of bricolage or effectuation would you recommend as best suited for this research? Again, keep your response within 200 words.

Response: For your research on entrepreneurial action among forcibly displaced persons in Northeast Nigeria, **bricolage** appears to be the most suitable theoretical lens. This is because bricolage focuses on how individuals in **resource-constrained and uncertain environments** creatively “make do” with whatever is at hand to generate value. Displaced individuals often lack access to formal markets, capital, and infrastructure—conditions under which bricolage theory is particularly powerful in explaining **improvised, necessity-driven entrepreneurship**.

Your context also highlights the development of **bridging social capital**—new relationships formed in adversity—which aligns with bricolage's emphasis on mobilising diverse and non-traditional resources, including social ties, in innovative ways. These actors are not necessarily co-creating ventures with known partners (as in effectuation), but rather responding to immediate survival and livelihood needs through **adaptive and resourceful combinations** of available tangible and intangible assets.

While effectuation offers insights into entrepreneurial logic under uncertainty, its assumption of **stakeholder involvement and co-creation**

may not fully reflect the ad hoc, survivalist nature of entrepreneurship in displacement camps. Thus, bricolage more directly captures the **emergent, improvised, and context-specific** strategies displaced individuals use to rebuild livelihoods.

ChatGPT used the information in the prompt well to provide a concise “analysis” before it recommended bricolage as the preferred theoretical hook. Note, however, that ChatGPT is working with the information it was provided with, and that information is but a snapshot of a wider pool of information in my head as the researcher. We have seen this before in the example in Chapter 1, when ChatGPT “declared” that the idea of Kukulajatism did not exist, but, given more specific information, proceeded to explain a theory of Kukulaja. Thus, in this specific example—given the information I have about the project and its context, and partly for illustrative purposes—I am rejecting ChatGPT’s recommendation of bricolage, choosing instead to go with effectuation. Let us now see what ChatGPT says:

Prompt: Thanks for the recommendation. However, I will go with effectuation as the theoretical hook for this research paper. Among other things, I want to (1)integrate the concept of social capital- especially in its bridging and linking forms- with the effectuation notion of "whom they know" (horizontal and vertical relationships) for entrepreneurial outcome; (2) explore how stakeholder co-creation interfaces with creation of new, and access to existing, markets;(3)explore the role of "what they know"- both in terms of information and skills; (4)examine the impact of "who they are" (aspects of identities- notably ethnicity and religion - given the empirical context of sectarian violence. What are your thoughts on how to make this work?

Response:

Your approach is conceptually rich and has strong potential to contribute meaningfully to both effectuation theory and research on entrepreneurship in extreme contexts. Here are some targeted suggestions on how to make this work effectively:

1. Integrating Social Capital with Effectuation:

Position *bridging* and *linking* social capital as mechanisms that expand the “**whom they know**” dimension. Bridging ties (across displaced groups) and linking ties (to NGOs, government actors, and external markets) can show how new and asymmetric relationships become central to entrepreneurial co-creation in displacement.

This allows for a meaningful extension of effectuation into more communal or necessity-driven contexts.

2. **Stakeholder Co-Creation and Market Access:**

Highlight how displaced entrepreneurs **co-create value** not only with peers but with *newly formed relationships*, including aid workers, market intermediaries, or even informal gatekeepers. Explore how these collaborations facilitate **market formation or re-entry**, especially in informal or disrupted economies.

3. **“What They Know” (Knowledge and Skills):**

Treat skills as both **pre-existing capabilities** (e.g., from their place of origin) and **newly acquired or adapted knowledge** (e.g., survival skills, market navigation within camps). Show how knowledge becomes recontextualised in response to displacement.

4. **“Who They Are” (Identity and Sectarian Dynamics):**

Deep-dive into **ethnicity and religion** as identity factors shaping access to networks, legitimacy, and trust. Examine how these identities affect **co-creation pathways**, inclusion/exclusion in opportunity spaces, and the development of social capital in volatile, sectarian settings.

5. **Empirical Framing:**

Use rich narratives or case studies to illustrate the interaction of these effectual elements. It will allow you to **show rather than tell** how displaced individuals navigate uncertainty through a logic of means-driven, identity-anchored, and socially embedded entrepreneurship.

6. **Theoretical Contribution:**

Consider framing your work as an **extension of effectuation** into “extreme and marginalised settings,” where co-creation, identity, and social capital are reconfigured. You could even argue for a **context-sensitive variant of effectuation** under displacement and crisis.

Let me know if you’d like help building the framework visually or drafting a structure for the paper. This is a powerful angle.

It is quite a useful response, but also interesting on several counts. First, you will recall that, in the previous output, ChatGPT has in fact recommended bricolage as the theoretical hook, arguing against a possible choice of effectuation. It was limited in its understanding of the research context that the study is situated. More importantly, it does not have the depth of specific subject expertise—and the immersion in the theory—required to make the final call on the suitable intellectual direction of travel with the project. This point cannot be overstated, that, in the

final analysis, it is the researcher who has, and must exercise, intellectual control of the knowledge production process. The turnaround is then fascinating with the more recent output, not least in terms of tone, as ChatGPT ended with the affirmation that effectuation as a theoretical hook, the idea it previously argued against, is, in fact, a “powerful angle”.

What this example equally demonstrates is the versatility and effectiveness of generative AI in the hands of a competent, confident, and engaged scholar. Such a user has the depth of knowledge to spot instances of hallucination and high-sounding, but ultimately misleading or inadequate recommendations. They are also able to provide the kind of concise, yet detailed prompts, that sets generative AI in its “best form” in the dialogic exchange.

6.6 SUMMARY AND CRITICAL REFLECTIONS

This chapter has explored how generative AI, through a custom-built tool named ROSAR (Review for Originality, Significance, and Rigour), can be effectively integrated into the research process as a developmental partner. ROSAR was introduced as a structured, criteria-based evaluation system aligned with the UK Research Excellence Framework (REF 2021) and supported by journal quality metrics. However, unlike traditional evaluations that often centre on journal prestige, ROSAR foregrounds the assessment of individual manuscripts, aligning with the San Francisco Declaration on Research Assessment (DORA) and its advocacy for content-focused research evaluation.

One of ROSAR’s major strengths lies in its ability to deliver granular, actionable feedback across the REF’s three core dimensions—originality, significance, and rigour. Through a step-by-step engagement with the user, ROSAR not only assigns scores and provisional ratings but also facilitates an interactive dialogue to help researchers strengthen specific sections of their manuscript. This makes it especially valuable for early-stage drafts, where structured feedback can make a significant difference in developmental trajectory.

Yet, the chapter also critically highlights ROSAR’s limitations. It cautions against over-reliance on its automated ratings, noting that in several instances, ROSAR’s star classifications were overly generous. The more useful aspect remains the tailored feedback, which, while helpful, sometimes lacks the depth required for theoretical innovation or disciplinary nuance. In such cases, the tool is most effective when guided

by researchers with clarity of purpose and a strong grasp of the relevant literature.

The chapter then shifted focus in Sect. 6.4 to explore how general-purpose generative AI, such as ChatGPT, can be used as a “creative assistant” in the broader knowledge production process. Unlike ROSAR, this use is not limited to structured evaluation but includes support for idea generation, concept clarification, and theoretical exploration. Through illustrative prompts, the section demonstrated how ChatGPT can engage in dynamic, dialogic exchanges that resemble informal scholarly conversations. While such tools cannot replace peer dialogue or disciplinary depth, they can enhance intellectual creativity, especially when researchers remain in charge of interpreting and refining the outputs.

In summary, this chapter has shown that generative AI—whether tailored like ROSAR or general-purpose like ChatGPT—offers complementary support to researchers navigating the complexities of academic writing and idea development. Used critically and thoughtfully, these tools can democratise access to feedback, enrich the creative process, and promote continuous scholarly improvement.

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Gen AI for Public Engagement and Knowledge Exchange

7.1 INTRODUCTION

Academic research has never existed in a vacuum. Yet, for much of its modern history, the formal outputs of scholarship—peer-reviewed journal articles, technical reports, monographs—have been written primarily for academic peers. As a result, valuable knowledge often circulates within narrow disciplinary silos, rendered inaccessible not only by paywalls but also by the specialised language and structure that define academic communication. In recent years, however, there has been a growing recognition that researchers must actively engage broader publics, translating insights into formats that resonate beyond academia (Dudo, 2015). This shift is not merely strategic; it is philosophical and ethical. It signals an evolving understanding of knowledge as a shared resource, one that must be mobilised across diverse sectors to address complex societal challenges.

Non-academic dissemination is now emerging as a critical part of the research lifecycle. The imperative to engage policy makers, practitioners, third sector organisations, industry actors, and the wider public is increasingly embedded within research agendas, funding requirements, and institutional strategies. Concepts such as open science, knowledge mobilisation, and the “Third Mission” of universities speak to this changing landscape—one in which the societal value of research is measured not

only by citations and scholarly recognition, but also by its accessibility, usability, and reach.

Yet, while the call for engagement is clear, the means of achieving it remain challenging. Most researchers are not trained in public communication or media production. Many lack the time or resources to repurpose their work for multiple audiences. There is often uncertainty about how much simplification is too much, or how to maintain fidelity to complex findings in formats that favour brevity and clarity. The demand for translation—of both content and tone—is real, but the tools to meet it at scale have not always been within reach.

In this context, the rise of generative artificial intelligence (Gen AI) presents a transformative opportunity. Gen AI tools—capable of producing high-quality text, images, audio, and even code—offer researchers new avenues to extend the impact of their work. By drawing on already published outputs, such as journal articles, book chapters, and technical reports, Gen AI can assist in crafting tailored materials for a wide range of dissemination formats. These include blog posts, policy briefs, infographics, LinkedIn posts, Instagram carousels, podcast scripts, video storyboards, and more (Luzón, 2013).

What makes this particularly promising is the capacity of Gen AI to automate some of the most laborious aspects of reformatting and reframing academic content. A researcher who once faced the daunting task of translating a dense 10,000-word paper into multiple public-facing outputs can now enlist AI tools to generate first drafts in various registers—each tailored for different platforms and audiences. This does not eliminate the role of human judgement, interpretation, or oversight; rather, it amplifies researchers' capacity to engage more often, and more effectively.

At the heart of this development is a deeper philosophical shift: one that positions researchers not only as generators of knowledge but also as communicators and collaborators across domains. The production of a policy-relevant summary, a podcast script, or a LinkedIn thread is not simply a dissemination activity. It is also a creative act of recontextualisation. It involves thinking carefully about audience, purpose, voice, and accessibility. Gen AI can support this process, offering scaffolds and suggestions, but it is the researcher who must still make the critical decisions about what matters, what can be translated, and how.

There are, of course, challenges and concerns. Gen AI is not infallible. Its outputs can be generic, inaccurate, or contextually inappropriate.

Ethical questions abound: Who owns the generated content? How do we ensure that AI-generated summaries or scripts do not misrepresent the nuance of the original research? What are the implications of automating engagement in fields where trust, credibility, and human connection are essential? These questions must be considered seriously, and they will be returned to in later sections of this chapter.

Equally, there are frontiers of opportunity. The same tools that generate social media posts can be used to create interactive research briefs tailored to specific industries. Complex datasets can be transformed into engaging visuals with narrative overlays. Long technical reports can be embedded into custom chat interfaces that allow stakeholders to explore their content conversationally. With proper oversight and creativity, Gen AI enables a reimagining of the ways in which research lives and circulates in the world.

This chapter explores these applications in detail. It considers how generative AI can assist in transforming traditional academic outputs into platform-specific, audience-sensitive, and purpose-driven formats. Examples include social media content across various platforms (LinkedIn, X, Instagram); infographics and visual storytelling; podcast and video scripts derived from journal articles; research briefs that frame academic findings in terms of industry relevance; and even patent analysis and drafting linked to innovation-based research. Through these use cases, the chapter illustrates not only what is possible, but also what is increasingly necessary.

Ultimately, this chapter argues that non-academic dissemination is not a soft add-on to research. It is a vital expression of scholarly responsibility. In a world of saturated information and growing mistrust, the role of researchers is not just to discover, but to connect. Gen AI, used critically and creatively, offers a powerful toolkit to support that connection.

7.2 SOCIAL MEDIA DISSEMINATION

Since the turn of the millennium, social media has emerged as an important tool for public engagement and communication. The influence of these platforms has grown even bigger within the past decade, as new products and new products are introduced, often gaining rapid traction in a market that already appear saturated. For academic researchers, the imperative of public engagement has taken on a new meaning and

urgency in the age of social media. In a contested space where public consumers of information are bombarded with increasingly sophisticated fake news and harmful content, academic researchers offer a salutary alternative of evidence-based, ethically sound content that addresses society's key priorities. This is the ideal vision of public communication of science.

Standing in the way of this idea is that the prevailing culture in the academy prioritises communication of research with, and validation by, peers. This communication is typically undertaken via scholarly manuscripts published in specialist journals—often behind paywalls. In effect, the target audience for these academic outputs is the expert community with shared understanding of the technical jargons and registers that are used to disseminate research in journals. The vast majority of the public—including end users and sometimes practitioners—are shut out, or left to peep through the window for a glimpse. On the other hand, do not typically have the training to engage with these publics through other channels, including social media. As we shall now demonstrate, AI tools can help accelerate this transition for researchers—from academic dissemination to public communication of evidence-based research. Let's take the examples of leading social media platforms: LinkedIn, Facebook/Instagram, and Threads/X.

Spotlighting Published Research on LinkedIn

Here, we are using an example of a paper I published with co-authors on the subject of social capital and livelihood recovery in the context of forced displacement in Nigeria (Kolade et al., 2022). Here, a prompt is issued for ChatGPT to generate a 300-word content suitable for a LinkedIn post that introduces the published research to a non-expert, albeit professional, audience. Below is the prompt, followed by the output:

Prompt: Use the attached to generate a 300-word content suitable for LinkedIn. The purpose of the post is to introduce the published paper to a non-expert, but professional, audience. The output should clearly and concisely highlight the key findings of the paper- emphasizing its practical value and potential impact to society. It should link with, and tag, relevant multilateral agencies at the forefront of work with displaced populations. Include a link to the pages where interested readers can

access the full article (journal page: <https://www.tandfonline.com/doi/abs/https://doi.org/10.1080/00220388.2022.2032669>; ResearchGate for AAM version: https://www.researchgate.net/publication/358008871-Picking_Up_the_Pieces_Social_Capital_Psycho-Social_Support_and_Livelihood_Recovery_of_Displaced_Populations_in_Northeast_Nigeria#fullTextFileContent).

ChatGPT: Certainly! Here's a 300-word LinkedIn post tailored to a professional, non-expert audience, introducing the published paper and its relevance. The tone is informative and accessible, with practical implications and key tags:

NEW **New Research on Displacement, Recovery & Resilience in Northeast Nigeria** **NEW**

How do communities rebuild after being torn apart by violent conflict?

Our recently published paper, *"Picking Up the Pieces: Social Capital, Psycho-Social Support and Livelihood Recovery of Displaced Populations in Northeast Nigeria"*, explores this question through in-depth research with internally displaced persons (IDPs) in one of the world's most fragile contexts.

Drawing on qualitative data from Borno State, we examined how **social capital** (networks, trust, and reciprocity) and **psycho-social support mechanisms** enable displaced populations not only to survive—but to begin rebuilding livelihoods and restoring a sense of normalcy. We found that:

◆ **Informal networks** are critical in facilitating access to resources, rebuilding livelihoods, and providing emotional and psychological support.

◆ **Faith-based and community-led groups** often step in where formal systems fail.

◆ **Livelihood recovery is closely tied to mental well-being**, social belonging, and agency—highlighting the need for holistic, not just material, interventions.

This research offers **practical insights for policymakers, NGOs, and humanitarian actors** working in conflict-affected regions—particularly in shaping recovery programmes that move beyond short-term aid to support long-term resilience and dignity.

We hope these findings will support ongoing work by partners such as @UNDP, @UNHCR, @IOM, @World Bank, and @African Union in rethinking durable solutions for displaced populations.

☞ Access the published paper here: <https://www.tandfonline.com/doi/abs/https://doi.org/10.1080/00220388.2022.2032669>.

■ Free AAM version on ResearchGate: https://www.researchgate.net/publication/358008871_Picking_Up_the_Pieces_Social_Capital_Psycho-Social_Support_and_Livelihood_Recovery_of_Displaced_Populations_in_Northeast_Nigeria#fullTextFileContent.

#Displacement #Resilience #SocialCapital #LivelihoodRecovery #Post-Conflict #HumanitarianWork #Nigeria #ForcedMigration #SustainableDevelopment #ResearchImpact.

Let me know if you'd like variations of this post for X (formerly Twitter), Facebook, or Instagram.

ChatGPT generated a good draft for the proposed LinkedIn post, using a clear and appropriate language suitable for a professional, non-expert audience. It has to be taken like a draft it is, though. Firstly, it suggests that the published paper was a “new research”, although it was, in fact, published in 2022, three years from the time of writing this book. It is not entirely ChatGPT's fault, as the prompt had indicated that the purpose of the proposed post was to “introduce” the paper. It underlines once again the garbage in garbage out rule that underpins the use of generative AI in this and many other contexts: the tool will work with whatever it is given in the prompt.

To further underline this point, let's issue another prompt for another published paper on circular business models (Kolade et al., 2024), this time using the abstract as the basis for the proposed content to be generated:

Prompt: Use the following abstract to generate a 100-word post about this new research, highlighting the empirical findings that underline importance of digitally enabled circular business models in five named African countries: “In recognition of the need for an economic logic that complements and reinforces the ecological imperative for the circular plastic economy, this paper explores the importance and impact of digitally enabled circular plastic business models across retailing and distribution systems. The paper

draws from 16 focus group discussions, complemented by 17 semi-structured interviews of frontline organisations incorporating digital innovations in their businesses to enable the management of plastic waste in Africa. The study finds that, across African countries, the transition to a circular plastic economy has been hampered by the limited uptake of circular products by consumers. In order to accelerate the transition, innovative business models are required to invigorate the ecosystem and simplify the logistics of retailing and distribution systems. The paper proposes a new conceptual framework that explicates the impact of digital innovations in the processes of value creation and value capture across a whole spectrum of circular economy reverse logistics activities: recycling, redistribution, and remanufacture. The study also highlights two important social and policy implications of digitally enabled circular business models: Firstly, the creation of new employment opportunities through the empowerment of a new labour force for the circular plastic economy; secondly, the heightened opportunity to enact an innovative sharing economy in typically resource-constrained contexts in which otherwise idle products and resources are more efficiently used in a process of collaborative consumption.”

ChatGPT:  **New Research Alert: Digitally Enabled Circular Business Models in Africa**  

Our latest study sheds light on how digital innovation is transforming the circular plastic economy across **Nigeria, Ghana, Kenya, Rwanda, Uganda, and South Africa.**

 Based on fieldwork with 16 focus groups and 17 interviews, we found that **limited consumer uptake** of circular products is slowing progress.

 However, **digitally enabled business models** are unlocking new opportunities for **recycling, redistribution, and remanufacture**, while also creating jobs and driving collaborative consumption.

This is a call to rethink retail and distribution systems for sustainable impact.

#CircularEconomy #DigitalInnovation #Africa #Sustainability #GreenBusiness

Once again, ChatGPT has generated a usable content—on the face of it. The challenge is that, in the absence of specific information about which countries are the five African countries, it has made up a list of its own—in a mild enactment of AI hallucination! It highlighted Nigeria, Ghana, Kenya, Rwanda, Uganda, and South Africa. Whereas, in the full published paper, the study countries are: Namibia, Zambia, Nigeria, Kenya, Uganda, and Rwanda—six of them, and no Ghana, Uganda, or South Africa included. The problem, in this case, is not that ChatGPT was fed with incorrect information, but it was given incomplete information to work with. The abstract did not include the names of the six countries that the prompt referred to. Thus, ChatGPT made up its own list of countries!

While LinkedIn serves as a valuable space for introducing academic research to a professional but non-specialist audience, platforms like Facebook and Instagram demand a different approach. Here, the reach is broader, encompassing both professionals and the general public, many of whom may have limited prior exposure to scholarly content. The shift in tone, format, and visual emphasis becomes critical. In the next section, we explore how generative AI can be used to craft compelling, accessible, and visually engaging content suitable for Facebook and Instagram, while preserving the integrity and impact of the research being communicated.

Promoting Published Research on Facebook/Instagram

Contents shared on LinkedIn and Facebook/Instagram share some similarities—mainly in terms of the non-expert profile of the target audience. There are notable differences, as well. One is that the audience on Facebook is more diverse—they include professionals, experts, non-experts, and general members of the public with varying levels of education, exposure, age, and other demographic characteristics. The audience on Instagram tends to be younger, also. In addition, contents posted on Facebook have less restrictions on word counts and, in the case of Instagram, put a premium on supporting visual contents.

Let us now return to our first example used for the LinkedIn post. In this case, because of limited space, we ask ChatGPT to generate a content suitable primarily for an Instagram post but can also be adapted for a Facebook post, or shared simultaneously, as the two platforms allow.

Prompt: Use the attached to generate a content suitable for an Instagram post but can also be adapted or shared simultaneously on Facebook. Include suggestions for accompanying images, and ensure that the content is appropriate for a diverse non-expert audience, especially young demographics.

ChatGPT: Here's a social-media-friendly caption and post draft inspired by the findings of Kolade et al. (2022)—"*Picking Up the Pieces: Entrepreneurship and Local Economic Development in Post-conflict Nigeria*". This version is perfect for Instagram and easily adaptable for Facebook, tailored to a younger and diverse audience:

🔊 *Post Caption (Instagram/Facebook)*

★ From Chaos to Comeback ★

In Northeast Nigeria, communities hit hard by conflict are rising again—and the heroes? Everyday entrepreneurs. 🧱💡

This research explores how people who've lost nearly everything are starting again, using what they *know*, *who they are*, and *who they know* to rebuild their lives and communities.

🌍 It's not just about survival—it's about *creating*, *collaborating*, and *co-creating* a new future.

📱 Want to know how local resilience and creativity are transforming economies post-crisis? Hit the link in bio or check our stories.

#Entrepreneurship #Resilience #Nigeria #SocialImpact #YouthIn-Business #Innovation #PostConflictRecovery #AfricanVoices #Inspiration #ResearchForChange

📷 *Suggested Visuals for Instagram/Facebook Post*

1. **Main Image:** A powerful photo of a young Nigerian entrepreneur (preferably smiling, working on a product, or interacting with community), ideally in an informal market, repair shop, food stall, or tailoring environment.
2. **Carousel Option:**

Slide 1: Eye-catching quote: "*We started again with what we had—ourselves.*"

Slide 2: Infographic summary—3 key takeaways from the study:

- People use local knowledge + social networks to recover
- Entrepreneurship = healing + hope
- Recovery is led by *the people*, not just aid

Slide 3: “Tag someone who’s rebuilding their dreams ★”

3. Instagram Stories / Facebook Reels Idea: 15–30 second clip of local entrepreneurs at work, with text overlays:

- “Conflict took everything.”
- “But they’re building it back.”
- “One step, one sale, one idea at a time.”

Would you like me to mock up the actual visual layout or caption graphics too?

ChatGPT generated a content with a language appropriate for a non-expert, especially younger, audience. But then again, as before, it is up to the researcher to exercise the agency of the insider who knows the research through and through. In this instance, ChatGPT has not given a sufficient detail of the context that most readers will find more compelling: for example, the sheer number of displaced people, and the stark reality of terrorist violence. Also, the suggestion of a young “smiling” entrepreneur is not quite appropriate for this study and the context. A more appropriate image will be, for example, that a beleaguered displaced young woman, children in tow, engaging in an entrepreneurial venture/activity, to make ends meet.

We can also ask ChatGPT to generate a longer, say 350-word version, suitable for a Facebook post. To do that, we do not need to issue an entirely new prompt from scratch, but simply ask the AI tool to now generate a longer version, as follows:

Prompt: Can you now generate a longer, 350-word, version suitable just for a Facebook post?

Chat GPT: Absolutely! Here’s a **350-word version** of the Facebook post, tailored for a general but thoughtful audience, combining accessibility with depth and emotion while retaining the core insights from the *Kolade et al. (2022)* study:

Picking Up the Pieces: How Displaced Communities Are Rebuilding Through Social Bonds and Resilience

What happens after conflict tears apart homes, livelihoods, and entire communities?

In Northeast Nigeria, millions have been forcibly displaced due to the Boko Haram insurgency. But beyond the headlines of crisis and humanitarian aid, there's a powerful story of survival, strength, and grassroots recovery—and it's being led by the people themselves.

Our new research, “**Picking Up the Pieces**”, explores how *social capital*—the strength of relationships, networks, and mutual support—plays a central role in helping displaced individuals recover emotionally and economically.

Key findings:

- Friends, families, and faith groups provide critical **emotional support**, helping people overcome trauma and rebuild confidence.
- Informal networks help displaced people access **livelihoods**, from small business ventures to shared resources.
- **Resilience**, not just skills, is the bridge between survival and success—and it's often nurtured through social connections.
- Recovery isn't just about aid; it's about the *agency* of people navigating hardship together.

This research challenges traditional views that only material aid drives recovery. Instead, it shows that *healing, entrepreneurship, and hope are deeply social processes*. Whether it's a neighbour offering encouraging words, a friend helping start a food stall, or a community leader linking people to services—it's human connection that makes recovery possible.

 Read the full study here: <https://www.tandfonline.com/doi/abs/https://doi.org/10.1080/00220388.2022.2032669>

 Free full-text (AAM) on ResearchGate: <https://www.researchgate.net/publication/358008871>

Let's reimagine how we approach displacement. Let's recognise displaced people not as passive recipients of aid—but as resilient individuals and communities actively shaping their futures. 

#DisplacementRecovery #Resilience #SocialCapital #Nigeria #CommunityStrength #Peacebuilding #Livelihoods #HumanitarianWork
#TripleNexus #ResearchMatters #FacebookReads

Let me know if you'd like a version that includes visuals or an animated summary clip to go along with the post.

Again, the generated content uses appropriate language and style to reach a wider audience, stimulating enough interest to encourage them to read the full paper. It is still a draft, though, and the researcher must always make the final call on the content generated by generative AI.

Keeping It Short and Sweet: Sharing Research on Threads and X

Some social media channels prioritise brevity in public communication. They invite users to, in effect, embrace the challenge of saying as much as they can in as few words as possible. It is, so to speak, a text version of an elevator pitch—and the format has gained popularity in the past decade. We will next explore how generative AI like ChatGPT can be used to craft shorter contents for platforms like Threads and X.

Firstly, we turn to our original example again to ask ChatGPT to generate two contents, one a 500-character limit for Threads, the other a 280-character limit for X. Since this series of prompts is now in a thread, we do not, once again, need to upload the material or issue an elaborate prompt:

Prompt: Now, using the same upload as before, generate two versions of content, one for Threads (500-character limit), and the other for X (280-character limit).

ChatGPT: Certainly! Here are two tailored versions of the content based on the *Kolade et al. (2022)* study—one for **Threads** (500-character limit) and one for **X (formerly Twitter)** (280-character limit):

□ Threads Version (500 characters max):

How do displaced communities rebuild after conflict?

Our research in Northeast Nigeria shows that *social capital*—family, friends, & community—is key to emotional healing & economic recovery. It's not just about aid. It's about resilience, agency, & rebuilding *together*. Read more: <https://www.tandfonline.com/doi/abs/https://doi.org/10.1080/00220388.2022.2032669>

#Displacement #Resilience #TripleNexus

✕□X (Twitter) Version (280 characters max):

Displaced but not defeated.

Our research shows that in Northeast Nigeria, social capital—friends, families & networks—drives resilience & recovery.

It's more than aid; it's about people rebuilding together.

 <https://doi.org/10.1080/00220388.2022.2032669>

#Resilience #Displacement

Let me know if you'd like a visual card or graphic to pair with these for better engagement.

The outputs are clear and succinct—in short, very good drafts to work use, with probably only minor edits from the researcher. However, let us try one more thing by way of a quick illustration (we will explore further in Sect. 7.4). In the following example, we ask ChatGPT to use the existing information to generate a poster that can be posted as an alternative to the texts on the platforms:

Prompt: Now, use the information provided to generate a poster that can be shared as an image on Threads or other social media platforms—as an alternative to the textual posts.

ChatGPT:

The generated image captures the core findings of the research in plain language suitable for a wider, non-expert audience. The researcher might want to present the summary in bullet points, rather than the sentence format in Fig. 7.1 above. Furthermore, in the JPEG format, the doi link is not of much practical value within the image itself, because it is not clickable. The link could therefore be something that the researcher includes separately under, or as an accompanying text, to the image.

7.3 BLOGS, OPEDs, AND NEWS ITEMS

Copy-Editing Blogs in Style

Blogs are similar to social media posts, especially in tone and style aimed at non-expert audiences. One key difference, perhaps, is that they tend to be longer in word counts. They are also more personal and reflective, bringing the researchers authentic voice to the fore as they share real-life account of their experiences in the field—including interactions with research subjects and stakeholders. Blogs provide a unique means of engaging stakeholders, away from the often-tedious jargons of academic



Fig. 7.1 ChatGPT-generated image for social media dissemination

research. In many ways, they uniquely bring research to life and get non-expert publics interested.

Given this background, we would argue that the most effective use of generative AI is to copy-edit, rather than copy-write, contents. In other words, the researcher should pen their thoughts, warts and all, and then use gen AI to refine it—keeping their authentic voice intact as much as

possible. To illustrate this, let us look at this blog post from 2019, in the immediate aftermath of a workshop related to the *Picking up the Pieces* project (and article) we started this chapter with.

Once upon two remarkable women

Over the course of two days (16 & 17th July 2019) I had the privilege of meeting two of the most incredible human beings one can ever meet on the planet. As many of you reading this are aware I have been leading a project looking at internally displaced peoples in Northeast Nigeria. The project is titled “picking up the pieces: social capital, human capital and coping strategies of households displaced by Boko Haram insurgency in Northeast Nigeria”. The project seeks to interrogate the traditional model of humanitarian intervention and how better long-term outcomes can be achieved by designing “interventions” around the agency of displaced peoples. In our workshop we decided it was important that representatives of the affected households are active participants in the workshop, including what we call the co-creation sessions. This approach is refreshingly and powerfully illuminating. These men and women did not hold back, and it was a teachable moment and humbling experience for the rest of us.

The two women I am writing about today epitomise the incredible resilience of the human spirit. Unbent, unbroken, they have shouldered on in the midst of the most dangerous, most challenging of conditions.

The older woman I shall call Mama J. When her town was overrun by the Boko Haram insurgents, she fled with her husband and three children to another village where there was an IDP camp. There, her husband and two children were welcomed, but she was refused entry? Why, because she had a 31-year old son with both learning and physical disability. She was practically given the choice of leaving her son behind if she was to be admitted to the camp. She refused. She decided that it was better for her to die than leave her son out there to rot. She decided to go back to her town that was overrun by the insurgents. She therefore made the journey back, walking over the next two days, practically carrying her son along. When she got back to town she found that the security forces had taken control and a new camp had been set up. But there again she was refused help. Unbroken, she started to run a vegetable business, with a 500 naira given to her by a soldier.

That was in 2017. Today (2019), she is no longer selling in measures but in big sacks. She has been able to put together a whole spectrum of vegetable combinations, and has become one of the key sellers in the community. She now makes up to 3,000 naira a day. When we asked her how she managed to succeed and expand her business within such a short period of time.

She answered that she was able to put together a unique combination that no one else was offering in the community. You can only begin to grasp the awesomeness of her business acumen when you realise that this woman has never had a single day of formal education. She understands the idea of unique selling point in such a deeply practical and effective way, more than management and entrepreneurship scholars can theorise. When asked what's kept her going against the odds, her response was brilliantly casual: "I have no choice but to find a way..."

The next story is equally humbling. I was going on about Mama J and got carried away a bit, forgetting that there is another woman, younger, that we have also invited along to the workshop. Let's call her Lady H. She sat quietly, unflustered, as I stood there singing the praises of her counterpart from Maiduguri. Colleagues reminded me that we need to hear her story too. Of course, she duly obliged in what became a truly remarkable, inspiring story of doggedness and unrelenting hope and ambition against the odds.

Lady H lost her husband, father and one son to the insurgents in one fell swoop. The sheer trauma of the losses in such tragic circumstances can only be imagined. Yet this woman was determined to move on with her life. She managed to escape with her three other children. She ended up in an IDP camp. There, she began to rebuild her life, block by block. Having lost her entire restaurant business to the insurgency. She volunteered for an NGO in the camp for several weeks, earning about 10,000 naira (£23) in the process. With this 10,000 Naira she set up a business that includes trading in agricultural produce. For good measure, she set up a support unit for other women in the camp to learn a trade/vocational skills and begin to earn a living for themselves. Crucially, she is especially passionate about the education of children, about which she has been leading advocacy efforts to raise standards of teaching in the camp schools. She laments that children sometime leave school by 10am, and many of them cannot write their own names. Today, while she remained in the camp, she has managed to raise enough income to send her two younger children to a private school far away from the camp, and the oldest is studying law in a higher education institution. Not bad at all for a widow who lost half of her family in very tragic circumstances.

One final comment about these two remarkable women: their infectious, unrehearsed cheerfulness is in and of itself a transforming experience. They are clearly not satisfied about their conditions, and they spoke openly and forcefully about it. But they would also not be denied the liberty to be joyful, to be grateful about little opportunities they have had to begin to rebuild their lives. Their story is powerful in more ways than one. Among others, it points to a new, and more effective pathway to engage with

humanitarian action. Affected people are of course desperate. Yet they are not without agency to turn things around, rebuild their lives and recover their livelihoods.

The draft blog does what a blog does: personal, reflective, and compelling. There are a few gremlins, though: minor typo and syntax errors; a few elaborate details that could be summarised here and there; and perhaps a few turns of phrases and words that are likely to be more easily understood by people familiar with the context. Finally, it can work better as a shorter piece, say 700 words (its current word count is 989 words). Thus, we ask ChatGPT to copy-edit—refine this into a shorter 700-word blog that retains the authenticity of the researcher’s voice:

Prompt: Refine the following draft blog into a shorter, 700-word piece. Keep it clear, simple and succinct, making it accessible and interesting to a wider international audience. Most importantly, keep intact the authentic voice of the researcher in the blog.

ChatGPT: Certainly! Here’s a refined, 700-word version of your blog, keeping the authentic voice and tone intact while making it accessible and engaging for a broader international audience:

Once Upon Two Remarkable Women

On the 16th and 17th of July 2019, I had the rare privilege of meeting two of the most inspiring women I’ve ever encountered. As many of you know, I’ve been leading a research project on internally displaced people (IDPs) in Northeast Nigeria. The project is titled *“Picking up the pieces: social capital, human capital and coping strategies of households displaced by the Boko Haram insurgency.”*

At the heart of our work is a simple idea: humanitarian interventions should not only focus on delivering aid, but on recognising the agency of displaced people. This is why, in our workshop, we insisted that representatives from affected communities should be active participants—not just observers. What followed was deeply humbling. These individuals—who have faced unthinkable hardship—shared their stories with such openness and strength that it became a lesson for the rest of us.

Let me tell you about two women who stood out.

The first, whom I’ll call *Mama J*, fled her hometown when it was overrun by insurgents. She sought safety with her husband and three children at a nearby IDP camp. But when they arrived, she was told she could not

enter—not unless she left her 31-year-old disabled son behind. Her answer was simple: no.

She chose to turn back. Over two days, she walked back to her hometown, carrying her son. When she returned, she found the military had taken control and another camp had been set up. But again, she was turned away.

Refusing to give up, Mama J started selling vegetables with just 500 naira (about £1) given to her by a soldier. That was 2017. By 2019, she was no longer selling by the cupful—she was selling by the sack. She built her business by creating a unique mix of vegetables no one else offered. She'd never spent a day in school, yet she understood what business schools call a “unique selling point” better than most.

When asked how she did it, her answer was simple: *“I have no choice but to find a way.”*

The second woman, *Lady H*, shared her story just after Mama J. I had been so caught up in praising Mama J, I almost forgot we had another equally extraordinary guest.

Lady H lost her husband, her father, and one of her sons in a single day to the insurgents. She fled with her remaining children to an IDP camp and began the slow, painful process of rebuilding her life. She volunteered with an NGO and earned 10,000 naira—roughly £23. That small sum became the seed for a new business trading in agricultural produce.

But she didn't stop there.

Lady H also set up a support group for women in the camp to learn vocational skills and start small businesses. Education is her biggest passion. She spoke with pain about the poor conditions in camp schools—how some children leave by 10am, unable to write their own names. But instead of waiting for change, she acted. Today, she has sent her younger children to a private school outside the camp. Her oldest is now studying law in university.

Not bad for a widow who lost half her family and everything she owned. What struck me most about these two women was not just their strength—but their joy. Their warmth. Their humour. They didn't sugarcoat their struggles, and they demanded more support. But they also refused to be robbed of the freedom to laugh, to dream, and to rebuild.

Their stories remind us of a simple truth: displaced people are not just victims in need of rescue. They are individuals with the courage, creativity, and resilience to rebuild their lives—if only we recognise and support their agency.

These women challenge us to rethink humanitarian action. Aid is important. But even more important is listening—truly listening—to those who

are living the reality of displacement. Because often, the best solutions come not from the outside, but from the people we assume are powerless. They are anything but.

Let me know if you'd like a visual quote graphic or pull-quote to accompany this for wider sharing.

The revised, copy-edited version conveys the message of the original draft clearly—and in fewer words (677 words). Of course, it should still be used as a draft and refined by the researcher to ensure that it is as authentic and compelling as it can be. Another point to make is that the original draft does not have to be as long, or as publishable as probably the exemplar “draft” above was—in truth, it was not quite a draft but a final “product” published on the project’s website. The practical utility of the generative AI tool applies, nonetheless—to rework a draft blog into a refined, “finished” product, while keeping intact its authenticity.

OPEDs are also longer formats compared with typical social media posts, although some writers use social media channels to share longer opinion pieces. The language of OPEDs is non-academic, but they are more formal compared with blogs. Once again here, it is better to generate a draft article, shorter or longer, and then use generative AI as and editorial assistant to refine and strengthen it. We will not include a full example, but it is important to remember, once again, that the quality of the output is largely a function of the prompts and instructions given to the generative AI tool. Oftentimes, the prompt does not work in one go! You have to give instructions in iterations to arrive at a desirable output.

Generating News Items for Research Projects

Sometimes, researchers need to promote events and activities related to research projects. These could be conferences, workshops, and a wide range of stakeholder events. Promotional outputs can be in form of emails and news items published on the project website and similar platforms. For many of these events, flyers and posters are also generated to publicise the events. In the following example, we illustrate how research teams can, in effect, “get two for the price of one”—by using flyers/posters to generate news stories. Below, we ask ChatGPT to use the flyer for the DIGEST ‘25 conference (Fig. 7.2) to create a promotional news item for the conference.



Sheffield
Hallam
University
Knowledge Applied

Sheffield
Business
School

DIGEST'25

DIGITAL TRANSFORMATION IN INDUSTRY, GOVERNMENT,
EDUCATION AND SOCIETY (DIGEST)

AI AND THE FUTURE OF INDUSTRY 4.0: TRANSFORMING TECHNOLOGY, GOVERNANCE, AND SOCIETY IN THE DIGITAL AGE

Conference Date:
12th -13th May 2025.

Time:
(12th May); 3-6PM
(13th May); 9AM-5PM

CONFERENCE SYNOPSIS

Artificial Intelligence (AI) is at the forefront of the Industry 4.0/5.0 revolution, driving transformation across sectors, from manufacturing and higher education to governance, finance, and cybersecurity. Across five tracks, this conference seeks to explore the evolving role of AI in the digital transformation of industry, government, business, and society, with a focus on its implications for economic growth, policy, and technological innovation worldwide.

CONFERENCE TRACKS

- AI Applications within Industry and Society
- AI in Higher Education
- The Politics and Ethics of AI in Government and Society
- Cybersecure Digital Adoption and Blockchain Applications
- AI and Fintech Innovations

SCAN TO REGISTER



PUBLICATION OPPORTUNITIES

Edited Books

- Digital Transformation in the Global South
De Gruyter | Ed. Prof. Seun Kolade
- Entrepreneurship and Employment in Africa
Palgrave | Eds. Dr Egbetokun & Dr Olofinyehun

Special Issues

- AI in Teaching & Learning EIJSDC
Workshop during conference
- AI and Inclusive Growth Proposed for
Development and Change (ABS 3)

To register click: <https://bit.ly/digestconf>
Deadline for submission of abstract: 7th April, 2025
For enquiries, email digestconference@shu.ac.uk

Venue: Sheffield Hallam View, Sheffield Hallam University, UK

Fig. 7.2 Flyer for DIGEST ‘25 conference

Prompt: Use the attached to generate a 400-word news items suitable for the project website and similar platforms. The news story should highlight the conference theme, the opportunities for publications, and details of venue and time. Also please note that the deadline for submission of abstract has been extended to Tuesday 15th April 2025.

ChatGPT: Here’s a 400-word news item suitable for the project website and related platforms, based on the DIGEST’25 conference flyer:

 **DIGEST'25 Conference: Exploring AI's Role in Shaping the Future of Industry, Governance, and Society**

The Sheffield Business School at Sheffield Hallam University is excited to announce **DIGEST'25: Digital Transformation in Industry, Government, Education and Society**, a dynamic two-day conference taking place on **12th–13th May 2025** at the **Sheffield Hallam View, Sheffield Hallam University, UK**.

With the theme “**AI and the Future of Industry 4.0: Transforming Technology, Governance, and Society in the Digital Age**,” the conference will explore how Artificial Intelligence is reshaping multiple facets of our world—from manufacturing and higher education to governance, finance, and cybersecurity. As AI technologies continue to evolve, DIGEST'25 provides a timely platform for critical reflection, scholarly exchange, and practical engagement with the challenges and opportunities of this digital era.

Running across five focused tracks, the conference invites contributions on:

- AI Applications within Industry and Society
- AI in Higher Education
- The Politics and Ethics of AI in Government and Society
- Cybersecure Digital Adoption and Blockchain Applications
- AI and Fintech Innovations

A core aim of DIGEST'25 is to highlight the transformative impact of AI not just on technology and business, but also on **policy, society, and inclusive development**. To this end, the conference offers exciting **publication opportunities**, including:

 Edited Books

- *Digital Transformation in the Global South* (De Gruyter)—Edited by Prof. Seun Kolade
- *Entrepreneurship and Employment in Africa* (Palgrave)—Edited by Dr. Egbetokun and Dr. Olofinyehun

◆ Special Issues

- *AI in Teaching & Learning* (EJISDC)—Linked to a conference workshop
- *AI and Inclusive Growth*—Proposed special issue for ABS 3 outlet

Researchers and practitioners are encouraged to contribute to this vital conversation. Please note that the **deadline for abstract submission has been extended to Tuesday, 15th April 2025**.

🔗 **Register now:** <https://bit.ly/digestconf>

✉ **For enquiries:** digestconference@shu.ac.uk

DIGEST'25 promises to be a landmark gathering for those at the intersection of AI, innovation, and social transformation. Don't miss it!

Let me know if you'd like this version formatted for email announcements or as a press release.

This approach obviously saves the time that would be otherwise required to create the new item. Moreover, because it is based on a content already generated by the project team, it is less at risk of hallucination—making up stuffs about the event. The above content is all accurate regarding the details of the conference. Of course, it is always important to doublecheck and make sure! There is just one final comment to make on this, and to which we shall return in the concluding chapter. In the final example above, we used the flyer to generate a news item. This is not only time-efficient, as already noted, but it is also energy-efficient: ChatGPT requires more energy to generate image than it does to generate text. Researchers must bring this environmental awareness to bear in their use of generative AI, using it in the most sustainable way. We recommend using generative AI to create image only when it delivers high value—and if the alternative will require more time and energy.

7.4 AUDIO-VISUAL CONTENTS

We have already explored the use of generative AI to generate image for research communication, and to, in turn, generate promotional items from images such as flyers and posters. These are less controversial use

cases. However, images for research are not only in the forms of flyers and posters, but they can also come in forms of graphical abstracts and other types of illustrative images within manuscripts. Now, this is an area of AI usage that has generated considerable controversies. One example of this was highlighted in Chapter 1, where a team of authors used an AI-generated image in a paper that ultimately passed peer review and editorial checks. In that example, the use of AI was exposed because the image used was bogus and improbable. Regardless of that exposure, academic journals and publishers discountenance the use of AI-generated image in manuscripts.

The evolving policies of major academic publishers like Springer and Elsevier on the use of generative AI for images in scholarly manuscripts reflect growing concerns around copyright, research integrity, and authors' ethical responsibilities. Both publishers adopt a cautious, largely prohibitive stance, underscoring the unresolved legal frameworks around AI-generated content. Springer Nature's policy prohibits the use of generative AI images outright, except under narrowly defined and reviewable exceptions. These include AI-generated visuals sourced from contracted image agencies or generated using scientific datasets that can be verified, provided clear attribution and ethical standards are met. Similarly, Elsevier forbids generative AI and AI-assisted image alteration in manuscripts, even for seemingly benign enhancements, unless such tools are part of the research design itself—such as biomedical imaging workflows—where detailed methodological disclosure is mandatory. These restrictions are based not only on current legal ambiguity regarding intellectual property, but also on long-standing principles of scientific transparency, where the authenticity of visual data must be verifiable and reproducible.

Critically, these policies highlight a broader philosophical tension between technological advancement and the safeguarding of academic standards for knowledge production. While both Springer and Elsevier acknowledge that AI tools are rapidly evolving and may soon play a legitimate role in visual research communication, their present regulations aim to preserve the trustworthiness of the scholarly record. They emphasise authorial accountability, requiring disclosures, permissions, and where applicable, raw or pre-altered images to enable editorial scrutiny. Notably, both publishers allow for limited exceptions—Springer permits generative AI use in academic outputs explicitly focused on AI and allows AI-generated visualisations from verifiable data sets; Elsevier, meanwhile,

makes allowances for cover art and graphical abstracts under strict permission protocols. The underlying message is clear: AI must not obscure the provenance of scientific visuals nor replace human responsibility in scholarly authorship. As the field matures, these policies may evolve, but for now, they serve as important guardrails against the potential misuse of generative technologies, aiming to uphold research ethics, legal clarity, and scientific integrity in an era of digital innovation.

To conclude this section, let us use an example of a generative AI-podcast generator to reflect on the current state of the technology in a rapidly evolving landscape (by the time this book is published, the technology is likely to have rapidly advance and probably overcome some of the limitations highlighted presently. Once again, we use the example of the *Picking up the Pieces* paper we started with. First, we issued prompts for NoteGPT—another generative AI tool—to summarise the paper. We then opened a new window and asked it to generate a podcast. It did just that, producing a 4 mins 23 seconds podcast that correctly summarises the key points in a two way dialogue.

Two things are immediately obvious, however. Firstly, the paper is co-authored by seven authors, in the following order: *Oluwaseun Kolade, Robert Smith, Demola Obembe, Abigail Taiwo, Joseph Eyong, Saliba James & Gaim Kibreab*. The generative AI tool appears to have ignored all the other listed authors, and went with *Dr Smith* as the “guest” for the simulated podcast. This is instructive, because Smith is the only Western name on the list of authors (and not the lead or corresponding authors, by the way). It underlines the continuing limitations of large language models and the biases inherent in their training data. Secondly, and in line with the first point, the accent of the podcast is decidedly non-African, although six of the seven authors were Nigerians—and the study itself was undertaken in Nigeria. This is an ongoing frontier, not only of technological developments but also of conversations around equity and representation. One potential way around this limitation is to provide customised voice recognition training for the generative AI tool, so that the podcast it generates can be more authentic and representative.

The use of generative AI for audio-visual content remains a promising yet unsettled frontier in academic research communication. While tools like NoteGPT demonstrate the remarkable potential of AI to simplify and scale dissemination through formats such as podcasts, the technology still reflects the biases and blind spots embedded in its training data. Issues of author representation, voice authenticity, and cultural alignment highlight

the need for more inclusive design and critical oversight. As generative AI continues to evolve, researchers and developers alike must address these ethical and epistemic concerns to ensure that innovation supports—not undermines—equity, accuracy, and integrity in scholarly communication.

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The Future of AI for Knowledge Production

8.1 INTRODUCTION

As we arrive at the concluding chapter of this book, we take a moment to reflect on the journey so far—a journey that has navigated the promises and pitfalls of generative AI in the domain of academic research. From foundational debates around intellectual rigour and AI-induced biases (Chapter 1), to specific use cases in research design (Chapter 2), data simulation (Chapter 3), and analytical processing (Chapter 4), each chapter has spotlighted AI's dual potential as both a disruptive force and an enabler of innovation. We have examined how generative AI can serve as a co-pilot in experimental design (Chapter 5) and manuscript review (Chapter 6), as well as a vehicle for public engagement and knowledge exchange (Chapter 7). Across these discussions, a consistent theme has emerged: the need for thoughtful integration of AI tools into the research workflow—an approach rooted in ethical awareness, methodological rigour, and responsible innovation.

This final chapter looks ahead, casting a reflective gaze on the future of human researchers in an increasingly AI-driven knowledge economy. As automation becomes more intelligent and embedded, researchers must cultivate a dynamic repertoire of AI-competencies and adaptive thinking to remain relevant and impactful. But adaptation alone is not enough; we must also question whether the evolving AI landscape amplifies or undercuts the case for open science. Does generative AI foster transparency,

accessibility, and collaboration; or does it risk consolidating expertise and limiting accountability? The chapter offers a dialectical exploration of these themes, arguing that the future of knowledge production lies not in choosing between human and machine, but in reimagining their interplay. This concluding discussion sets the stage for a redefinition of what it means to be a researcher in the age of intelligent systems—one who is both critically aware and creatively empowered.

8.2 HUMANS IN KNOWLEDGE PRODUCTION: REPLACED, RETREATING, OR RE-INVENTED?

As artificial intelligence rapidly evolves, their applications in research are continually expanding and deepening. What began as assistance with simpler, routine tasks—such as grammar correction, literature search, and summarisation—has evolved into intermediate-level functions, including formulating research questions, generating hypotheses, designing data collection instruments, and conducting thematic analysis. Increasingly, AI tools are being deployed in more advanced tasks once reserved for human expertise: building statistical models, identifying patterns across vast datasets, synthesising findings from complex experiments, and even—controversially—drafting substantial sections of manuscripts. Customised GPTs and AI-driven simulations are now capable of replicating participant behaviour, testing variables, and predicting outcomes with remarkable speed and consistency. As these capabilities continue to mature, the boundary between human and machine-driven research becomes increasingly blurred—raising important questions about what roles, decisions, and creative contributions remain uniquely human in the evolving research landscape.

AI Applications in the Research Process: Any Room Left for Humans?

Let us now explore these in some details. The research process can be categorised into five sequential steps: (1) problem identification and conceptualisation; (2) research design and planning; (3) data collection; (4) data processing and analysis; and (5) reporting and dissemination.

1. *Problem Identification and Conceptualisation:* AI tools like ChatGPT are increasingly used to refine research questions, conduct

rapid literature scans, and suggest theoretical frameworks based on large-scale pattern recognition. For instance, researchers can input a broad topic, and the AI returns current debates, key thinkers, and possible gaps in the literature. Yet, this stage still demands deep human insight. It is important that researchers engage directly and deeply with previous research, not merely rely on AI-generated summaries of debates. This direct engagement is a cornerstone of scholarly inquiry, and should not be outsourced to AI. The researcher can, of course, use AI to generate draft summaries of papers they have already read. In addition, the task of determining what questions should be asked—based on social value, ethical implications, or disciplinary needs—remains a human prerogative. AI lacks the moral compass and contextual wisdom required for value-driven research prioritisation. As AI evolves, it may better synthesise diverse perspectives or propose interdisciplinary angles, but final decisions on research direction will always require human critical thinking and leadership to avoid superficial or ethically flawed pursuits.

2. *Research Design and Planning:* AI can assist in developing robust methodological plans by suggesting appropriate sampling strategies, evaluating variables, or even simulating scenarios to test feasibility. Platforms using generative AI can help create customised questionnaires or model experiments tailored to specific populations or constraints. For example, tools like DALL-E or synthetic data generators can simulate experimental environments or participant behaviours. However, AI often assumes a level of linearity or objectivity that real-world research rarely offers. Researchers must determine which methods align with epistemological frameworks or are culturally and ethically appropriate. AI might eventually predict which research designs yield better validity in certain fields, but humans must govern these tools to ensure methodological integrity, inclusivity, and contextual sensitivity. In qualitative research especially, where nuance and reflexivity matter, AI's support must be carefully curated by humans.
3. *Data Collection:* AI is increasingly involved in automating data collection, especially through scraping online platforms, deploying bots for surveys, and using smart sensors or IoT devices for real-time data capture. Generative AI also supports the creation of virtual research assistants and simulated participants for studies where access

to real populations is limited. For instance, researchers studying rare diseases or marginalised groups may benefit from synthetic data generation when ethical or logistical barriers arise. However, concerns around data authenticity, consent, and bias become critical here. While AI can enhance reach and efficiency, it lacks moral reasoning about how data should be gathered. Human oversight is crucial to ensure ethical clearance, obtain informed consent, and maintain trust with participants. As AI capabilities advance, its role may expand into adaptive data collection based on real-time inputs, but without rigorous human checks, such automation could easily violate research ethics.

4. *Data Processing and Analysis:* AI excels at processing vast, complex datasets—cleaning, coding, analysing, and visualising patterns far beyond human capability. Natural language processing tools can analyse qualitative interview transcripts, while machine learning algorithms predict trends or classify large-scale survey data. Researchers are already using tools like IBM Watson or custom GPTs to streamline thematic coding and statistical analysis. As these tools improve, they may even suggest new theoretical inferences. However, blind reliance on AI analytics can result in misinterpretation or overlook contextual subtleties. For example, an AI may flag correlations but fail to understand socio-political implications. Interpretive judgement, awareness of disciplinary conventions, and ethical reflection remain human responsibilities. As algorithms become more autonomous, it becomes even more important that researchers remain literate in their limitations, biases, and black-box operations, ensuring AI complements—not replaces—human understanding.
5. *Reporting and Dissemination:* AI tools are transforming how research findings are communicated. Researchers now use AI to generate plain-language summaries, design infographics, convert articles into social media content, or draft policy briefs tailored to specific audiences. AI can even assist in structuring manuscripts, editing for clarity, or translating research into multiple languages. Tools like Grammarly or Quillbot, and even AI-powered video generators, make dissemination faster and more accessible. However, what AI cannot yet do is determine which findings are socially responsible to promote, how to frame messages for sensitive communities, or how to engage meaningfully with stakeholders.

Human researchers must lead these decisions, ensuring responsible knowledge translation. Future advances may see AI integrating real-time public feedback or crafting tailored engagement strategies. Still, the integrity, nuance, and relational dynamics of knowledge dissemination require human judgement to avoid miscommunication, exaggeration, or public mistrust.

AI-Enabled Research: The Case for Augmentation and Complementarity

Previous epochs of technological progress have been loosely described as extensions of human physical capabilities. The steam engine amplified physical strength; electricity revolutionised energy use; and computing systems automated complex physical processes. Conversely, the Fourth Industrial Revolution—and particularly the advent of artificial intelligence—marks a fundamental shift: this is the era of extending human cognitive capabilities. AI systems do not merely execute tasks faster or with less fatigue; they interact with language, detect patterns in massive data sets, generate insights, and simulate reasoning. This revolution does not substitute human hands with machines. Instead, it introduces cognitive co-pilots that enhance human thought, reflection, and creativity. It is against this background that we explore the case for AI as a tool that complements and augments, rather than replaces, human capabilities in academic research.

Rather than displacing researchers, AI offers possibilities for deep collaboration. Its ability to process vast quantities of information, identify relationships across disciplines, and produce instant feedback enables researchers to focus on what matters most: interpretation, ethical reflection, creativity, and social relevance. From aiding in literature reviews to co-creating data simulations and generating policy-relevant summaries, AI can free researchers from time-intensive tasks, opening space for deeper conceptual engagement and innovation. This redistribution of cognitive effort represents a strategic reorientation of the researcher's role—from one of mechanical execution to one of visionary direction. In this way, AI becomes a cognitive partner, not a competitor, helping to reframe human focus on tasks that require nuance, judgement, and contextual depth.

As AI assumes responsibility for routine and repetitive aspects of research—such as data cleaning, basic statistical analysis, or formatting

citations—it liberates researchers to engage more fully in higher-level intellectual work. With more time to think critically about theoretical implications, challenge assumptions, and develop new conceptual frameworks, researchers can cultivate the very qualities that distinguish human inquiry: reflection, synthesis, and original thought. Over time, the regular practice of engaging in such higher-order thinking nurtures advanced competencies through the force of habit. Researchers become more adept at strategic thinking, interdisciplinary analysis, and ethical foresight, even as they retain an informed understanding of the underlying technical processes AI handles. This retained understanding is essential, as it prevents over-reliance on AI and ensures that human researchers remain the ultimate arbiters of scholarly quality and relevance.

However, the meaningful augmentation of human capabilities through AI is not automatic. It requires deliberate effort, strategic intention, and a reimagining of the researcher's identity in an AI-driven age. The modern researcher can no longer rely solely on disciplinary knowledge and traditional methods; instead, they must evolve into adaptive, digitally fluent thinkers who can navigate both the intellectual and technological dimensions of research. This reinvention involves more than just learning to "use" AI tools. It requires developing a conceptual understanding of how these tools function, what drives their outputs, and where their boundaries lie. Just as a pilot must understand not only how to fly a plane but also how the aircraft operates under different conditions, researchers must learn to steward AI thoughtfully and responsibly. Doing so protects the rigour of the research process while opening doors to new creative possibilities.

This transformation demands an active shift in mindset. Researchers must embrace a hybrid role: part subject expert, part data strategist, and part AI-informed decision maker. The ability to frame meaningful prompts, discern the strengths and weaknesses of AI-generated outputs, and know when to rely on human intuition over automated efficiency will become a hallmark of academic excellence. This does not mean becoming a computer scientist or AI engineer, but rather cultivating a working literacy—enough to engage critically, delegate wisely, and intervene effectively. In short, the modern researcher must become a skilled supervisor of intelligent tools. This brings us to a crucial imperative in this evolving landscape: the urgent need for AI-competencies in research.

8.3 COMPETENCIES FOR AI-ENABLED RESEARCH

With AI tools, and generative AI in particular, the value that can be accessed and harnessed is a function of the researcher's skill sets. In this section, we begin by proposing a new framework to explicate the interaction between three core variables at play in AI-enabled research: Gen AI capacity, the researcher's capability, and research outputs.

Between AI Capacity, Researcher Capability, and Research Output

The relationship between generative AI capacities, researcher capabilities, and the quality of AI-enabled research outputs can be understood as a dynamic framework comprising three interdependent constructs: *capacity*, *capability*, and *output* (Fig. 8.1). At its core, generative AI offers immense capacity—from data summarisation and simulation to manuscript drafting and real-time analysis. The latest ChatGPT models demonstrate significantly enhanced computational power, with GPT-4 estimated to have over 1 trillion parameters—far surpassing GPT-3's 175 billion. They offer improved reasoning, image and code interpretation, and memory capabilities, unlike earlier versions limited to text generation and lacking real-time adaptability or multimodal processing.

These capacities represent what AI can do in theory: a wide array of computational, linguistic, and analytical functions that can support nearly every phase of the research process. However, the real-world output—the quality, relevance, and scholarly rigour of AI-generated contributions—does not arise solely from the tool's inherent capacity. Instead, it hinges significantly on how the human researcher engages with the tool. This is where the second construct, *capability*, becomes critical. The researcher's capability encompasses their domain expertise, digital literacy, ethical judgement, and ability to supervise, prompt, and critically evaluate AI outputs.

Crucially, the *gulf of quality* between AI's raw capacity and the research output's actual usefulness or scholarly merit is bridged by the researcher's capability. A highly capable researcher can transform generic AI outputs into refined, contextually nuanced insights that meet academic standards and ethical expectations. Conversely, low researcher capability may result in superficial, misleading, or even unethical outputs, regardless of the AI's sophistication. Thus, capability acts as a mediating force—a quality filter,

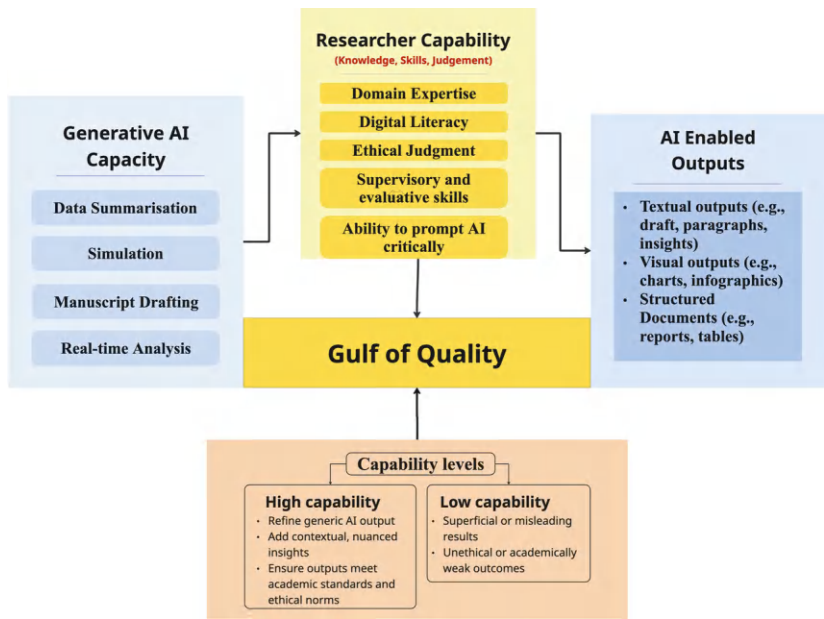


Fig. 8.1 Generative AI capacity, researcher capability, and AI-enabled outputs

a directional compass, and a safeguard. This framework not only underscores the importance of researchers understanding what AI can do, but more importantly, how and when to use it effectively. The implications are clear: meaningful AI-human collaboration in research is only as good as the researcher’s preparedness to lead that partnership. With this in mind, we now turn to explore the specific competencies and skills researchers must develop to thrive as informed supervisors of generative AI in the evolving knowledge economy.

Overview of AI-Competencies for Researchers

1. *AI Literacy*: The starting point for researcher’s AI capability is AI literacy. This entails a basic understanding of how large language models (LLMs) like ChatGPT. By this, we mean functional understanding, not an elaborate grapple with the technical architecture of LLMs. This foundational, functional knowledge engenders an

understanding of the limitations of LLMs, and how they continue to evolve. These include challenges relating to AI hallucinations, algorithmic bias, and data dependency. With regard to hallucinations, LLMs generate responses by predicting likely word sequences, which can lead to plausible-sounding but entirely false information. Furthermore, because LLMs learn from historical data, they can replicate and reinforce biases embedded in the datasets they are trained on. In effect, their performance is shaped by the quality and scope of training data, making outputs highly dependent on available data that may be incomplete, ethically questionable, or even incorrect—thus reinforcing the need for continuing oversight and supervision by the researcher.

2. *Prompt Engineering*: In generative AI applications for research, the quality of outputs is directly influenced by the quality of the prompts provided. We highlighted examples of this in the previous chapters. Crafting clear, precise, and well-structured prompts is essential to elicit accurate, relevant, and insightful responses. Poorly phrased or vague prompts can result in generic, off-topic, or misleading outputs that compromise the integrity of the research process. For example, asking “Explain climate change” may yield superficial results, whereas “Summarise three key policy responses to climate change in sub-Saharan Africa since 2010” prompts a more targeted and useful response. Researchers must also iterate prompts based on task complexity and refine them through feedback to enhance specificity and relevance. Understanding this prompt-response dynamic is a crucial skill for using AI effectively and responsibly in scholarly contexts. Interestingly, for this particular competency, researchers can only learn how to use AI by actively engaging with it. It is therefore reasonable to say that one’s knowledge of AI is directly proportional to the extent to which they use AI tools.
3. *Critical Evaluation*: Even with good prompts, researchers should not take generative AI outputs hook, line, and sinker. Critical evaluation is essential to ensure the accuracy, relevance, and scholarly integrity of AI-generated content. Researchers must carefully assess whether outputs align with established academic standards and detect errors, misinterpretations, or potential biases. For example, when asked to summarise a historical event, AI might generate a coherent narrative but omit key contextual factors or misattribute quotes—errors that could compromise academic credibility.

A researcher trained in critical evaluation would cross-check facts, assess sources, and revise outputs accordingly. This vigilance not only protects the quality of research but also ensures ethical accountability. AI can assist, but it cannot replace the researcher's responsibility to uphold rigour, nuance, and scholarly depth throughout the research process. It is the researcher that holds authorial responsibility, not the generative AI tool.

4. *Ethical Awareness*: The need for continuous critical evaluation is interlinked with the importance of ethical awareness. This skill is not merely peripheral; it is central to ensuring that AI technologies are used responsibly, fairly, and in alignment with both legal and professional standards. Ethical awareness involves the capacity for ongoing critical evaluation, especially in contexts where AI-generated content, data-driven decisions, and automated processes intersect with human values, academic integrity, and societal norms. It is important to note that we cannot discuss ethical awareness without also considering the broader concept of responsibility. Researchers must use AI responsibly, an obligation that is both personal and intrinsic, involving professional judgement about what one should or should not do with AI tools. At the same time, ethical awareness is contextual, requiring knowledge of the laws, frameworks, and policies that govern AI use in specific settings. These regulations can vary significantly across contexts, institutions, and publication environments. For instance, the ethical expectations surrounding AI-generated content may differ based on the policies of a particular journal publisher or the internal guidelines of a research organisation. In this regard, ethical awareness is an essential competency for any researcher engaging with AI.
5. *Research Design Insight*: Technology serves as an enabler in research, and this is no less true for generative AI. Like a catalyst in a chemical reaction, AI can significantly accelerate processes, enhance productivity, and support analytical thinking. However, just as a catalyst requires an existing reaction to act upon, AI requires a well-conceived research design to be effective. It cannot create the foundational thinking that precedes it.

At the heart of effective research lies a deep understanding of research design, the capacity to frame questions, define problems, and select appropriate methodologies grounded in both context and purpose. This is a human intellectual process, shaped by social

reasoning, contextual judgement, and philosophical orientation. While AI can assist in synthesising these activities, it cannot replace the critical thinking and adaptability required to craft a coherent, context-sensitive research design. This is where the researcher's role becomes irreplaceable, and the need to develop the foundational research design skill becomes non-negotiable. Designing research involves thinking through with questions of ontology (what is real?), epistemology (how do we know it?), and axiology (what values influence our inquiry?), these are philosophical foundations that inform methodological choices and determine how knowledge is pursued. These elements are dynamic, disciplinary, and evolving in response to research contexts.

Moreover, the interconnectedness of these philosophical and methodological dimensions often requires researchers to “stitch together” different approaches and perspectives in creative, reflexive ways. These interpretive and integrative skills are core to what makes a researcher a researcher. They cannot be outsourced to AI, which, while powerful, is bound by algorithms and lacks human intuition, contextual awareness, and ethical discernment. In essence, AI may enhance the efficiency of research, but it cannot substitute the insight and interpretive agility required in research design.

6. *Interdisciplinary Fluency*: This remains one of the most essential and emerging skills for researchers. Interdisciplinary fluency can be regarded as the ability to navigate, integrate, and apply concepts, methods, and perspectives from multiple disciplines to address complex problems. By design, genAI tools are trained on vast, diverse datasets that include knowledge from fields as varied as computer science, philosophy, law, education, medicine, art, and the social sciences. As such, researchers using these tools must possess the capacity to critically engage with information beyond their own domain of expertise to recognise, interpret, and meaningfully apply ideas from adjacent or even distant disciplines. Moreover, interdisciplinary fluency supports collaborative research environments, where teams increasingly consist of individuals from different disciplinary backgrounds (e.g., data scientists, ethicists, domain experts). Researchers must be able to translate and integrate diverse vocabularies, conceptual frameworks, and evidence standards to produce coherent and impactful research outcomes.

This skill becomes even more critical because AI-generated outputs may blend disciplinary assumptions without clearly delineating them. Misinterpretation of cross-disciplinary content can lead to misuse or superficial applications of AI-generated insights. Therefore, interdisciplinary fluency empowers researchers to interpret AI-generated content critically, adapt insights to context, and ensure responsible and relevant application. It also enables a more nuanced understanding of how AI might reproduce biases or overlook key perspectives that a more singular disciplinary approach might miss.

7. *Communication and Translation*: As research becomes increasingly interdisciplinary (and technologically mediated as with the responsible use of AI), the ability to clearly communicate complex ideas, methodologies, and findings across a wide range of audiences through diverse means and platforms is essential. With the rise of GenAI tools that can generate text, visualisations, and data-driven insights, researchers are now required not only to interpret and validate AI-generated content but also to effectively translate these outputs into meaningful narratives for various stakeholders, be it policymakers, collaborators, or the public. The value of GenAI lies not just in what it can produce, but in how researchers critically engage with, adapt it, and use it appropriately for targeted communications. Therefore, a researcher's ability to bridge the gap between machine (AI) output and human understanding is fast becoming a core competency in the digital research landscape.
8. *Continuous Learning and Adaptability*: Researchers can no longer rely solely on static expertise or fixed disciplinary knowledge; instead, they must cultivate a mindset of lifelong learning—one that embraces curiosity, openness to change, and intellectual humility. The pace of advancement in AI technologies, particularly Generative AI (GenAI), demands that researchers stay consistently abreast of new tools, platforms, and capabilities, while also critically engaging with the broader implications of their use. This includes keeping up with evolving ethical considerations such as algorithmic bias, data privacy, and responsible AI governance, as well as recognising the increasingly fluid boundaries between disciplines. Adaptability, in this situation, goes beyond merely adjusting to new tools; it reflects the ability to proactively evolve one's methods, thinking, and collaborations in response to a dynamic research landscape. Whether it involves integrating GenAI into literature reviews, data

analysis, or creative synthesis; reconfiguring methodologies in light of automated capabilities; or navigating interdisciplinary collaborations shaped by digital platforms, researchers must be ready to reimagine their roles and responsibilities.

In a GenAI-enabled research ecosystem, the capacity to continuously learn, unlearn, and re-learn becomes foundational, not just to remain competent and relevant, but to thrive as a future-ready scholar. Those who embrace this mindset are more likely to lead innovation, adapt to uncertainty, and contribute meaningfully to knowledge production in a world shaped by rapidly evolving landscape.

8.4 OPEN SCIENCE IN THE AGE OF AI

Open science and artificial intelligence (AI) are converging in ways that appear to reshape the production, validation, and dissemination of knowledge across disciplines. The rapid uptake of AI tools, particularly LLMs and other GenAI systems, has initiated a shift in how research is conceptualised, conducted, and communicated. We have shown in earlier chapters that AI affordances are increasingly embedded in research workflows—and are likely to become even more integral over time. AI tools are now being applied across the entire research cycle, from literature review and hypothesis generation to data collection, analysis, writing, and dissemination. The increasing application of AI in research both advances and complicates the core ideals championed by the open science movement: transparency, accessibility, reproducibility, collaboration, and inclusivity.

The promises of AI include democratising access to complex research tools, reducing technical barriers, increasing the efficiency and scale of scientific inquiry, and facilitating collaborative work. At the same time, its perils, such as opacity, algorithmic bias, and uneven access to computational resources, pose real challenges to equity and epistemic justice. The implications are not merely technical but also ethical and philosophical. This section draws on insights from the broader arguments developed throughout this book, to critically assess the intersection of AI and open science. It explores how GenAI can reinforce or challenge open science principles—not simply as a suite of technical tools, but as an evolving research ethos. The discussion moves beyond the affordances of AI to

examine how it may amplify, reformulate, or even jeopardise the open science agenda in contemporary academic practice.

Framing Openness in the AI Era

Open science and GenAI are not inherently aligned, but they are increasingly intertwined. If left unexamined, AI tools may accelerate existing inequities in science under the veneer of innovation. Yet, if used critically and ethically, they can reinforce the ideals of transparency, accessibility, reproducibility, collaboration, and inclusivity that lie at the heart of open science. As demonstrated in earlier chapters, GenAI can support many aspects of research; however, researchers must remain vigilant stewards of both method and meaning. They must view openness not merely as access to content, but as active participation in a shared, auditable, just, and equitable process of knowledge production. In other words, in the age of AI, open science is no longer just about what is shared; it is about how knowledge is produced, who is included in producing it and what values guide its production. To understand how GenAI may strengthen or undermine this vision, it is useful to revisit the foundational principles that define open science. Table 8.1 presents a selection of AI-enabled tools that support each of these principles.

Transparency

One of the central tenets of open science is transparency—making processes, methods, and data accessible and auditable. AI tools can facilitate this in several ways. As already demonstrated in earlier chapters, LLMs can generate structured code for data processing, summarise workflows, and produce visualisations with clear explanatory notes. These capabilities make it easier for researchers to document and share their methods, especially when embedded in notebooks, scripts, logs, or automated reports. Moreover, AI-assisted research design lends itself to open methodologies. For example, when hypotheses are generated or refined using ChatGPT, and when literature reviews are structured with the help of Elicit, every prompt and output can be logged and shared. Such records support reproducibility and open peer review by revealing how AI shaped early research decisions. Yet, the inherent opacity of AI models presents a fundamental paradox: how transparent can research truly be when it relies on tools whose inner workings remain largely inscrutable?

Table 8.1 AI-powered tools that support open science

<i>Theme</i>	<i>Tools</i>	<i>Functionality, Access, URL</i>
Transparency	Jupyter Notebooks Code Ocean	Interactive computing and documentation (Free/Open) Executable research capsules with version control (Freemium)— https://codeocean.com
Accessibility	Elicit SciTranslate	AI-powered literature review and reasoning assistant (Free)— https://elicit.org Scientific translation tool for global researchers (Freemium)— https://scitranslate.org
Collaboration	Overleaf Authorea	Collaborative LaTeX writing tool (Freemium)— https://www.overleaf.com Collaborative manuscript writing and preprint publishing (Freemium)— https://www.authorea.com
Reproducibility	GitHub Binder	Code and data version control (Free)— https://github.com Create executable environments from code repositories (Free)— https://mybinder.org

Source ChatGPT 4o

Accessibility

Open science also seeks to democratise access to scientific knowledge and tools. GenAI can help bridge gaps for researchers in low-resource settings or those without formal training in statistics, programming, or systematic review methods. As highlighted in earlier chapters, AI can generate code, translate technical jargon into plain language, and simulate datasets or research instruments for learning and replication—all without requiring specialised software or infrastructure. These benefits are particularly salient in postcolonial or underrepresented contexts, where access to proprietary tools is limited. AI thus extends the ethos of open science from access to articles towards access to methods, analytics, and scientific participation itself. Yet, this promise of accessibility is not without its contradictions. When access to powerful AI tools is itself gated by computational resources, proprietary models, non-trivial subscription costs or linguistic and cultural biases embedded in training data, the goal of democratising science may be subverted. In such cases, what appears as inclusion may merely replicate old exclusions in new, algorithmic forms; and it raises the question of whether true accessibility is possible when

the tools of access are unevenly distributed or unevenly attuned to diverse epistemic worlds.

Reproducibility

Reproducibility—the possibility for other researchers to replicate the findings of a study using the same data and procedures—is perhaps the most fundamental standard of scientific rigour. GenAI can enhance reproducibility by generating consistent code, automating data pipelines, and producing logs of the steps involved in data coding, transformation, or analysis. However, reproducibility also depends on transparency about how AI tools were used. Without access to the specific prompts, models, versions and processing parameters employed, reproducing AI-assisted research may be impossible. To uphold open science values, researchers may deliberately deploy GenAI to document and share their AI workflows, including datasets, model specifications, prompt libraries, and version histories. This will enable not only technical replication but also critical scrutiny of how AI influenced the study design and interpretation. In this way, GenAI can support a richer and more accountable culture of reproducibility, particularly when embedded within responsible research practice. Still, the reliance on GenAI introduces a deeper epistemic tension: how reproducible can research truly be when some of its core processes are mediated by systems that are themselves difficult to replicate or even fully understand? If reproducibility rests on the ability to trace and reapply methods, then the opacity, variability and proprietary nature of many AI models may erode the very conditions that make scientific claims verifiable. In this light, the challenge is not only to document AI use, but also to confront what it means to reproduce knowledge in an age when part of its production is shaped by agents that neither think nor reason, but compute.

Collaboration

Collaboration, another principle of open science, is often facilitated through shared platforms, data repositories, and collaborative writing tools. AI adds a new dimension to this by acting as a silent co-author or research assistant. There is no argument that researchers now routinely use GenAI to brainstorm ideas, structure arguments, design methods, and prepare figures. This raises questions about authorship, attribution, and intellectual responsibility. Should AI-generated code be cited? Should prompt logs be included in appendices? Open science frameworks must

evolve to accommodate the hybrid agency of human–machine collaboration. It is undoubtedly important to ensure that the collaborative processes AI enables do not obscure human accountability. Yet, as AI becomes an ever more integrated collaborator, it unsettles long-standing assumptions about what it means to work together in the production of knowledge. When machines contribute to intellectual labour without intention or consciousness, the very notion of collaboration begins to shift—from a shared human endeavour to a distributed process of co-creation across fundamentally different agents. The task for open science is not only to clarify responsibility, but also to reimagine collaboration itself: not simply as joint authorship, but as a new kind of epistemic relationship that demands transparency, reflexivity, and ethical foresight.

Inclusivity

Brings together the above principles of open science. By definition, inclusivity implies the broadest possible participation in the creation, validation, and dissemination of knowledge. GenAI offers both opportunities and risks in this regard. On one hand, it can help diversify academic engagement by lowering technical and linguistic barriers, thereby enabling researchers from underrepresented regions and institutions to contribute meaningfully to global research conversations. For example, AI-driven writing aids and translation tools can assist non-native English speakers in articulating their ideas more fluently and accessing a wider range of literature. On the other hand, if not critically managed, GenAI may inadvertently reinforce epistemic exclusions—by privileging dominant paradigms, replicating biases embedded in training data, or marginalising alternative knowledge systems. Ensuring inclusivity, therefore, requires deliberate efforts to design and deploy AI tools in ways that foreground diverse perspectives, support epistemic justice, and amplify voices historically sidelined in scholarly discourse. It also requires a deliberate shift away from helicopter science, a practice that may be amplified by AI tools. In the context of open science, genuine inclusivity means resisting the urge to make all knowledge fit a single, standardised model shaped by algorithms. Instead, it calls for embracing the richness, context, and diversity of knowledge traditions from across the world.

Tensions and Challenges of Open Science

Ultimately, what is at stake in the encounter between GenAI and open science is not just the optimisation of research tasks, but the shaping of research values. The affordances of AI invite us to reconsider foundational questions: What does it mean to participate in science ethically and inclusively? Who has the authority to frame problems and validate solutions? As open science evolves in the age of AI, it must not only adapt its protocols but also reaffirm its commitments to justice, epistemic humility, and collaborative knowledge creation. Openness, in this sense, is not just a matter of access, but a stance towards how knowledge is produced, shared, and situated in society. In this context, three issues must be acknowledged and addressed: the black-box problem, concerns over data privacy, and epistemic inclusion.

The Black-Box Problem

Despite its utility, GenAI can also undermine transparency. Many AI models operate as black boxes: they generate outputs based on abstract representations of training data, with limited interpretability. This obscurity complicates the documentation of analytical decisions and weakens the auditability of research processes. In open science, where every decision should be traceable, this is a critical limitation. Researchers must therefore adopt practices that compensate for this lack of clarity. This includes sharing prompts, AI-generated code, and rationale statements for automated choices. It also requires critical reflection on when AI should or should not be used in analytical workflows.

Data Privacy and Openness

Open data is important to open science; thus, transparency about data generation, anonymization, and use of AI must be integral to any open science protocol. As earlier mentioned in Chapter 4, many datasets (particularly in health, education, and social policy) contain sensitive personal information. The use of AI complicates the trade-off between openness and privacy. GenAI models trained on sensitive data may inadvertently reproduce identifying information or biased patterns. Emerging solutions like synthetic data generation and differential privacy, often implemented with AI support, offer partial remedies. However, researchers must navigate the tension between making data openly available and protecting the privacy and rights of individuals represented

in that data. This balance is particularly challenging because legal and ethical requirements vary across jurisdictions—for example, the European Union’s General Data Protection Regulation (GDPR) emphasises individual consent and data minimisation, while California’s Consumer Privacy Act (CCPA) focuses on consumer rights and transparency. As a result, researchers working across borders must carefully consider which rules apply, how to implement them responsibly, and what trade-offs openness may entail.

Bias, Fairness, and Epistemic Inclusion

AI systems are only as unbiased as the data they are trained on. If those datasets underrepresent certain regions, genders, or epistemic communities, then AI-generated outputs will reproduce those imbalances. This is not merely a technical flaw; it threatens the normative goal of open science to make knowledge production more inclusive. Even in research design, GenAI may amplify mainstream theories and methods while overlooking alternative or indigenous paradigms. Researchers have a responsibility to recognise and counter the biases that AI tools may introduce. This means using these tools thoughtfully and in varied ways, rather than relying on default settings or mainstream datasets alone. It also involves being transparent about how prompts are crafted, what kinds of outputs are generated, and how those outputs influence the research process. Such transparency allows others to scrutinise and challenge the role of AI in shaping knowledge claims. Then, and only then, can real collective progress in equitable open science be achieved.

Best Practices and Future Directions for Open AI-Driven Research

Broadly speaking, the discourse so far suggests that the integration of GenAI into research practices raises questions about how core scientific norms (such as authorship, peer review, and methodological accountability) may be redefined in subtle but profound ways. A critical task for the open science community, therefore, is not only to make AI workflows transparent and auditable, but also to reflect collectively on how such technologies may reconfigure what counts as legitimate knowledge and who is recognised as its producer. Against this background, we provide some specific suggestions on how researchers, institutions, and scholarly communities can adapt their practices to ensure that the integration of GenAI aligns with the foundational commitments of open science.

Emerging Best Practices

Aligning the use of GenAI with the principles of open science requires both methodological rigour and ethical reflexivity. First and foremost, researchers should document their use of AI tools with care. Maintaining a log of prompts—particularly those used in research design, literature review, and data analysis—ensures that others can trace the logic behind decisions and reproduce results with fidelity. Alongside prompt logging, researchers are encouraged to create versioned outputs. Draft hypotheses, visualisations, or analytic scripts generated with GenAI should be archived at different stages in open repositories, allowing others to track the evolution of a research project and understand the role AI played in shaping it.

Another emerging best practice is the use of explainability tags. These are annotations that help clarify the rationale behind AI-generated outputs, flag corrections made by human researchers, and offer interpretive notes where appropriate. Such tags make the use of GenAI tools more transparent and support collaborative learning. Closely linked to this is the need for ethical disclosure. Researchers should clearly and explicitly state where, how, and why GenAI tools were used in any publication or research output. At the time of writing, a growing number of academic journals and book publishers have begun to require such disclosures as part of their submission guidelines. This reflects a broader shift towards greater transparency and accountability in AI-assisted scholarship.

As GenAI becomes a routine partner in academic workflows, researchers should engage in collaborative reflexivity. Co-authors, reviewers, and broader research teams must evaluate the appropriateness of AI use at each stage, questioning not just the outputs but the assumptions that guide them. Open science in the AI era also demands tools that facilitate accountability. Where feasible, automated systems should be deployed to check reproducibility and detect potential biases in AI-generated analyses, serving as a form of open validation. Examples of such systems include Code Ocean, or use of GitHub actions in open peer review pipelines).

Anticipated Transformations

Looking ahead, several trends are likely to reshape how AI supports open science. Journals and funders may introduce embedded transparency frameworks, requiring researchers to disclose AI usage alongside data

availability and ethics statements. Peer review may increasingly include GenAI-powered tools that assist in verifying code, replicating statistical analyses, or scanning for methodological inconsistencies. These developments will require clear protocols to ensure AI augments rather than replaces human judgement in evaluative processes. Moreover, GenAI tools hold significant promise for enhancing multilingual accessibility. Translation models can open scientific content to non-English-speaking researchers and readers, reducing linguistic barriers that have long skewed global knowledge exchange. At the same time, the development of equity-by-design AI, that is, models trained with diverse data sources and sensitive to epistemic variation, will be critical. These systems should aim to amplify underrepresented voices and knowledge systems rather than reinforce existing disparities. To support these transformations, institutions must go beyond technical training. They should invest in interdisciplinary education that includes ethical, social, and epistemological dimensions of AI use in research. Infrastructure must also evolve to support open-source AI development, promote international collaboration, and create mechanisms for peer feedback on GenAI-integrated research.

8.5 CONCLUDING THOUGHTS

As we bring together the key points of reflection in this book, it is evident that generative AI is not merely a passing innovation, but a transformative force reshaping how research is conceived, conducted, and communicated. This book has explored AI's wide-ranging capabilities—from literature synthesis to data analysis and dissemination—while also underscoring the enduring necessity of human judgement, critical reflection, and scholarly integrity. The central message is clear: AI should be neither idolised nor feared, but understood, evaluated, and harnessed. As tools of cognitive augmentation, generative AI systems offer unprecedented potential to enhance the research process. Yet, their effectiveness is not automatic. It depends on the researcher's capacity to guide, supervise, and apply these tools with discernment and ethical awareness.

Across the chapters in this book, we have argued for a future in which human researchers are not displaced by intelligent machines, but redefined and empowered through collaboration with them. The modern researcher must evolve, not into a technician, but into an adaptive knowledge leader who bridges disciplinary boundaries, curates

prompts, questions outputs, and communicates research meaningfully. This reinvention is not an erosion of scholarship, but its revitalisation. It involves reclaiming time and attention for high-level conceptual work by delegating routine, typically time-intensive, tasks to AI. In doing so, researchers are not outsourcing their intelligence, but extending it. They are sharpening the skills that define rigorous inquiry: framing problems, making ethical choices, interpreting complexity, and engaging with the world through ideas.

At the same time, this transformation demands a new kind of literacy, an awareness of what AI can and cannot do, and how it may subtly shape what we take to be knowledge. It also calls for collective reflection on the systems of power, access, and inclusion that AI tools may reinforce or disrupt. As we have shown in our discussion on open science, the convergence of generative AI and research practice is as much about values as it is about tools. It challenges us to redefine transparency, rethink collaboration, and reimagine inclusivity in a digitally mediated knowledge economy.

In the end, the future of research will not be determined by the capabilities of AI alone, but by the wisdom with which human researchers use them. The central question is not whether AI will transform academia—it already has—but whether that transformation will deepen or diminish our shared pursuit of knowledge. This book offers a hopeful but cautious answer: the path forward lies not in replacing researchers, but in retooling them. With the right capabilities, ethical commitments, and collaborative mindset, researchers can lead the next chapter of knowledge production, one that is not only faster and more powerful, but also more just, reflective, and profoundly human.

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