BRITISH ACADEMY OF MANAGEMENT

Charting the Future:

Responsible Generative AI for Research

WHITE PAPER

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Note

This White Paper references certain commercial AI tools, platforms, and web services solely to illustrate concepts and provide examples. We do not endorse or recommend any specific product or provider, and all mentions are for informational purposes only. Product capabilities, availability, and terms may change over time; readers should conduct their own due diligence and consult institutional policies before selecting or using any tools. Any trademarks or brand names remain the property of their respective owners.

The principles and practices outlined in this White Paper extend to the use of AI and including its variants like generative AI tools (and platforms) in the business and management research.

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MESSAGE FROM THE CHAIR

Professor Emma Parry
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One of our most significant challenges in academia currently is how to deal with the growth and increasing functionality of artificial intelligence (AI). Many of us have struggled to understand how we can best use AI to create efficiencies, improve the quality of our research, teaching and assessment and reduce the burden of an ever-increasing amount of admin. The feedback that we received from our members was that they needed support not only to understand how to use the technology, but also to navigate its use in a way that is ethical and responsible.

With this in mind, we agreed that one of the strategic priorities of the British Academy of Management (BAM) (2024-2028) would be to support the sector in addressing the challenges brought by AI and digitisation. We are developing a range of initiatives in this area: one of which is the launch of a white paper series that aims to provide rigorous evidence and case study examples of how AI might be used in academia, alongside practical guidance to help academics to use AI responsibly. Through this series we hope to both support academics to use AI effectively but also to shape the global conversation on responsible and ethical AI adoption for academic and research communities.

This white paper is the first of the series, focusing on the responsible use of AI in research. It represents an enormous effort in bringing together the evidence in this dynamic field and distilling this to provide practical guidance for our community. I would like to thank the authors for their hard work and for creating such an informative and comprehensive paper to start our series.

I hope you find the paper useful and interesting. We recognise that the field of AI in research is moving quickly and would like this paper to be the start of a conversation. We are therefore keen to hear your thoughts relating to the use of AI in research and education. Please get in touch and share your experiences so that we can all support our community in addressing the challenges and benefit from the opportunities that AI brings.

THE WHITE PAPER

AI will not replace humans, but those who use AI will replace those who don’t”.

Ginni Rometty, Former CEO of IBM

This white paper adopts the OECD's (2024a) definition of AI: "An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.

Different AI systems vary in their levels of autonomy and adaptiveness after deployment". This definition covers technique families such as machine learning and knowledge-based methods, and application areas including computer vision, natural language processing, speech recognition, intelligent decision support, and robotics, alongside their novel uses across domains. Within this, GenAI refers to a category (variant) of AI that creates new content (e.g., text, images, video, and music), using text-to-image models and large language models (LLMs) (OECD, 2024b).

With AI technology and its evolving variants like GenAI tools and services rapidly transforming higher education academic research (e.g., Fernandes & Mason, 2025), the urgency for a purposeful ethical framework to use AI responsibly in research has never been greater. Responsible AI use is not simply about regulatory compliance or risk management; it is a moral imperative and a strategic cornerstone for preserving the integrity and rigour of scholarly advancement.

The aim of this white paper is to lead a critical dialogue to not only guide researchers and institutions through the evolving AI and GenAI landscape but also set the benchmark for ethical excellence and rigour in business and management research while using AI. To achieve this, amidst ongoing debates on the responsible application of AI throughout the research process, from ideation to publication and peer review, this paper illuminates the path forward by focusing on the following interrelated pivotal themes.

1. **Responsible AI research scholarship**
2. **Navigating risks and unlocking the benefits of AI in research**
3. **Drawing the boundaries for the use of AI in research**
4. **Responsible AI principles for research – the 'REINFORCE' framework**
5. **The road ahead – emerging challenges and boundaries**

We delve into each theme to highlight the main developments, provide a critical analysis of the current state of affairs and, where possible, prescribe a way forward. At times, we only pose questions to guide future debate and further reflection.

The White Paper puts forward a series of recommendations for the responsible use of AI in research. Their effective implementation will require sustained commitment from all stakeholders - researchers, institutions, decision-makers, policymakers, and those responsible for developing and maintaining supporting infrastructure. It also warrants collective effort to broaden the knowledge base and foster a shared sense of responsibility at every level. While some of these recommendations may, at present, appear challenging, particularly as these are not yet on the immediate radar of scholars or institutions, the intent of the White Paper is both forward-looking and anticipatory. Its purpose is to prepare the research ecosystem for the opportunities and risks that lie ahead by forecasting emerging needs and proposing proactive strategies to address them.

1. RESPONSIBLE AI SCHOLARSHIP

1.1 Case for Responsible AI Use in Research

For researchers, responsible AI scholarship aims to diligently utilise AI technologies by bearing in mind their legal, moral-ethical, socio-cultural and environmental implications for its related stakeholders. Responsible AI use in research are principles that will drive ethical, transparent, and scientifically rigorous integration of artificial intelligence across the research lifecycle (European Commission, 2025; Infosys Knowledge Institute, 2025a, Papagiannidis et al., 2025; International Standards Organization, 2024; World Economic Forum 2024a; 2024b; UNESCO, 2022).

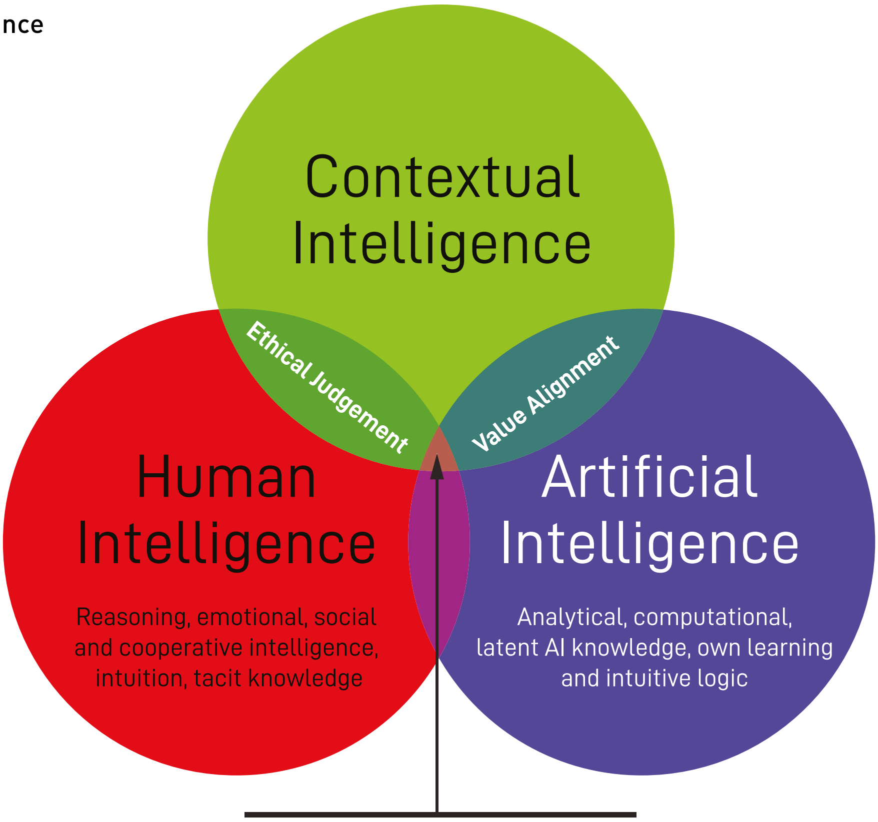
Researchers must uphold established standards of accuracy, validity, and reproducibility while leveraging AI's capabilities. Responsible AI requires ethical awareness of potential social, cultural and ecological impacts, ongoing assessment and improvement of AI integration, full transparency regarding AI tools and methodologies, and meaningful engagement with all relevant stakeholders. By adopting this approach, AI-augmented research can advance knowledge, protect human rights, and serve the broader interests of society, and eventually of the planet.

As the field of AI continues to evolve (e.g., new and sophisticated GenAI tools are being released), in order to consistently push for responsible use of AI in research, we first consider how different forms of intelligence - human, artificial, and contextual, interact, and then propose a consideration for the concept of "responsible collective intelligence" (RCI), emerging from the interplay of the above mentioned three intelligences, fits within the broader landscape (as shown in Figure 1).

Responsible Collective Intelligence integrates the three key domains: Human Intelligence, Artificial Intelligence, and Contextual Intelligence. Human intelligence (of the researcher) captures natural cognitive abilities such as reasoning, emotion, and tacit knowledge (Budhwar et al., 2023). Artificial intelligence includes computational and data-driven capabilities. The contextual intelligence represents the ethical, cultural, societal, and environmental contexts in which intelligence operates.

The overlaps between these domains highlight essential concepts: the intersection of human and artificial intelligence forms cognitive collaboration, where machines and humans work synergistically; the overlap of human and contextual intelligence gives rise to ethical

Figure 1: Responsible Collective Intelligence



Responsible Collective Intelligence =
Human learns from AI + AI learns from Human + Ethical Judgement + Value Alignment

judgment, emphasising the role of societal and ethical values in human decision-making; and the intersection of AI and contextual intelligence leads to value alignment, which ensures AI systems operate in accordance with human values like fairness, transparency, and accountability. At the centre of all three lies RCI, a dynamic convergence of human cognition, machine capability, ethical judgement and value alignment. This shifts the narrative from simple human-AI interaction to a more holistic, context-sensitive, and ethically grounded form of intelligence that will support responsible decision-making in research. Therefore, a framework for responsible AI use in research guidelines and practices must address not just how humans and AI collaborate, but also how both are influenced by, and responsive to, the contexts in which research takes place. By holistically integrating these domains, the framework will ensure that research outcomes are robust, trustworthy, and aligned with ethical standards, ultimately fostering innovation that is both effective and socially responsible, and upholds academic integrity.

The proliferation of AI in academic research offers powerful services and tools for data analysis, literature synthesis, and content generation, yet their unguided application poses significant risks (Messeri & Crockett, 2024). This rapid expansion has been driven not merely by technological merit, but also by AI hype cycles and bandwagon effects that characterise technology adoption in academia. Researchers have been proactive in debating the negative consequences of these tools, though such discussions often lag behind adoption patterns and may themselves be subject to academic fad and fashion cycles that prioritise specific concerns over others (Chowdhury et al., 2024).

The challenge is compounded by what appears as 'AI washing' and inflated valuations which can incentivise startups, investors, and shareholders to push for rapid adoption, in the absence of commensurate frameworks for responsible use.

This pattern of adoption-first, followed by debate, and governance-later tends to create particular risks in academic contexts, where the stakes involve not only research integrity but also the formation of future scholars and the production of knowledge that influences policy and practice.

Therefore, this context requires the development of overarching frameworks and guiding principles for responsible AI use in business and management research scholarship that can withstand the volatility of technological fads while safeguarding integrity, honesty, and genuine progress (The Guild of European Research-Intensive Universities, 2024). Such frameworks must be designed to counteract the bandwagon and 'fad and fashion' effects that lead to uncritical adoption of AI tools simply because they are popular or widely discussed, while simultaneously avoiding the opposite trap of reflexive resistance to potentially beneficial innovations. The framework development process itself must be insulated from academic fashion cycles that might prioritise certain principles or approaches based on their novelty or alignment with contemporary discourse rather than their practical effectiveness in ensuring responsible AI use.

1.2 Significance of Responsible AI Scholarship in Research

The emergence of an attribution economy has fundamentally transformed scholarly publishing, where AI's ability to remix and repurpose existing research scholarship blurs lines of originality, increasingly complicates traditional notions of authorship, threatens intellectual property, and academic credit as well as honesty (So, 2025). Current detection systems struggle with high false positive rates and inconsistent performance across different AI models, creating an overwhelming burden on human reviewers who must manually verify the authenticity of academic work. This detection challenge is exacerbated by the combination of open access publishing and AI proliferation, which has created an unprecedented volume of potentially AI-generated content that requires human labour-intensive scrutiny. Perhaps most critically, the fundamental question emerges whether increased production through AI tools genuinely translates to meaningful progress in business and management research scholarship and contribution.

Research suggests a concerning 'production-progress paradox', where exponential growth in publication volume has coincided with stagnating or declining rates of genuine scientific advancement across all disciplines (Kang et al., 2024; Kapoor & Narayanan, 2025). The risk that AI might enable researchers to produce more while understanding less threatens the core epistemological foundations of academic inquiry, potentially creating monocultures of knowing that narrow rather than expand intellectual horizons. Without responsible AI frameworks for researchers that address transparency, accountability, human oversight, and the preservation of scholarly integrity, business and management research risks becoming overwhelmed by quantity at the expense of quality, authenticity, and meaningful contribution to knowledge. Such frameworks must balance the productivity benefits of AI tools with the fundamental academic values of originality, critical thinking, and genuine intellectual advancement that drive scientific progress. Later in this paper, we present a framework to fill this gap.

1.3 Mitigation Mechanisms for Unethical AI Use in Research

As AI capabilities continue to expand across all research domains, the potential for both transformative advancement and significant harm has grown exponentially, and hence a balanced perspective of AI use is necessary (Aharonson et al., 2025). The challenge lies not merely in developing technological solutions, but in creating comprehensive frameworks that address the complex intersection of technical, ethical, and human factors that govern responsible AI use by business and management researchers (Brown et al., 2024). Current approaches to mitigating AI misuse in research often operate in isolation, with institutions implementing disconnected policies for training, governance, and oversight that fail to provide researchers with coherent

guidance for navigating the evolving landscape of AI-assisted research. This fragmented approach is particularly problematic given the diverse needs of researchers at different career stages, from doctoral students conducting their first independent research to established scholars managing complex funded projects (Knight et al., 2024).

The European Research Area Forum (2025) recommends that research organisations actively monitor the evolution and use of GenAI systems within their institutions, providing training for all career levels and disciplines while promoting an atmosphere of trust where researchers can transparently disclose AI use without adverse consequences. Furthermore, institutions should implement locally hosted or cloud-based AI tools, governed by human beings to ensure data protection and maintain control over research processes.

Comprehensive training programmes represent a critical mechanism for preventing AI misuse by building researchers' capacity for responsible AI use (AAUP, 2025). These programmes must address multiple dimensions of AI literacy, including technical understanding of how AI systems work, awareness of inherent biases and limitations, and knowledge of ethical implications. The European Commission's guidelines emphasise that research organisations should provide training on verifying AI output, maintaining privacy, addressing biases, and protecting intellectual property rights. Effective training approaches should incorporate hands-on experience with AI detection tools, ethical reasoning frameworks, and transparent disclosure practices. Educational interventions should also focus on developing critical thinking skills that enable researchers to distinguish between legitimate AI assistance and


AI

inappropriate substitution of human intellectual work. Universities must integrate responsible AI education into existing research integrity training, ensuring that all researchers understand both the opportunities and constraints associated with AI use in their specific disciplinary contexts.

Transparency mechanisms serve as fundamental safeguards against unethical AI use while promoting accountability in research practices. Research institutions and funding organisations could mandate explicit disclosure requirements that specify when, how, and to what extent AI tools have been used in research processes. These disclosure requirements must go beyond simple acknowledgement to include detailed descriptions of AI's role in different research phases, from literature review and hypothesis generation to data analysis and manuscript preparation.

The University of Illinois exemplifies best practice by requiring researchers to clearly disclose AI use in content creation, specify potential biases introduced by AI tools (for example using instruction-tuned LLMs – Infosys Knowledge Institute, 2023b, comparing outputs for diverse input data points), and detail how AI tools are implemented in research workflows. Researchers will need training to understand and implement methods that will help to detect, report and rectify bias in AI-generated outputs.

Transparent disclosure should also extend to peer review processes, where reviewers must be informed about AI assistance to enable appropriate evaluation of research contributions. Such transparency requirements help maintain the integrity of scholarly communication while enabling the research community to develop collective wisdom about appropriate AI applications.

Most journals and their publishers have initiated initial steps in this regard. While these individual mechanisms represent important steps toward responsible AI use in research, the academic community must move beyond siloed approaches to develop comprehensive, overarching frameworks that consolidate guiding principles and provide coherent direction for researchers across all career stages and research contexts (e.g., Floridi & Cowls, 2022). The complexity of AI's role in modern research requires integrated guidance that helps early-career researchers, doctoral students, postdoctoral fellows, mid-career academics, and established scholars understand not only how to use AI tools responsibly, but when and why certain applications are appropriate or problematic within different phases of the research lifecycle.

Such frameworks must address the unique challenges and pressures faced by researchers at different career stages: doctoral students navigating academic integrity expectations while building foundational skills, postdocs balancing productivity demands with methodological rigour, and established researchers managing complex funded projects with multiple stakeholders and accountability requirements. For instance, the NIST AI Risk Management Framework (2023) and similar initiatives (UK Government, 2023) provide valuable models for creating comprehensive approaches that integrate technical standards, ethical principles, and practical guidance.

However, these frameworks must be specifically adapted for the research context, incorporating disciplinary differences, institutional variations, and the distinctive epistemological values that govern scholarly inquiry. The development of these overarching frameworks represents not merely a technical challenge, but a fundamental responsibility to future generations of researchers who will inherit the academic culture and standards we establish today.

2. NAVIGATING RISKS AND UNLOCKING BENEFITS

Building on the concerns highlighted above related to the misuse of AI to support research, below we focus on the increasing use of AI in quantitative and qualitative research and the benefits and risks this poses, using selected illustrative examples. While AI offers numerous use cases, we focus on specific new issues emerging from distinct research designs and/or methods.

2.1 Benefits and Risks for Quantitative Research

Synthetic Data

AI is transforming academic research not just AI is transforming academic research not just by refining scholarly writing, but by refining and disrupting the quantitative methods used across the social sciences. Fields like marketing and management are now experimenting with silicon samples, entirely artificial (synthetic) datasets generated from real-world information using LLMs (Sarstedt et al., 2024). These synthetic datasets are designed to replicate the statistical features of genuine data closely, promising enhanced privacy and robust anonymisation while minimising the risk of exposing confidential records, and substituting human participants (Demszky et al., 2023). Despite exponential data growth, up to two-thirds of it goes unused due to poor accessibility and quality. These challenges are fuelling rapid adoption of synthetic data, which is expected to surpass real data volumes in enterprises by 2030 (e.g., Infosys Knowledge Institute 2023a).

Proponents argue that synthetic data can accelerate research, promote open science through easier sharing, and mitigate privacy concerns (Wang et al., 2024; Manning et al., 2024). However, one primary concern is that the technology enabling synthetic datasets can also facilitate new forms of data manipulation and fabrication. Unlike traditional research misconduct, which can often be uncovered by reviewing original data and analytic procedures, synthetic datasets may sever the connection to their real-world origins, making fraud far harder to detect (Bechky& Davis, 2025). Further, as artificial samples find their way into the training sets of future AI models, distinguishing between authentic and synthetic information becomes ever more difficult (Bechky & Davis, 2025). This continual recycling risks a critical threshold: as the proportion of synthetic data grows, the reliability of AI systems may erode, leading to data contamination and model collapse, where AI systems lose touch with social reality and begin to propagate fundamentally distorted representations of the world (Shumailov et al., 2024).

Finally, synthetic data tends to inherit and occasionally magnify the biases and blind spots embedded in the original data. If underrepresented populations are missing from the source, artificial datasets will replicate or even exaggerate these exclusions, all while creating the illusion of diversity. This can mask persistent inequalities and present a façade of representativeness that does not genuinely exist (Jordon et al., 2022). The increasing reliance on deep learning methods further complicates matters; as models become more opaque, tracing results back to either real-world processes or synthetic generation steps becomes almost impossible, compounding concerns about accountability.

These issues are not merely theoretical. In high-stakes areas such as healthcare or law, substituting synthetic for real data without robust safeguards can endanger lives and justice, respectively (Susser et al., 2024). Additionally, synthetic data is capable of creating convincing but entirely fictitious cases or individuals, which might facilitate misinformation, undermining the reliability of scientific knowledge and confusing public discourse.

Finally, an overreliance on artificial data could erode the motivation to gather fresh, empirical data from the world. As synthetic data proliferates and becomes entrenched, the foundation of empirical research may weaken, creating a feedback loop in which studies are increasingly disconnected from lived reality (Shumailov et al., 2023).

In summary, while AI-driven synthetic data offers powerful opportunities for efficiency and privacy in research, it also presents profound ethical and epistemological challenges that demand careful, ongoing scrutiny. This reflects the broader tension between innovation and integrity in the evolving landscape of digital science.

Psychometric Scale Development

When conceptualising new constructs and developing psychometric scales, a rigorous qualitative process forms the essential foundation for valid and reliable measurement. This process starts with a careful definition of the construct, grounded in a thorough review of existing literature and robust theoretical frameworks. The next critical step involves crafting items that capture the essence of the construct, again drawing from both scholarship and expert judgment. Crucially, these items are then refined through qualitative studies such as interviews or focus groups with people from the relevant context, ensuring the scale reflects real-world meanings and experiences (for details see Hinkin, 1995). This iterative process of contextualisation and empirical refinement is indispensable for developing robust measurement tools.

Against this backdrop, the increasing use of LLMs to generate items for psychometric scales introduces both opportunities and serious challenges. While LLMs offer efficiencies and creative breadth, their outputs cannot substitute for the intellectual contributions of expert researchers, particularly in the nuanced work of construct conceptualisation and contextual adaptation.

Automated item generation may accelerate scale development, but it will bypass critical steps such as extensive theoretical integration, contextual relevance, and direct human feedback, all of which are vital for ensuring that a scale genuinely measures what it intends to. Moreover, AI-generated items often lack empirical grounding; their apparent plausibility masks the absence of rigorous testing for clarity, relevance, or validity. LLMs may produce questions/statements that look credible yet are inconsistent, ambiguous, or irrelevant to the construct at hand.

A grave concern is the risk of amplifying biases embedded in the data on which LLMs are trained, resulting in items that unintentionally reflect or reinforce stereotypes, be they gendered, racial, or cultural. This not only threatens the fairness of assessments but also raises significant legal and ethical issues. In summary, while LLMs may offer valuable support in the initial generation of psychometric items, they cannot supplant the fundamental contributions of human expertise and the rigorous empirical validation central to the discipline of psychometrics. Safeguarding validity, fairness, and contextual relevance demands that expert judgment, empirical testing, and transparent methodology remain at the core of scale development regardless of the tools employed. Robust safeguards, empirical scrutiny, and adherence to established best practices are critical if AI is to be integrated responsibly into the psychometric toolkit.

Data Analysis and Interpretation

GenAI offers considerable promise for enhancing the research process, particularly in data analysis (Delios et al., 2025). By enabling streamlined analysis of complex datasets and suggesting appropriate analytical strategies based on research questions and data types, AI can help researchers accelerate their analytical workflows. Natural language interfaces allow users to interact intuitively with these tools, facilitating the exploration of patterns, hypothesis testing, and the interpretation of statistical outputs. These capabilities also extend to producing well-structured reports and interpretations, further supporting the research process.

However, the effectiveness of GenAI responses (output) depends heavily on the quality and clarity of user inputs. Clear, precise, and contextually relevant prompts are essential, poorly formulated queries can yield inaccurate, overly broad, or misleading analyses. Users must also have enough domain expertise to critically evaluate and validate the outputs, since AI models themselves lack genuine understanding of methodological rigor or ethical standards. Several key concerns arise with the integration of GenAI in the research process, particularly data analyses. Poorly crafted prompts and insufficient user expertise can result in flawed analyses or uncritical acceptance of AI-recommended methods.

There is also a risk that AI-generated interpretations may oversimplify complex statistical relationships or be accepted without sufficient scrutiny. Additionally, biases present in an AI's training data can be perpetuated in its analytical suggestions, reinforcing existing issues within research contexts. GenAI inherently lacks nuanced understanding of research context, theoretical frameworks, and disciplinary subtleties—elements vital for proper data interpretation.

Reliance on AI for data analysis introduces ethical and epistemological challenges related to academic integrity, transparency, and reproducibility. Researchers must therefore disclose their use of AI and thoughtfully assess how its outputs shape their findings. Finally, while the convenience and speed of AI tools are attractive, they may lead users to bypass rigorous methodological scrutiny, resulting in superficial or compromised research practices. Furthermore, AI tools may struggle to handle specialised, qualitative, or multimodal data that require intricate, human-centred judgment.

2.2 Benefits and Risks for Qualitative Research

Data Extraction and Synthesis

The potential of AI tools for qualitative research is large. As a data extraction and synthesis tool, AI has the potential to both scale and significantly accelerate time-consuming steps of data selection and reduction through coding, as well as offering potential support for analysis of qualitative data (Decker, 2025b). Here, the benefits could be analogous to the introduction of VisiCalc (Excel's predecessor) and other spreadsheet software for quantitative researchers: it removed the most tedious part of many jobs It allowed staff in quantitative data analysis roles like accountants to move on to more strategic and creative tasks (Harford, 2019, 2025).

Another aspect of qualitative practice that is relevant to all researchers, regardless of approach, relates to both monitoring for, and abstracting relevant contributions to the literature in a field, on a topic or a theory. While much of the hype around AI agents is countered by privacy, safety and data security concerns, automated literature search and summarisation AI agents

can use de facto public online information on academic publishing, obviating security concerns. Few academics have research assistants on permanent call to monitor the literature for them, and here agents can potentially improve the quality and efficiency of academic research. Tools such as Research Rabbit, Semantic Scholar and many others may become as central to literature review practices as citation management software such as Endnote, Zotero and Mendeley already are. Here, AI tools may function like research assistants or "team mates" (Mollick, 2025) – engaging with, questioning and double-checking results. Research suggests that AI integration should focus not on replacing human work but flexibly switching or blending human and AI-led tasks (Dell'Acqua et al., 2023).

Reflecting on the Risks

Employing AI tools for qualitative research is clearly still at an emergent stage and it is difficult to predict the practices and applications that will become more dominant over time. However, some of the potential risks of an extensive adoption of AI by qualitative researchers are now becoming clearer. While there are valid concerns about AI use leading to more shallow engagement with content and tasks, it is clear that the issue is the amount of attention that is paid when AI replaces human voice, thinking and writing (Bauschard, 2025; Kosmyna et al., 2025). For qualitative research approaches, which are predominantly based on a deep understanding of the material underpinning the study, this is an obvious risk.

Kapur and Narayanan (2025) argue that "AI could short circuit the process of building human understanding, which is essential to scientific progress". Reflecting on the rapidly increasing number of publications, they call this the "production-progress paradox"; drawing on meta-science they argue that while the number of papers are increasing, attempts to measure ideas and scientific progress suggest this is slowing down. AI helping academics to publish more quickly is not going to address the underlying issues, but it may also be contributing to the issues as one potential explanation for the slowing progress of innovation, which misdirects efforts into the wrong directions, disproving existing approaches, as well as too much time spent on synthesising existing work.

Alongside the substantial efficiency gains that AI tools create in the writing and publication process, academics face an open access environment that incentivises academic publishers to produce greater volume for commercial gains, leading to a perfect storm not just in terms of academic misconduct but also further ratcheting up expectations in terms of the volume of publications expected from academics (Decker, 2025a). This dynamic could exacerbate workload pressures, erode time for deep scholarship, destabilise work–life boundaries, amplify stress and burnout risk (for early-career researchers, who feel acutely the pressure to publish frequently to remain competitive). These effects directly undermine academic wellbeing, and signals the need for responsible AI use in research, and institutional safeguards that protect time for impactful and meaningful scholarship.

Clearly, these are even more fundamental issues for qualitative researchers, who use methodological techniques such as data reduction, tables and diagrams to create confidence in their results as much as an aid for their understanding of the underlying data. Increasing the volume of published articles employing qualitative methods without improving the understanding of the areas under investigation could significantly undermine the important role of qualitative research in the knowledge production of business and management.

Good research allows problems and questions to be reframed and adjusted by conceptualising phenomena and critically evaluating existing theoretical assumptions. A key risk of adopting AI tools for qualitative analysis is "the illusion of understanding", creating more closed and less interdisciplinary knowledge communities (Messeri & Crockett, 2024). Mollick similarly cautions against "going on autopilot … falling asleep at the wheel" when using AI tools (Mollick, 2023). For a multi- and interdisciplinary field such as business and management, the risks are perhaps even greater than for the sciences. Going forward, such concerns ought to be addressed also as part of doctoral and early career researchers' training.

3. DRAWING THE BOUNDARIES: PERMISSIBLE, PROHIBITED, AND GREY ZONES

As AI rapidly reshapes scholarly publishing, navigating its opportunities and pitfalls has never been more urgent or more complex. The first section below focuses on how leading academic publishers are responding, adapting their policies and workflows to harness AI's potential while safeguarding the core values of scientific integrity and ethical authorship. Shifting the focus from the institutions to individual researchers, the second section unpacks the subtle boundaries and unresolved questions surrounding everyday AI use in academic writing and research. It sheds light on the real-world challenges, shifting attitudes, and new possibilities unfolding in the global research community.

3.1 Stance of Publishers

Leading academic publishers including Springer Nature[1], Wiley[2], Taylor & Francis[3], and Emerald Publishing[4], share a clear stance on the use of AI in research and scholarly publishing. Across these organisations, AI systems and generative tools cannot be credited as authors since authorship entails legal and ethical accountability that only humans can assume. All the four mentioned publishers require authors to disclose any use of AI in manuscript preparation, data analysis, or editing, typically in the acknowledgments and/or methods section. They universally prohibit publishing AI-generated images, figures, or original research data, citing unresolved legal, ethical, and integrity concerns. The use of AI by peer reviewers and editors is strictly regulated or forbidden when it may compromise confidentiality or scholarly standards, and none of the publishers permit GenAI to review or generate confidential content. These publishers emphasise that their policies are living documents, regularly updated to keep pace with advances in AI technologies and evolving research norms. While minor, disclosed use of AI for language refinement or similar non-substantive edits is sometimes acceptable,

[1] https://www.springernature.com/gp/policies/editorial-policies
[2] https://www.wiley.com/en-fr/terms-of-use/ai-principles
[3] https://taylorandfrancis.com/our-policies/ai-policy/?_ga=2.42081125.1713326521.1754579885-1205133758.1754579885
[4] https://www.emerald.com/ijhg/article-pdf/29/3/193/9614632/ijhg-09-2024-163.pdf

any substantial reliance on AI requires explicit disclosure and editorial approval. Furthermore, publishers such as Wiley and Springer Nature use in-house AI tools to enhance editorial workflows (e.g., improve author experience, plagiarism detection or reviewer matching), but always under human oversight.

Journal editors are increasingly encountering instances where human peer reviewers use AI tools to evaluate manuscripts. This trend raises significant concerns. First, many AI review tools require uploading unpublished manuscripts to third-party platforms, which is problematic because it typically occurs without the explicit, informed consent of the original authors (Mollaki, 2024). This not only risks breaching confidentiality but may also inadvertently contribute to the training of these AI models using sensitive, proprietary research data (Naddaf, 2025). Second, automated tools can produce superficial or generic peer review reports that lack the critical, specific feedback needed to improve scholarly work, provide developmental feedback, ultimately diminishing the value of peer review itself (Naddaf, 2025).

Publishers should prioritise collaboration over competition to jointly develop robust policies and invest in technologies that effectively identify AI-driven reviews. Similarly, editors from different journals can come together to consolidate diverse perspectives that will help to establish some guidelines and best practices consistently (which are more than a check-box exercise), promoting transparency, ethical conduct, and consistency in the peer review process. Such cooperative efforts are essential for upholding the integrity of academic publishing through responsible use of AI in editorial and review process.

However, access to these tools almost always comes at a cost, which risks entrenching substantial disparities within global research communities (Heeks, 2022). Universities and institutions in developed countries, or well-funded schools with extensive library subscriptions, are far more likely to afford the latest AI-powered review and verification services. By contrast, researchers from the Global South or institutions without such resources face significant barriers, not only in publishing and peer review quality but also in safeguarding their intellectual property (Global Research Council, 2025; Capraro et al., 2024). This creates a growing digital and opportunity divide, reinforcing patterns of inequality in academic knowledge production and dissemination (Aldirdiri, 2024). As AI tools continue to evolve over the coming years, the true value they bring to peer review and research integrity remains to be seen; it is equally important to ensure that equitable access and ethical oversight are at the forefront of policy development and adoption.

3.2 Permissible Boundaries and Grey Areas

There is a broader discussion about how and where AI is acceptable in the preparation of a journal manuscript, which is perhaps more developed than the evolving consideration of employing AI as part of the research process. Nature published the result of an authors and reviewers survey on attitudes towards AI use, which highlighted not just diverging attitudes towards different tasks, but also generational differences among scientists (Kwon, 2025).

Acceptance is highest for AI as editing support, improving clarity and flow of drafts written without AI assistance. Far less acceptable is, using AI for initial drafting of research papers, though among different sections, the abstract is least controversial (23 per cent consider it appropriate, 45 per cent with an AI disclosure and 33 per cent against AI use).

The newer researchers are to academia, the more likely they are to use AI to edit their papers. Most critically viewed is AI in support of peer review activities, with an overwhelmingly negative response (78 per cent), not even considering using AI for peer review. Nevertheless, tools designed for peer review, even if primarily marketed at authors preparing for submissions, such as Paper Wizard and imitators, have been launched and are likely to transform practice (Naddaf, 2025).

However, what perhaps most noticeably emerges from the Nature survey is the overall low numbers of academics willing to disclose their AI use at all, even in the least controversial use case of editing: only between 10-12 per cent of those indicating having used AI for editing disclosed it, vs. 18 per cent indicating use without disclosure. This suggests that in the absence of clear guidance and norms for AI use in the research process, most scholars are wary of the stigma associated with AI use.

The International Association of Scientific, Technical and Medical Publishers (STM) has outlined a range of manuscript preparation tasks with an indication of what would constitute acceptable and unacceptable uses (STM Association, 2025). Wiley, the publisher of BAM's journals and the largest scholarly society publisher, recently provided a more wide-ranging study of the use cases that matter to researchers beyond the preparation of manuscripts (Wiley, 2025). This survey indicates that our community of business and management researchers are among the most likely to have already adopted AI in their research process (55 per cent, second only to Computing Sciences at 57 per cent).

Wiley's report presents a variety of use cases in terms of a familiar two-by-two matrix organised by current AI capability and researcher interest. Many of the popular use cases where AI capabilities are adequate are effectively those of a research assistant: monitoring literature in the research area, populating citations, automated processing of unstructured data, and creating plain language summaries for the dissemination of existing work. The report is particularly interesting when it comes to AI use cases for the research process before publications. In the research process, they identified some data collection and processing tasks, especially the automated processing of unstructured data (such as cataloguing video data), monitoring and summarising new publications in the subject area, and reviewing large amounts of studies (Wiley, 2025).

New AI-driven tools (web platforms) such as Paper Wizard[5] have emerged that claim to process data securely promising never to share users' data or incorporate it into future training cycles, and offering users the option to delete their submissions permanently. Despite these improvements, vulnerabilities remain; for instance, some researchers have experimented with embedding covert signals in their manuscripts to manipulate AI-generated reviews, highlighting both the limitations of artificial intelligence and the irreplaceable role of expert human oversight in assessing scientific rigour, authenticity, and novelty (Tetzner, 2024). Additionally, advanced platforms like those developed by Grounded AI[6] offer sophisticated citation checking and integrity verification, supporting researchers, reviewers and editors (identifying hallucinated citations and references) in evaluating quality and authorship as the volume of publications is increasing at pace.

A lot of these use cases reflect on the uses of AI in core academic activities. There is less information on academics using AI for the many other pedestrian chores that are part of their work but decidedly more generic (though still remarkably time consuming): email, engaging with many university processes requiring documentation, as well as many forms of applications and cover letters of all types. Wiley's survey (2025) included researchers' expectations of AI being commonly accepted to handle administrative tasks. Potentially the biggest advantage of AI for academic research may lie outside of research applications by reducing the amount of time and mental effort spent on the many ways in which academic productivity being audited and evaluated.

[5] https://paper-wizard.com/
[6] https://groundedai.company/

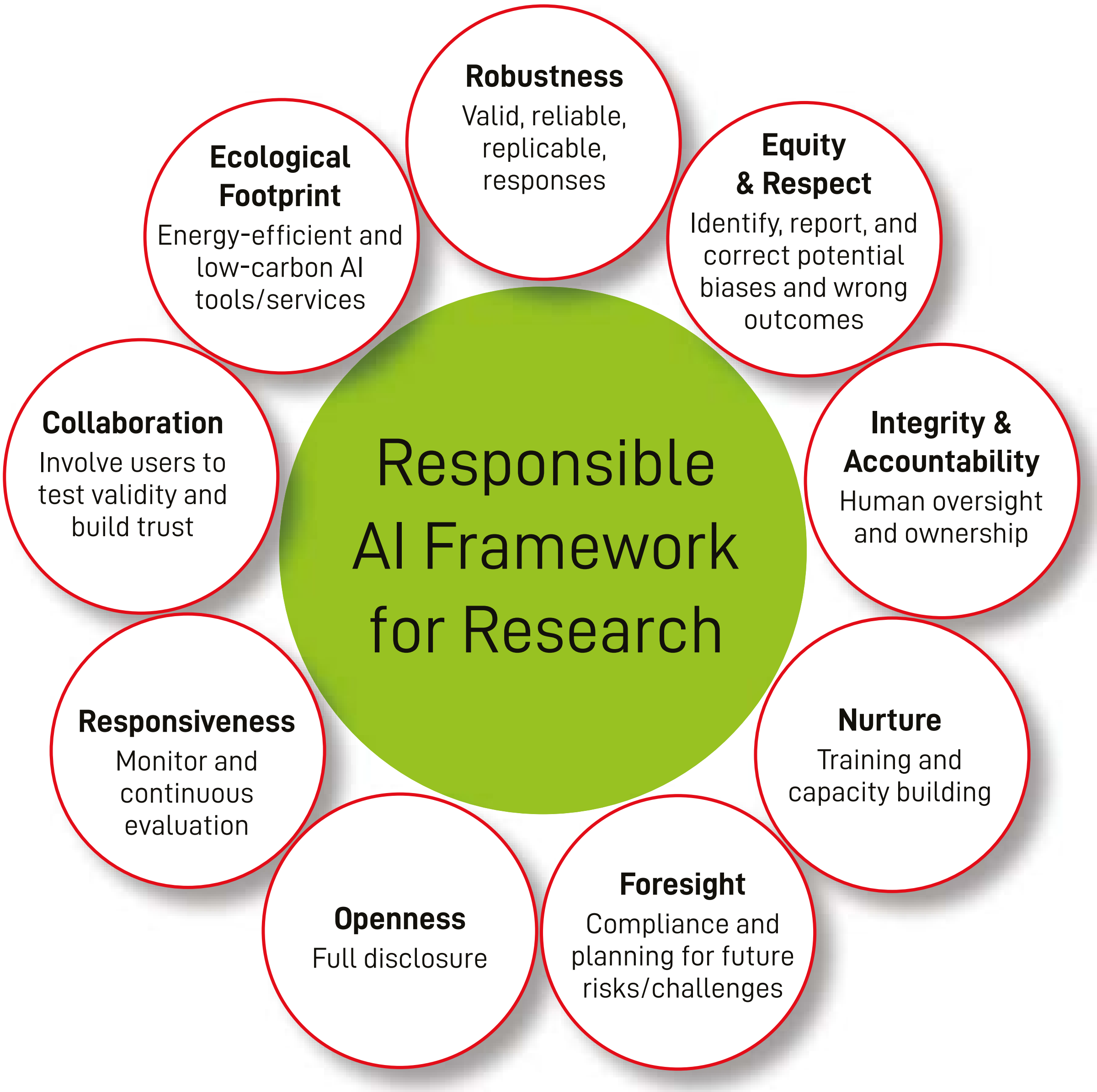
4. RESPONSIBLE AI PRINCIPLES FOR RESEARCH – THE **REINFORCE** FRAMEWORK

To support the creation of responsible AI-driven scholarship, we present the REINFORCE framework (**see Figure 2**) comprising nine key principles. These principles have been developed based on recommendations by internationally recognised responsible AI guidelines, frameworks, and best practices proposed by leading bodies and agencies, including the European Commission's Ethics Guidelines for Trustworthy AI (2022)[7], France AI Hub[8] (2024), the OECD's Principles on AI[9], the NIST AI Risk Management Framework, European Research Area Forum guidelines on responsible generative AI in research, UNESCO ethics in A[10], the embassy of good science[11], guidance published by Medical Research Council, UK[12], UK's AI Regulatory Principles[13],[14], UK Ethics, Transparency and Accountability Framework for Automated Decision-Making[15], Responsible AI principles and framework published by Infosys[16], Microsoft's[17] and Google's Responsible AI Principles[18], and guidelines for the responsible use of GenAI in research (e.g., Porsdam Mann et al., 2024).

The *REINFORCE (Robust, Equity, Integrity, Nurture, Foresight, Openness, Responsiveness, Collaboration, Ecological Footprint)* framework for responsible AI in business and management research does not simply prescribe a static checklist; rather, it is designed to dynamically support and enhance ethical practice throughout all phases of the research lifecycle. Below we present the main principles, how they can be operationalised in practice and some illustrative examples.

[7] https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai
[8] https://www.inria.fr/en/trustworthy-ai-europe
[9] https://verityai.co/blog/oecd-ai-principles-global-implementation-guide
[10] https://www.unesco.org/en/artificial-intelligence/recommendation-ethics
[11] https://embassy.science/wiki/Main_Page
[12] https://www.ukri.org/wp-content/uploads/2024/10/MRC-25102024-Interim-MRC-guidance-AI_software-v1.6.pdf
[13] https://assets.publishing.service.gov.uk/media/65c0b6bd63a23d0013c821a0/implementing_the_uk_ai_regulatory_principles_guidance_for_regulators.pdf
[14] https://www.gov.uk/government/publications/ai-regulation-a-pro-innovation-approach/white-paper
[15] https://www.gov.uk/government/publications/ethics-transparency-and-accountability-framework-for-automated-decision-making/ethics-transparency-and-accountability-framework-for-automated-decision-making
[16] https://www.infosys.com/iki/perspectives/responsible-ai-design-principles.html
[17] https://www.microsoft.com/en-us/ai/principles-and-approach
[18] https://blog.google/technology/ai/responsible-ai-2024-report-ongoing-work/

Figure 2: The REINFORCE Framework for Responsible AI Driven Research



Principle 1: **Robustness**

Researchers are expected to ensure that AI-assisted findings at any research stage are valid, reliable, replicable, non-fabricated, and non-plagiarised.

For example, validity can be verified by checking sources cited in the text; reliability by using practitioner approaches like perplexity, BLEU, or ROUGE scores (Infosys Knowledge Institute, 2023b); and replicability by testing the AI model with a wide variety of similar inputs. These practices could ensure that AI outputs are trustworthy and transparent throughout the research process.

Principle 2: **Equity & Respect**

In absence of suitable training, researchers are encouraged to actively identify, report, and address potential biases in training data and AI-generated outputs, by examining outcomes across diverse datasets that represent varied populations. This process could help to prevent the perpetuation of unfairness or discrimination, including both false positives and false negatives.

Researchers must ensure that all data and materials used to train or run AI models comply with copyright and intellectual property laws, including proper attribution and adherence to licensing agreements, particularly when analysing published research manuscripts.

During data collection, researchers must clearly inform participants about how and when AI will analyse their data, specifying the tools, capabilities, limitations, risks, and any third-party data sharing (especially when using AI web services). Participants should have opportunities to ask questions and make informed decisions.

Principle 3: **Integrity & Accountability**

Researchers must ensure AI systems remain under meaningful human control, with authority to intervene or halt AI operations as needed. In this context, researchers are accountable for analysing the authenticity of research outputs and interpreting the results, critically evaluating AI-generated content and retain ownership of all research decisions.

For instance, during the data analysis stage, researchers are encouraged to monitor AI-generated results for anomalies and intervene to correct errors or misclassifications. They critically review the outputs, verify their authenticity, and remain accountable for all research interpretations.

Illustrative Example

A PhD student uses ChatGPT to draft a research methods section but thoroughly reviews the validity and accuracy of the text, citing only verifiable and authentic information linked to the text, and clarifies in the paper how the AI was used, ensuring the student (not the system) is responsible for the final content's accuracy and originality.

Principle 4: **Nurture**

Researchers are expected to take personal initiative and adopt a proactive approach to building AI literacy and ethical awareness.

This should include continuously updating their knowledge by engaging in training programmes and self-directed learning, keeping pace with evolving AI technologies, tools, and understanding emerging ethical challenges of AI use in research.

This could also take the form of mandatory training provided by academic institutions.

Principle 5: **Foresight**

Researchers are encouraged to stay compliant and plan for what-if situations, adjusting research trajectories as new ethical, legal, or societal issues arise (when working with trans-national teams and/or cross-border data). In this context, researchers could:

- Stay current with evolving laws like the GDPR and AI Act, ensuring their AI research practices meet the latest legal standards, including strict data privacy, transparency, and security requirements.
- Develop alternative methods or backup protocols to quickly adapt research practices without compromising compliance or integrity.

Illustrative Example

A research centre is conducting a longitudinal study using AI to analyse financial transaction data from retail banks in several countries. Anticipating new amendments to cross-border data rules and stricter AI transparency obligations, the team holds periodic reviews of regulatory guidance and consults with legal advisors. They develop scenario plans for this proactive approach to protect research validity, ensure compliance, and could also help maintain stakeholder trust.

Principle 6: **Openness**

Researchers are expected to clearly describe how, when, and why AI tools were used in their research, including which systems and settings were applied, and what types of outputs were generated.

They are also encouraged to share decision-making workflow, software scripts, and (de-identified) data when legally permissible and ethical, using repositories like GITHUB. This will help other researchers to learn and build confidently upon published work.

Illustrative Example

An academic journal article presents a systematic literature review on digital transformation in organisations using GenAI for literature search and synthesis. The authors should explicitly state why and how AI is used. All code (and/or output files) for AI-driven analysis, search and analysis protocols and de-identified reference datasets should be made accessible through open repositories. The paper should provide a supplementary appendix documenting all workflows and human checks, so that others can fully re-run the review from scratch.

Principle 7: **Responsiveness**

In future, researchers are likely to develop and train their own instruction-tuned LLMs or AI assistants tailored to specific research tasks.

When using such customised models, researchers are encouraged to:

- Monitor the performance of the LLM over time (e.g., accuracy and relevance of the outputs, against set ground truth and established benchmarks).
- Engage in adaptive correction by retraining and fixing errors, and transparently maintaining a changelog of all modifications to ensure ongoing reliability and research integrity.

Illustrative Example

An academic team is conducting a three-year study using AI to predict foresight based on annual CEO letters from thousands of companies around the world. They could set up a dashboard to automatically flag anomalous predictions across years or geographies (monitoring). When AI misclassifies for instance, certain culturally specific idioms, the research team investigates, retrains the model with new examples to fix the error, and maintains a changelog.

Principle 8: **Collaboration**

Business and management researchers are encouraged to involve end users (e.g., academic scholars, employees, managers, customers, and communities, amongst others) to ensure the validity and relevance of AI-driven outcomes, and build trust with the project stakeholders and beneficiaries. This engagement is vital when:

- Developing new ideas.
- Constructing research frameworks from literature reviews.
- Generating synthetic data that mirrors real-world phenomena.
- Analysing data and interpreting results.

Traditional validation methods, including focus groups and interviews, can be employed to authenticate findings and enhance the legitimacy of the research process.

Illustrative Example

A research team uses AI to analyse employee feedback after a major organisational change. Once the AI processes and flags key themes, the researchers invite both HR managers and employee representatives to jointly review and interpret the AI response. Input from employees ensures results reflect lived experience, while insights from managers and academic scholars will add policy and theoretical context.

Principle 9: **Ecological Footprint**

Researchers are encouraged to minimise the ecological footprint of AI use at any stage of research by:

- Comparing candidate models/tools/services on accuracy and energy consumption.
- Adopting online AI tools and/or services that use green energy (sustainable AI operations, Infosys Knowledge Institute 2024), and contribute to green projects (e.g., carbon offsetting).

This information could be included in manuscript's methodology section (or funding application), demonstrating how choice of model/AI tool aligns with ecological impact considerations.ownership of research decisions.

Significance of Responsible AI Principles & Research Stages

To offer guidance on how researchers can utilise each of the above presented principles at different stages of research, we logically map each stage of the research process to the most relevant responsible AI principles **(see Table 1)**.

Table 1: Relevance of Responsible AI Principles to Different Stages of Research

Stage	Relevant Principle (P)	Rationale
Idea Initiation	P1: Robustness; P3: Integrity & Accountability; P5: Foresight; P9: Ecological Footprint	**Robustness** ensures that AI-generated research ideas are valid and reliable through proper verification methods. **Integrity and accountability** require researchers to maintain ownership over research decisions and critically evaluate AI-suggested concepts rather than blindly accepting them. **Foresight** involves anticipating potential ethical implications and societal impacts of the research direction from the outset. **Ecological footprint** consideration is important when choosing AI tools and approaches that minimise computational resource consumption during the exploratory phase.
Literature Review	P1: Robustness; P2: Equity; P3: Integrity & Accountability; P6: Openness	**Robustness** is critical for ensuring AI-assisted literature searches produce valid, reliable results that can be verified through source checking and consistency measures like BLEU or ROUGE scores, as mentioned in the framework (and also suggested by practitioners). **Equity** ensures comprehensive and unbiased coverage of literature across different perspectives and demographics. **Integrity and accountability** require researchers to verify the authenticity of AI-generated summaries and maintain responsibility for citation accuracy and intellectual property compliance. **Openness** demands transparency in documenting search strategies, AI tool usage, and any limitations in the review process.
Theory Development	P1: Robustness; P3: Integrity & Accountability; P4: Nurture; P8: Collaboration	**Robustness** will ensure theoretical constructs generated with AI assistance are logically consistent and can withstand scrutiny through multiple validation approaches. **Integrity and accountability** are essential as researchers must retain ownership of theoretical insights and critically evaluate AI-generated theoretical frameworks. **Nurture** requires continuous learning about emerging theoretical developments and AI capabilities in theory building. **Collaboration** facilitates peer review and collective validation of AI-assisted theoretical development to enhance rigour.
Research Design	P1: Robustness; P2: Equity & respect; P3: Integrity & Accountability; P5: Foresight; P9: Ecological Footprint	**Robustness** will ensure that research designs are methodologically sound and can produce reliable results through proper validation mechanisms. **Equity** requires consideration of fairness, bias prevention, and inclusive participant representation in AI-assisted design decisions. **Integrity and accountability** involve compliance with legal standards (GDPR, AI Act) and maintaining human oversight over design choices. **Foresight** anticipates potential risks and unintended consequences of the research approach. **Ecological footprint** will consider the computational and resource efficiency of planned AI applications.
Data Collection	P2: Equity & Respect; P3: Integrity & Accountability, P6: Openness; P1: Robustness and P8: Collaboration	**Equity** ensures representative and unbiased data collection practices, avoiding systematic exclusions or discriminatory sampling when using AI tools. **Integrity and accountability** require strict adherence to copyright laws, intellectual property rights, proper attribution, and licensing agreements as emphasised in the framework, particularly when analysing published research manuscripts. **Openness** demands transparent documentation of data collection methods, AI tool usage, and any limitations or constraints encountered during the process. If using/generating synthetic data, **collaboration** will help ensure robustness and credibility of the data.
Data Analysis	P1: Robustness; P3: Integrity & Accountability; P7: Responsiveness; P9: Ecological Footprint	**Robustness** is crucial for validating AI-generated analytical results using reliability measures such as perplexity, BLEU, or ROUGE scores referred to in the framework. **Integrity and accountability** requires researchers to monitor AI-generated results for anomalies, intervene to correct errors or misclassifications, and maintain critical evaluation of outputs. **Responsiveness** involves comparing candidate models and tools on accuracy and energy consumption, and adapting analytical approaches based on emerging issues or stakeholder feedback. **Ecological** footprint will consider the computational impact of analytical processes.
Data Interpretation	P1: Robustness; P3: Integrity & Accountability; P6: Openness; P7: Responsiveness	**Robustness** will help ensure that interpretations are valid and can be replicated through systematic verification processes. **Integrity and accountability** are paramount as researchers are accountable for analysing the authenticity of research outputs and interpreting results, critically evaluating AI-generated content while retaining ownership of all research decisions. **Openness** requires transparent reporting of interpretation methods and AI assistance used. **Responsiveness** will facilitate adaptive interpretation based on new evidence or stakeholder input.
Write-up Research	P1: Robustness; P3: Integrity & Accountability; P4: Nurture; P6: Openness	**Robustness** will ensure written outputs are accurate, well-supported, and can withstand peer review scrutiny. **Integrity and accountability** requires proper attribution, citation accuracy, intellectual property compliance, and transparent disclosure of AI assistance in the writing process. **Nurture** involves continuous improvement of writing skills and staying current with evolving publication standards and AI disclosure requirements. **Openness** demands clear documentation of methodologies, limitations, and the extent of AI tool usage in manuscript preparation).

5. THE ROAD AHEAD: EMERGING CHALLENGES AND OPPORTUNITIES

As AI and its variants like GenAI mature, it is poised to take on an increasingly transformative role within research and scholarly publishing workflows. Leading publishers like Springer have begun integrating GenAI to produce plain-language summaries, making complex research accessible to broader audiences. Researchers, too, are embracing AI-powered tools such as Notebook LM, to enhance the dissemination of their scientific findings. These platforms can automatically generate rich, multimedia outputs, such as video abstracts and podcast-style audio, from academic manuscripts or notes. This shift is redefining science communication by enabling researchers to amplify their impact with minimal manual effort and reach a wider, more diverse audience. Major academic publishers, including Taylor & Francis, Wiley, and Oxford University Press, are entering extensive licensing agreements with AI companies. Through these deals, AI firms gain access to vast repositories of scholarly articles as training data for LLMs. Since publishers retain the rights to published works, they can permit such uses without needing direct permission from individual authors. As a result, the academic sector can expect the emergence of highly specialized, AI-driven research tools designed to accelerate discovery and foster innovation.

5.1 Enhancing Validation, Translation, and Accessibility

Future AI variants opens new avenues for improving the integrity and inclusivity of academic research and publishing. For reference and content validation, AI models can automatically check manuscripts for fabricated citations, incorrect references, or questionable content, drawing on authoritative databases to ensure accuracy and reliability. This reduces the risk of misinformation and strengthens research credibility.

AI-powered translation tools also promise to democratise access to scientific knowledge by quickly translating research outputs into multiple languages. Beyond mere translation, these tools can create plain-language summaries and simplified versions of research articles, allowing non-specialists and policymakers to meaningfully engage with scientific findings. By breaking down language barriers and enhancing clarity, such innovations broaden the reach and societal relevance of academic work. However, these tools raise critical ethical concerns around accuracy, context, and cultural sensitivity. Mistranslations or oversimplifications can introduce bias or misrepresent findings. To guard against these

14,687
2,653
LC 88.01
PD 52.06

pitfalls, it is crucial to augment AI with expert human oversight, ensuring reviews by subject-matter and language specialists preserve nuance and scientific integrity.

5.2 Transforming Editorial Decision-Making

Customising AI language models for individual academic journals has the potential to revolutionise editorial decision-making. The process could begin by assembling a dataset containing prior submissions, reviewer reports, editorial decisions, and detailed guidelines. These guidelines, covering originality, significance, methodological rigor, and other criteria, are encoded into machine-readable rules, which will enable the AI to align closely with the journal's evaluation standards. Once trained, the AI system can assess new submissions through the lens of a journal's unique criteria, offering preliminary recommendations (such as acceptance, requests for revision, or rejection) complete with rationales grounded in historical editorial decisions. Editors can then use these analyses as the basis for their judgment, ensuring that essential human oversight and contextual interpretation are maintained.

Publishers might be also developing AI-driven tools to help researchers identify the most suitable journals for their work. By analysing manuscript content and methodology, these systems can suggest journals aligned in scope and editorial priorities, providing clear explanations for their recommendations. This guidance can empower researchers to make informed submission choices, increasing the likelihood of successful publication and streamlining the peer review process.

One notable concern is the potential for the AI to inadvertently codify and perpetuate historical editorial biases. For example, if a journal has a track record of undervaluing interdisciplinary work or favouring submissions from specific regions or institutions, the model may learn and reinforce these tendencies, even if the editorial board seeks to change its approach going forward. This baked-in bias could hinder innovation and diversity within published research. Another issue is the risk of overfitting the model to past decisions: journals evolve, adopt new standards, and respond to emerging research areas. Reliance on historical data can make the AI resistant to recognising and valuing truly novel or paradigm-shifting research that doesn't fit prior patterns, potentially stifling scientific progress.

5.3 Implications for Research Assessment and Panel Review

The rapid progression of GenAI also brings new possibilities to the evaluation of research quality, as seen in processes such as the Research Excellence Framework (REF). It is now feasible to encode assessment criteria and historical panel decisions into AI systems, enabling models to objectively evaluate new submissions against established standards. This can help standardise assessments, reduce individual bias, and improve both transparency and efficiency. REF panels could use AI-generated recommendations as informed starting points for calibration and deliberation, providing consistency while preserving the vital role of expert human judgment in final decisions. However, this approach carries risks: rigid adherence to historical evaluation patterns may disadvantage breakthrough research that diverges from established rubrics or norms.

The years ahead promise profound changes across scholarly publishing as AI continues to evolve. While these technologies bring immense opportunities in accessibility, efficiency, and discovery, they also surface new challenges, especially around bias, accuracy, and the preservation of human judgment. Addressing these challenges with rigorous human oversight, transparent guidelines, and continual calibration will be critical to ensuring that the benefits of AI empower the scholarly community while upholding its core values.

CONCLUDING REMARKS

This British Academy of Management's Responsible Generative AI for Research White Paper highlights both the transformative potential and the ethical responsibilities tied to AI adoption in scholarly work. AI and its variants like GenAI offer unprecedented opportunities to enhance efficiency, creativity, and impact across all stages of research, from conceptualisation and literature synthesis to analysis, interpretation, and dissemination.

Yet these benefits can only be realised if underpinned by rigorous REINFORCE principles: robustness, equity, integrity, nurture, foresight, openness, responsiveness, collaboration, and ecological footprint.

At its core, responsible collective intelligence - RCI (see Figure 1) puts human intellect in the loop to calibrate when and how AI outputs are trusted, adapted, or rejected, preserving originality, contextual fit, and epistemic soundness. Researchers must frame constructs, scrutinize AI-generated items, and interpret qualitative insights with reflexivity and domain context, ensuring transparency, documentation, consent, and fairness across all stages while resisting the drift toward volume over value. This human-led, context-aware governance enables cautious ethical judgments aligned with human values, allowing AI knowledge to augment rather than displace scholarly rigor and ensuring that collective intelligence remains accountable, equitable, and genuinely progressive.

Effective integration of AI into research is not simply a matter of technical proficiency and governance, it demands sustained commitment from a broad coalition of actors, including researchers, academic institutions, policymakers, technology providers, amongst others. This entails not only embedding responsible practices into existing workflows but also cultivating shared accountability, expanding collective expertise, and making responsible AI literacy a cornerstone of scholarly culture.

The guidance offered in this White Paper is deliberately forward-focused, anticipating scenarios and challenges that may not yet be visible to many key actors in our wider business and management research ecosystem. Its purpose is to future-proof the research ecosystem, equipping scholars and decision-makers with proactive strategies to harness opportunities, mitigate risks, and ensure that AI serves to advance inclusivity, innovation, and rigour.

As AI and variants like GenAI matures, continuous reassessment of tools, policies, and norms will be essential. By embedding transparency, robust validation, and stakeholder engagement into AI-supported research, the academic community can shape a future where these technologies amplify human judgment rather than replace it, ensuring that progress in AI strengthens the integrity and societal contribution of scholarly work.

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APPENDIX

Appendix 1: List of AI Tools, Their Capabilities and Cautionary Advice

Note: We do not endorse or promote any of the tools listed below. The information is provided solely for educational and informational purposes to help you understand available options and their potential uses. Inclusion in this list does not imply recommendation, certification, or guarantee of accuracy, legality, or fitness for a particular purpose. Researchers should exercise independent judgment, verify details from official sources, and ensure compliance with all relevant institutional policies, licensing terms, copyright laws, and ethical guidelines before using any tool. We have consulted several sources including Gatrell et al. (2024) and Delios et al. (2025) to develop the below list.

Research Stage	Tools	Overview of capabilities	Cautionary advice
Idea Generation	OpenAI Deep Search Claude Gemini Deep Research Perplexity Grok Consensus DeepSeek	Multi-step web research with browsing, reasoning, and citation-backed synthesis based on the prompts provided by the user. **Note** Perplexity is a mash-up GenAI platform which contains all the models (used by other GenAI platforms), except DeepSeek.	• Use multiple tools to cross-validate the content and/or improve and optimise the prompt. • Check the bibliography provided in the output for hallucinated content. • Please select the model (within the tool) which is capable for advanced reasoning and thinking. • Please verify the contextual relevance and fit of the cited references.
Literature discovery, review and Synthesis	Semantic Scholar	Similar to Google Scholar, SCOPUS, Web of Science, includes AI-powered Ask this paper. Elsevier.	• Use institutional subscriptions to research databases like Web of Science (WoS) or Scopus to discover literature. • Before uploading any published or unpublished work to an AI tool or model, consult your librarian and review licensing and fair use policies for compliance. • If using a plugin connected to databases such as WoS, Scopus, or ScienceDirect, especially those that let you query papers with AI, exercise discretion and always verify AI-generated responses for accuracy. • Grey areas exist, for example, open access does not automatically grant permission to upload a paper to any AI tool. • If using your own R/Python code or offline software (not connected to web/cloud services) to analyse text or abstracts, this is generally permissible.
	Research Rabbit	Knows as Spotify for papers. Visualises networks of related research papers, authors, and topics based on your interests.	
	Elicit	Upload multiple papers, and extract key fields to create summaries.	
	PDF.ai	Chat with PD Fs for Q&A, summaries, and extracted answers with citations.	
	SciSpace	Conversational PDF reader to question papers, verify claims, and navigate sections.	
	Notebook LM	Creating reports, mind maps and audio/video overviews from uploaded sources (text, weblinks, Video links etc.).	
	All idea generation tools	Can upload papers, and summarize, ask questions, knowledge synthesis.	

Coding and programming	Open AI, Gemini, Perplexity Grok, Deep Seek, Co-Pilot (especially in Microsoft Excel), Google AI Studio. Tableau, PowerBI, SPSS Modeller	Can generate R or Python code for data cleaning, analysis, visualisation, and presentation of heterogeneous data. Also supports advanced code for synthetic data creation and predictive modelling, with line-by-line explanations and expected outputs. No coding tools, can be used to analyse data (and these also include different AI capabilities, depending on your needs). Visual analytics for interactive dashboards and data storytelling.	• When using generative AI to create code, always cross-validate outputs with multiple tools and test against diverse datasets to check for inaccuracies or bias. • Always explain and justify the logic of any AI-generated code before using it in practice. • Document the origin and edits made to AI-generated code to maintain transparency and accountability. • Never expose sensitive data or credentials. • Be aware that open access or code snippets from public sources do not guarantee ethical or legal right to reuse or redistribute the code in any context.
Writing and Editing	Paperpal Thesify QuillBot Grammarly	AI academic writing assistant for grammar/style, paraphrasing etc. Grammarly also checks from plagiarism and detects patterns within the text often found in AI generated content. All idea generation tools (including Co-Pilot) can also assist in writing and editing.	• While the aim is to improve efficiency and productivity, always verify that the meaning, tone, and intent of the AI-edited text match your original intentions. • Be mindful of plagiarism and copyright issues; verify that AI-generated suggestions don't inadvertently copy protected material. • Re-read in full context after edits; ensure the flow, logic, and overall argument remain coherent and consistent.
Transcription and Translation software	Coral AI Microsoft Office 365	Converts speech to text, if audio is uploaded, also translates to English. Office 365 (Word/PowerPoint) can also generate live transcriptions, and these can be used for translation subsequently.	• Do not submit sensitive, personal, or confidential information unless you are certain the platform will not store or reuse your data. Many services may retain and use your uploads for model training, raising privacy and intellectual property concerns. • AI translations and transcriptions may introduce errors, omit cultural context, or misinterpret technical or field-specific terms. Always verify that the output is accurate and maintains the intended meaning. • AI may hallucinate—generating plausible-sounding but incorrect text. Never accept transcripts or translations without careful human review. • When working with personal data, ensure all processing follows data protection and privacy standards relevant to your country or institution.

Reference management	Zotero (with AI add-ons) EndNote Petal	Open-source reference manager with plugins enabling AI summaries, Q&A, and library search Offers advanced features for organizing large libraries, annotating PDFs, AI-powered tools for summarizing papers and suggesting relevant citations. Offers automatic metadata extraction, advanced search, and AI summarization and translation	• Always verify that every citation points to a real, credible source. • Manually complete or correct missing information in references as needed. • AI tools can sometimes recommend irrelevant, outdated, or non-peer-reviewed content. • Use AI tools as aids, but retain responsibility for the accuracy and integrity of your reference.
AI-generated feedback on your paper	Paper Wizard	Receive feedback on your paper. The platform does not share or allow training on uploaded content and user can delete the uploaded content.	AI-driven or automated feedback is not a substitute for domain expertise. Evaluate its relevance critically.
Citation checking	Grounded AI	Supports editors, reviewers, and authors by making citation verification and fact-checking faster, easier, and more accurate.	Even if an AI tool claims citations are accurate you must personally check. Supplement with manual database searches where needed.

List of Tools (in Appendix 1) and Corresponding Web Links

Tool	Web Link
Claude	https://claude.ai
Consensus	https://consensus.app
CoralAI	https://www.getcoralai.com/
DeepSeek	https://deep-seek.chat
Elicit	https://elicit.com
EndNote	https://endnote.com
Gemini Deep Research	https://gemini.google/overview/deep-research/
Google AI Studio	https://aistudio.google.com/prompts/new_chat
Grounded AI	https://www.grounded.ai
Grok	https://grok.x.ai
Microsoft Office 365	https://www.microsoft.com/en-ww/microsoft-365
Notebook LM	https://notebooklm.google
OpenAI Deep Search	https://openai.com/index/introducing-deep-research/
Paper Wizard	https://paperwizard.ai
Paperpal	https://paperpal.com
PDF.ai	https://pdf.ai
Perplexity	https://www.perplexity.ai
Petal	https://petal.org
PowerBI	https://powerbi.microsoft.com
Quillbot	https://quillbot.com
Research Rabbit	https://www.researchrabbit.ai
SciSpace	https://scispace.com
Semantic Scholar	https://www.semanticscholar.org
SPSS	https://www.ibm.com/products/spss-statistics
Tableau	https://www.tableau.com
Thesify	https://www.thesify.ai
Whisper	https://openai.com/index/whisper/
Zotero	https://www.zotero.org

Appendix 2: Training Requirements

The training is proposed to progress from foundational literacy and evaluation metrics, to applied compliance and stakeholder validation, and finally to intermediate topics in generation, evaluation, bias, and sustainability, enabling researchers to integrate AI responsibly across the research lifecycle.

Level 1: Foundation

Module	Title	Focus
1.1	AI tools and services for business and management research	Overview of mainstream AI tools (e.g., LLMs, summarisers, coding assistants, qualitative coders, analytics copilots), their core capabilities, typical use cases in literature review, coding, data preprocessing, survey design, and limitations such as hallucinations, domain drift, and data privacy constraints; includes hands-on prompt engineering and prompt optimization patterns (role, context, constraints, exemplars, iterations).
1.2	Reporting standards: what, how, why	Practical reporting frameworks for AI-assisted research, including documenting model versions, data provenance, prompts, parameters, human oversight steps, and validation procedures; aligns with transparency, reproducibility, and editor/reviewer expectations.
1.3	Validating AI-generated outputs	Techniques to verify AI outputs beyond simple source attribution: adversarial prompting, fact-checking workflows, triangulation with external datasets, inter-rater reliability when AI is a coder, measuring perplexity, BLEU, ROGUE
1.4	Human oversight and accountability	Defining human-in-the-loop responsibilities across research phases, establishing approval gates, audit trails, authorship accountability, and escalation procedures; covers ethical review considerations and delineation of human vs. AI contributions.

Level 2: Intermediate

Module	Title	Focus
2.1	AI regulations and law (journals and publishers)	Orientation to policy requirements from journals and publishers: disclosure, authorship restrictions, data rights, copyright, licensing of model outputs, and compliance with privacy/GDPR/IRB; data anonymisation techniques; including checklists for submission readiness.
2.2	All about data fairness	Foundations of equity and fairness; diagnosing unfair data and approaches to post-hoc adjustments and reporting without undermining scientific rigour and credibility.
2.3	Stakeholder engagement for AI validation	Methods to involve domain experts, practitioners, and affected communities to validate AI-derived insights; co-design workshops, Delphi panels, practitioner walkthroughs, and documenting external validity.
2.4	Pros and cons of AI tools/services for data analysis	Critical assessment of AI in quantitative (coding, model selection, error analysis) and qualitative (thematic coding, synthesis) workflows; reliability, reproducibility, bias, and data security trade-offs.
2.5	IP, Open Access, licensing, attribution, and plagiarism	Help understand ownership of AI-assisted outputs and underlying data/code, distinguishing copyright, database rights, and patentability in research contexts; explain Open Access routes (gold, green, hybrid), funder mandates, and how to choose and apply licenses (CC BY variants, open-source licenses) aligned with journal policies; sets rules for proper attribution of models, datasets, and prompts, including citation of AI assistance; and define plagiarism risks unique to AI (undisclosed AI use, verbatim reuse, self-plagiarism, and training data leakage).

Level 3: Expert

Module	Title	Focus
3.1	Synthetic data: pros, cons, best practices	When and how to generate synthetic data (privacy, class balance, scenario testing), methods (diffusion, LLM-based augmentation), risks (mode collapse, spurious correlations, leakage), and validation protocols to ensure downstream fidelity.
3.2	Detecting and mitigating bias and errors	Bias taxonomies (representation, measurement, societal), detection approaches (counterfactuals, subgroup metrics), mitigation (re-weighting, debiasing prompts, post-hoc calibration), and documentation via model cards and datasheets.
3.3	LLMs to evaluate other LLMs	Creating your own LLM, training your LLM, instruction-tuning your LLM for specific tasks, check the performance of your LLM, and enhancing the explainability of your LLM
3.4	Ecological footprint of AI	Measuring carbon/energy impacts of training and inference, estimating compute and emissions, choosing greener architectures, and reporting environmental metrics alongside methodological details.

Level 4: For Editors

Module	Title	Focus
4.1	Red flags in reviews	Developing awareness of the distinctive patterns, linguistic features, and structural tendencies often present in machine-generated text. Learn to recognize hallmarks such as lack of nuanced critique or context-specific insight, and failing to reference details unique to the manuscript.
4.2	Tackling hidden text in manuscripts	Understanding how hidden text in manuscript can generate favourable and positive reviews; understanding the specific manipulation tactics; spotting probability of hidden text in empirical manuscripts by comparing the review text corresponding to specific elements in the manuscript, e.g., theoretical framing, research design, etc.
4.3	Legitimacy of research review and conceptual papers	Understanding the capabilities and limitations of existing AI tools and platforms which generate reviews (text), can analyse research manuscripts and then consolidate the analysis to develop theoretical frameworks. Appreciating and valuing tacit experience – how to differentiate between human contributions Vs. AI-assisted content; Assessing the adequacy and balance of citations, and contextual relevance of citations.

BIOGRAPHIES

Pawan Budhwar is the 50th Anniversary Professor of International HRM and Associate Deputy Vice Chancellor International, Aston University, UK. Pawan is the Co-Vice Chair Research & Publications at the British Academy of Management, and the Co-Editor-in-Chief of Human Resource Management Journal. He is globally known for his research in the fields of AI in HRM, strategic and international HRM, sustainability and emerging markets, with a specific focus on India.

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