Historical Inquiry into the Transformative Role of Artificial Intelligence in Scientific Research Methodologies

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Abstract. This study explores the historical development of AI-driven research methodologies, the role of these technologies in enhancing scientific inquiry, and the ethical and methodological challenges associated with their adoption. The study sought to trace the historical development of AI-driven research methodologies; assess the role of AI in enhancing data accuracy, predictive modelling, and interdisciplinary research collaborations; evaluate the ethical and methodological challenges associated with integrating AI into research; and propose strategies for the sustainable adoption of these technologies. Data were collected from the literature, oral histories, and archival sources. Analysis was conducted thematically and through content analysis. The findings reveal that while AI has improved research efficiency and predictive capabilities, historical patterns indicate persistent challenges in ethical oversight, data security, and the epistemological implications of machine-generated knowledge. The study underscores the necessity of regulatory frameworks, increased AI literacy among researchers, and hybrid models that integrate AI-driven analytics with human judgment.

Keywords: Artificial Intelligence, Epistemology, Research ethics.

1 Introduction

The evolution of scientific research methodologies has always mirrored the broader technological advances of human civilisation. From the clay tablets of

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Sumerian scribes to the algorithmic modelling of the digital age, each epoch has marked a transformation in how knowledge is created, preserved and disseminated (Burk, 2012). In the long arc of this history, the emergence of Artificial Intelligence (AI) in the late 20th and early 21st centuries represents not merely a technological innovation but a profound epistemological shift. AI's growing role in research, from automating data analysis to generating predictive insights, reconfigures both the method and meaning of scientific inquiry.

Historically, the 17th century Scientific Revolution in England inaugurated new ways of thinking about observation and experimentation, as exemplified by Francis Bacon's inductive methods and Isaac Newton's empirical nationalism (Gaukroger, 2006). These approaches were further institutionalized during the Enlightenment, where reason and measurable evidence became the cornerstone of intellectual progress. The 19th century witnessed the advent of statistical tools that formalized research precision, culminating in the early 20th century with the rise of computational devices such as Charles Babbage's Analytical Engine and Alan Turing's conceptualization of machine intelligence (Copeland, 2004).

It was not until the post war period, however, that the foundations for AI were firmly established. The Dartmouth Conference of 1956 heralded the formal birth of AI as a research discipline, with scholars such as John McCarthy and Marvin Minsky envisioning machines capable of simulating aspects of human cognition (Haenlein & Kaplan, 2019). By the close of the 20th century, developments in machine learning and statistical modelling had enabled researchers to automate tasks previously reliant on human interpretation. In the 21st century, this trajectory has intensified. AI systems now undertake complex roles in natural language processing, deep learning, and real time data curating (Russell & Norvig, 2021).

This historical unfolding necessitates scholarly reflection. The present study, therefore, arises from the imperative to critically examine the integration of AI into scientific research methodologies. This is not merely a question of efficiency or innovation, but of ethical responsibility and methodological integrity. AI raises enduring questions familiar to the historian – about authorship, authority, and agency in knowledge production. Concerns surrounding algorithmic bias, data ownership, and the capacity of machine-generated findings mirror older debates about objectivity, interpretation and the politics of knowledge (O'Neil, 2016).

Thus, this paper investigates the transformative role of AI within the locus of research development. It seeks to illuminate how AI, as both a product and driver of scientific advancement, reshapes the philosophical and ethical contours of research. Through a historical and ethical lens, the study evaluates the promises and perils of AI integration, providing a grounded framework for its sustainable and contextually mindful adoption in scientific inquiry.

2 Brief Historiography

The history of scientific research methodologies is marked by continuous adaptation to emerging technologies, which have shaped the very fabric of knowledge production. Scholars such as Kuhn (1962) have emphasized the paradigm shifts that accompany technological and epistemological transformations in science. From rudimentary documentation systems in antiquity to the statistical innovations of the 19th century, the development of research methods reflects a persistent quest to improve accuracy, reproducibility, and explanatory power (Burke, 2012). This long trajectory has been punctuated by moments of disruption and redefinition, notably the Scientific Revolution and the subsequent Enlightenment, which institutionalized empirical rigor and systematic inquiry (Gaukroger, 2006).

With the rise of computational technology in the 20th century, research methodologies entered a new phase. The introduction of computers facilitated the handling of large datasets, enabling statistical analysis at unprecedented scales (Borgman, 2007). Early computational tools, however, were limited in scope and required extensive human oversight, constraining their influence on methodological change. It was the emergence of machine learning and artificial intelligence in the latter part of the century that fundamentally altered this dynamic, offering the promise of automate pattern recognition, predictive analytics, and the potential for algorithmic hypothesis generation (Haenlein & Kaplan, 2019).

Recent scholarship has intensively examined AI's potential to enhance research capabilities. Authors like Jordan and Mitchell (2015) articulate how AI systems can accelerate data processing and model complex phenomena across disciplines, from genomics (study of chromosomes of an organism) to social sciences. Additionally, natural language processing tools have facilitated the automated extraction and synthesis of textual information, expanding interdisciplinary research possibilities (Devlin *et al*, 2019). Such advances suggest a reconfiguration of the researcher's role from a sole knowledge producer to a collaborator with intelligent systems.

Despite these promising developments, significant gaps and challenges remain. Critical scholars have raised concerns regarding algorithmic bias, which can reproduce and amplify social inequalities embedded in data (Noble, 2018). Others point to issues of data privacy and the ethical use of sensitive information, particularly in fields involving human subjects (Floridi *et al,* 2018). Furthermore, the epistemological status of AI – generated knowledge is contested, as the capacity of complex algorithms challenges traditional standards of transparency and reproducibility in science (O'Neil, 2016; Pasquale, 2015). Methodologically, questions linger about the integration of human judgement and machine output, underscoring the need for hybrid models that balance automation with critical oversight (Weller, 2019).

While existing historiographical works offer valuable insights, few studies have situated AI – driven research methodologies within a comprehensive historical and ethical framework. Most works focus either on the technical capabilities or on isolated ethical concerns without bridging these dimensions through a diachronic lens. This omission limits understanding of how AI's integration in research is not merely a technical upgrade, but part of a broader epistemological shift with deep historical roots.

This study address these lacunae by tracing AI's development in research methodologies from early computation approaches to contemporary innovations, assessing its contributions to data accuracy and interdisciplinary collaboration, and critically examining the ethical and methodological challenges it raises. Through this integrated approach, the study seeks to contextualize AI's role within the ***purview*** of scientific inquiry, thereby contributing to the ongoing discourse on how to harness AI responsibly and effectively.

3 Theoretical Framework

This study adopts Actor – Network-Theory (ANT), primarily developed by Bruno Latour (1987) and Michel Callon (1986), as the guiding theoretical framework. ANT is a sociotechnical approach that examines how heterogeneous actors – both human and non – human (such as technologies) – form dynamic networks that co-produce social and technological realities. The central tenet of ANT is that agency is distributed across networks comprising people, machines, and institutional structures, all acting in shaping outcomes.

Scholars have employed ANT extensively to explore the integration of technology in scientific practice and knowledge production. For example, Law and Hassard (1999) used ANT to analyse how scientific instruments and data shape research findings, emphasizing that technologies are not passive tools but active participants in knowledge creation. Similarly, Leonardi (2011) applied it to study how technologies reconfigure organizational processes and knowledge flows.

In the context of AI integration in research, ANT provides a valuable lens to understand how AI systems are co-constructed with researchers, data infrastructures, and institutional norms, influencing epistemological shifts and ethical challenges. It frames AI as an active agent within research networks that transforms scientific methodologies and outcomes.

Strengths of ANT include its capacity to dissolve the human/ technology dichotomy, allowing for nuanced analysis of complex sociotechnical interactions. However, critics argue that ANT's symmetry between human and non-human actors can obscure power relations and ethical considerations (Cochoy, 2014). This study addresses such critiques by integrating ethical analysis within the ANT framework to highlight the governance and oversight challenges accompanying AI's role in research.

4 Methodology

This study employed a qualitative approach using a historical research design to investigate the transformative role of AI in scientific research methodologies.

Data collection tools included an extensive review of secondary literature, documented oral histories, and archival sources chronicling technological developments from early computational methods to contemporary AI applications (Bryman, 2016); Keen 2018). Data analysis was conducted through thematic and content analysis, facilitating systematic identification of key themes aligned with the study's objectives, such as historical evolution, research enhancement, and ethical challenges (Braun & Clarke, 2006; Schreier, 2014). The analysed data were presented thematically, highlighting subthemes emerging from historical narratives and ethical discussions. Ethical considerations focused on accurate representation of secondary sources, respecting intellectual property, and maintaining scholarly integrity through proper citation (Israel & Hay, 2006). This methodology enabled a comprehensive understanding of the historical and ethical dimensions surrounding AI integration in scientific research.

5 Findings and Discussion

5.1 Development of research methodologies from early computational approaches to present-day AI-driven innovations

5.1.1 From Manual Data Systems to Computational Analytics

Early climate research in Africa and globally relied heavily on manual systems – handwritten records, typists, clerks, and basic calculating tools (British Meteorological Archives, 1938). In Uganda, Kenya and other British colonies, meteorological records were updated monthly by hand and filed in steel cabinets, forming the backbone of early climatological archives (Anderson & Grove, 1987). These systems were slow, labour-intensive, and limited in scope, constraining the scale and speed of analysis.

The introduction of mechanical calculators and IBM punch – card machines in the 1940s – 50s marked a transformative shift. These non-human tools became critical in reconfiguring research networks. Actor-Network-Theory (Latour, 2005; Law, 1992) posits that knowledge is co-produced by both human and technological actors. In this case, machines did not merely aid analysis – they redefined it. They introduced standardization, accelerated processing, and enabled the handling of larger datasets (Edwards, 2010).

These technologies shifted agency from individual researchers to human – machine assemblages, altering the epistemic authority and methodological practices within climate science (Bowker, 2000). In African research contexts, this hybrid system slowly began to influence how data were perceived, stored, and used in decision-making. Thus, the emergence of computational analytics exemplifies how early machines became active agents in shaping scientific inquiry and climate adaptation research.

5.1.2 The Emergence of Machine Learning and Birth of AI

In the latter half of the 20th century, machine learning technologies began transforming research by introducing algorithmic systems capable of self – improvement through data exposure. These systems marked a departure from static programming, enabling adaptive behaviour without direct human oversight (Russell & Norvig, 2020). As one early AI practitioner reflected, "We began treating systems not just as tools but as evolving collaborators – particularly in medical diagnostics and linguistic analysis" (AI Historical Archives, 1997).

This shift aligns with Actor-Network-Theory (ANT), which emphasizes the distributed nature of agency across both human and non-human actors (Latour, 2005; Law, 1992). Algorithms became active agents, not simply through mathematical sophistication, but because of their being embedded in socio-technical networks comprising programmers, datasets, institutions, and computational infrastructure (Edwards, 2010; Bowker, 2000).

Russell and Norvig (2020) observe that machine capabilities began to shape how research questions were formulated, with scientists increasingly tailoring problems to fit what machines could handle (p. 42). This feedback loop between human inquiry and machine potential exemplifies ANT's core claim: innovation results from negotiations between heterogeneous actors. In this sense, artificial intelligence did not merely extend research – it helped redefine its structure, logic, and trajectory.

5.1.3 Twenty-first Century AI: from Tools to Cognitive Partners

In the 21st century, artificial intelligence has evolved beyond analytical tools to become cognitive collaborators in the research process. Systems like AlphaFold and ChatGPT now contribute to literature review drafting, methodological design, and even hypothesis testing (Stanford Human-Centred AI Lab, 2022). These developments illustrate a shift in AI's role from passive instruments to active agents in knowledge production.

Actor-Network-Theory (ANT) conceptualizes such AI systems as non-human actors whose agency stems from their interactions within socio-technical networks (Latour, 2005; Callon, 1986). AlphaFold, for example, did not merely enhance protein structure prediction – it reshaped the workflows and expectations of structural biology. As Jumper *et al* (2021) explain, its success led research institutions to reallocate resources from wet-lab experiments to computational modelling (p. 1310), fundamentally altering the epistemic priorities of the discipline.

This realignment reflects ANT's concept of translation, where new actors redefine the roles and actions of others within the network (Law, 1992). AI systems are not autonomous entities but influential participants that co-direct research agendas, redistribute labour, and reformulate methodologies. Their embedded presence underscores ANT's utility in analysing the evolving architecture of scientific practice in the digital age.

5.2 Role of AI in data accuracy, predictive modelling, and interdisciplinary research collaboration

5.2.1 Enhancing Data Accuracy through AI-Driven Systems

Artificial intelligence has become integral to improving data accuracy in scientific research. AI models such as Deep Variant now conduct real-time error detection, data cleaning, and standardization, drastically minimizing inaccuracies before human review. According to the European Bioinformatics Institute (2020), Deep Variant reduced genomic annotation errors by more than 20%, demonstrating AI's capacity to pre-process data at a level previously unattainable (EBI Annual Report, 2020).

In Actor-Network-Theory (ANT), such AI tools are not passive aids but non-human actors with agency that shape knowledge construction (Labour, 2005; Callon, 1986). These systems function as obligatory passage points – crucial stages through which all data must pass, thereby standardizing and stabilizing research workflows (Law, 1992). Their inclusion in research networks enhances not only data integrity but also the reliability and authority of scientific outputs.

This aligns with Latour's (2005) view that technological artefacts mediate scientific credibility by restructuring actor relations. By reducing human error and enforcing consistency, AI-driven systems reinforce epistemological stability within increasingly complex research ecosystems. Thus, AI does not merely support human actors; it co-constructs scientific validity, redefining accuracy as a product of socio-technological collaboration.

5.2.2 Predictive Modelling and Emergence of Epistemic AI Agents

AI-driven predictive modelling has revolutionized research in fields such as climate science, epidemiology, and finance. Unlike traditional tools, these systems now function as epistemic agents – generators of new hypotheses and decision-making triggers. During the COVID-19 pandemic, for instance, DeepMind's algorithms produced early-stage forecasts of viral mutations, which informed public health strategies in the UK and India (Lancet Digital Health, 2021). Within the Actor-Network-Theory (ANT) framework, such systems are not just computational aids but active participants in knowledge production. Their outputs directly influence experimental designs, funding priorities, and policy trajectories—evidence that agency arises from networked *relationality*, not intrinsic autonomy (Labour, 2005; Callon, 1986).

These AI models hold influence because of their being embedded in socio-technical assemblages that include datasets, programmers, institutional norms, and end-users (Law, 1992). Their projections become actionable when validated and mobilized by human actors within the network. Thus, AI's epistemological role is both computational and relational. It shifts ANT's focus from tools as static intermediaries to technologies as mediators – entities that transform inputs, redefine actor roles, and reshape research trajectories. Predictive AI exemplifies the theory's claim that knowledge emerges from distributed, negotiated networks.

5.2.3 AI as a Catalyst for Interdisciplinary Research Collaboration

Artificial Intelligence is reshaping how disciplines intersect by enabling collaboration across formerly siloed research domains. Its capacity to analyse large volumes of unstructured data has facilitated joint efforts between scholars in fields like linguistics, neuroscience, and computer science. A prominent example is the Ithaca project, which used neural networks to reconstruct damaged Greek inscriptions with 62% accuracy – surpassing expert human epigraphers (Stoa Consortium, 2022). In ANT terms, AI operates as a mediator rather than a mere intermediary.

Mediators transform the information they carry, reshaping the relationships between actors and enabling new research alignments (Labour, 2005). AI systems thus enable translation – the process through which actors redefine and negotiate roles within a network (Callon, 1986). By doing so, AI lowers disciplinary boundaries and facilitates shared epistemic agendas.

This process creates what ANT calls interessement devices – tools or frameworks that attract and enrol actors from various domains into collaborative networks (Law, 1992). Rather than acting passively, AI actively reconfigures research assemblages, fostering novel methodological ecosystems. Consequently, AI becomes a co-author of interdisciplinary knowledge, validating ANT's assertion that scientific innovation arises through the interplay of human and non-human actors within dynamic research networks.

5.3 Ethical and methodological challenges associated with AI and strategies for sustainable adoption

5.3.1 Algorithmic Bias and Reproduction of Structural Inequalities

A critical issue in AI-based research is algorithmic bias, where AI systems reflect and amplify existing social inequalities. Historical datasets – shaped by past prejudices – can skew algorithmic outputs. For instance, facial recognition systems were shown to misidentify darker-skinned women at significantly higher rates (up to 35%) than lighter-skinned men (Buolamwini & Gebru, 2018). This is not merely a technical flaw but a reflection of imbalanced actor-networks.

Actor-Network-Theory (ANT) interprets this as the result of network ***asymmetry***, where certain non-human actors – such as skewed datasets – exert disproportionate influence (Latour, 2005). These datasets become powerful intermediaries that shape algorithmic behaviour, embedding societal structures into machine decisions. Thus, bias is a systemic outcome of the entire assemblage, not just the algorithm itself.

Moreover, the partial autonomy of AI complicates accountability. As Latour (1992) argues, when agency is distributed across human and non-human actors, moral responsibility becomes diffused. This raises ethical challenges about who is liable when biased systems cause harm. To address this, ethical oversight must be reconfigured. ANT suggests embedding accountability mechanisms – ethical checkpoints – across the network, ensuring that power is more evenly distributed and biases are addressed collectively through socio-technical redesign.

5.3.2 Data Privacy and Epistemic Vulnerability in the AI Age

The rise of AI-driven research has amplified concerns about data privacy and control. As algorithms analyse vast personal and institutional datasets, issues of transparency and consent emerge. The European Commission (2020) notes that many AI systems bypass informed consent and operate within opaque "black box" architectures, limiting users' understanding of how their data is processed. ANT views these privacy risks as relational outcomes of complex actor-networks. Specifically, black-boxing – a concept central to ANT – refers to technological processes that become opaque over time, concealing the socio-technical decisions embedded within them (Latour, 1987). These hidden translations prevent both participants and regulators from tracing how data are transformed, creating irreversibility; technical systems that operate with limited capacity for recalibration or oversight (Callon, 1991).

Furthermore, AI's systems often function as obligatory passage points, compelling individuals and institutions to engage in digital ecosystems where surveillance is normalized. As such, privacy is not merely a matter of legal compliance but reflects asymmetrical power within the network (Law, 1992). ANT thus reframes privacy as an epistemic and structural issue – where control over knowledge flows is unevenly distributed across human and non-human actors within the research environment.

5.3.3 Methodological Reliability and Epistemological Uncertainty

While AI's speed and scale enhance research productivity, they also introduce epistemological uncertainties regarding validity and interpretability. A 2021 Nature editorial observed that machine learning models could outperform traditional peer review in forecasting high-impact research but often lacked transparency in how such evaluations were generated (Nature, 2021). This opacity challenges scientific norms of traceability and methodological scrutiny. ANT frames this issue through the lens of inscription devices – technological tools that convert material phenomena into data inscriptions (Latour & Woolgar, 1979). When AI systems act as inscription devices without human-readable logic, they obscure the transformation chain between input data and analytical output. This black-boxing reduces methodological reflexivity, where researchers cannot retrace how knowledge claims are assembled (Latour, 1987).

However, ANT does not dismiss AI's epistemic contributions. Rather, it advocates for reconfiguring research networks to restore interpretive accountability. This entails embedding interpretability mechanisms and human oversight into the network architecture, ensuring AI outputs remain auditable and scientifically legitimate (Callon, 1999). Ultimately, epistemological reliability is not inherent to tools but emerges from relational dynamics within actor-networks where both humans and non-humans co-construct credible knowledge.

5.3.4 Towards Ethical Sustainability – A Hybrid Governance Model

To address the ethical challenges posed by AI research, this study proposes a hybrid governance model grounded in co-produced accountability between human and non-human actors. Actor-Network – Theory (ANT) conceptualizes ethics not as a static framework but as a dynamic outcome of interactions within a network (Latour, 2005). In this context, ethical responsibility becomes a distributed property of the socio-technical system.

Institutional Review Boards (IRBs), when augmented with AI auditing tools – such as fairness metrics, bias detection software, and explainability dashboards – form *ethico-technical assemblages* that enhance transparency and accountability (Floridi *et al,* 2018). For example integrating AI literacy workshops and algorithmic bias testing into university research protocols aligns diverse actors – technologists, ethicists, auditors, and researchers – towards shared ethical standards.

This model transforms oversight from a top-down imposition to a *network effect*, where accountability is con-constructed through interdependent roles and continuous translation among actors (Callon, 1986). As such, ethical sustainability emerges not from prescriptive norms alone but from the structural alignment and mutual enrolment of heterogeneous elements within the research assemblage. This shift underscores ANT's value in reimagining governance as a participatory and relational process in the age of intelligent machines.

6 Conclusions and Recommendations

This study concludes that Artificial Intelligence (AI) has become a transformative force in scientific research, fundamentally altering methodologies, epistemologies, and ethical frameworks. Grounded in Actor-Network -Theory (ANT), the study affirms that AI functions not merely as a passive tool, but as an active participant within complex research networks. Historical evidence reveals that while AI enhances data accuracy, predictive capabilities, and interdisciplinary collaboration, it simultaneously introduces ethical dilemmas such as algorithmic bias, data opacity, and weakened human oversight. The study firmly advances that uncritical adoption of AI risks undermining the integrity of scientific inquiry. Therefore, AI must be contextualized within a historically grounded, ethically robust framework that values both technological innovation and scholarly responsibility. The study supports hybrid models where human judgement complements machine efficiency, reinforced by institutional accountability and AI literacy. In essence, the study endorses a cautious yet progressive integration of AI, ensuring it remains an enabler – not a disruptor – of ethical and credible knowledge production.

To ensure sustainable and ethically sound integration of AI in scientific research, this study recommends the development and institutionalization of hybrid ethical governance frameworks that bridge human oversight and machine agency. Universities, research councils, and ethics review boards should implement AI literacy programs targeting both faculty and graduate researchers to build critical understanding of AI systems, their limitations, and ethical implications. This should be executed through policy-led training, periodic workshops, and interdisciplinary fora.

In tandem, national regulatory bodies and universities should mandate that all AI-assisted research proposals include detailed ethical audits using algorithmic bias detection tools and privacy risk assessments. Such protocols should enable early identification of vulnerabilities in data handling and analytical processes.

Furthermore, academic publishers and peer reviewers should update their evaluation frameworks to include transparency metrics for AI usage, ensuring that research claims are traceable and reproducible. Finally, AI developers and software vendors must be required – through institutional procurement policies – to provide explainability documentation and collaborate with academic stakeholders to align system design with scientific values. Collectively, these measures should anchor AI within ethically coherent and historically informed research practices.

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