AI-Assisted Microscopy in Geoscience

A Practical Metascientific Investigation of Changing Research Practices, Skills, and Human Roles

Kerswell B.

23 February 2026

Contents

Summary

Artificial intelligence (AI) is reshaping scientific research by introducing new analytical, interpretive, and decision-making capabilities. However, credible empirical evidence about how AI integration alters research practice, what competencies researchers require, and where human expertise remains indispensable is limited. This empirical scarcity constrains research organizations, funders, policymakers, and educators in making evidence-based decisions about training, infrastructure, governance, and the organization of AI-augmented research. This fellowship seeks to generate new insights by directly observing AI-assisted microscopy workflows in critical mineral characterization.

The central premise is that AI's impact must be studied in situ. Rather than evaluating algorithms in isolation, the project embeds an AI assistant within an operational microscopy facility to examine how research questions, interpretive strategies, and decision pathways evolve. This aligns with UKRI's objective of generating systematic evidence on AI adoption's effects on research practice, capability development, and governance.

The fellowship advances three interrelated metascientific themes. First, how AI reshapes research topics, methods, and practices: How do AI-assisted interpretations influence data collection? Does AI shift the balance between hypothesis generation and hypothesis testing? Does it amplify certain lines of investigation while obscuring others? Second, educational and training implications: What competencies are required across career stages for effective and responsible AI use? Does AI accelerate skill acquisition or create dependencies? Third, the human role in AI-augmented research: Which tasks remain human-led, and under what conditions can AI reliably automate routine analysis?

Methodologically, the project configures an AI assistant for geological sample characterization using open-source vision-language models fine-tuned on electron microscopy images from the University of Liverpool's Scanning Electron Microscopy Shared Research Facility (SEM-SRF). Experts will annotate training data for scientifically meaningful categories. AI models will support interpretation, planning, and feature detection alongside traditional microscopy workflows. Researchers across career stages will perform matched tasks with and without AI, with sessions recorded via screen capture, think-aloud protocols, structured lab notes, and debriefing interviews.

The study will generate empirically grounded insights into how AI affects moment-to-moment research practice, revealing changes in decision pathways, attention allocation, error modes, and confidence. Findings will provide guidance for funders and organizations on where AI investment yields gains, for educational institutions on required competencies, and for policymakers on governance frameworks for AI integration. Methodological frameworks, including comparative workflow design and competency mapping, will offer transferable tools for other scientific domains and commercial exploration for critical mineral resources. This fellowship documents the reality of integrating AI assistants into authentic research settings, moving beyond anecdote and speculation surrounding AI adoption.

1 Vision

1.1 Excellence and Importance of the Work

AI integration in scientific research raises questions of fundamental importance to how knowledge is produced, who can participate in that production, and what institutional conditions support rigorous inquiry. Despite the rapid adoption of machine learning, deep learning, and foundation models across the sciences, empirical understanding of how these technologies alter research practice remains limited (Birhane et al., 2023; Channing & Ghosh, 2025; Leontidis, 2024). The tendency to adopt AI tools without systematic evaluation has been termed "convenience AI," reflecting a pattern of uncritical uptake driven by availability rather than evidence of benefit (Leonelli & Mussgnug, 2025). This fellowship addresses this lack of credible empirical evidence directly by generating process-level observations about AI's effects on research workflows, researcher competencies, and the division of labor in an operational scientific setting. That evidence is important not only to the specific domain of microscopy but to the broader scientific community navigating AI adoption, and to the funders, institutions, and educators who must respond to it.

1.2 Advancing Understanding: The Knowledge Gap

Existing literature on AI in science tends to emphasize algorithmic performance and broad ethical concerns while largely neglecting the micro-practices of scientific work. How AI affects the moment-to-moment decisions researchers make during data acquisition and interpretation is poorly understood, as are the competencies required to work effectively and responsibly alongside AI, and the conditions under which human judgment remains indispensable (Branda et al., 2025; Douglas, 2025; Ferrario et al., 2024; Ludwig & Mullainathan, 2024; Resnik & Hosseini, 2025; Yang & Ma, 2025). Cognitive science offers established methods for analyzing expertise and decision-making in complex environments (Crandall et al., 2006; Ericsson & Charness, 1994; Klein, 2017), yet these approaches have rarely been applied to scientific research in the context of AI assistance. This fellowship bridges that knowledge gap by combining cognitive task analysis, comparative workflow design, and human-automation research to study AI-assisted microscopy in a live laboratory setting (Endsley, 2017; Lee & See, 2004; Mosier et al., 1996; Parasuraman & Riley, 1997).

1.3 Timeliness

Three developments make this work timely. First, advances in vision-language models and multimodal architectures trained on large image-text datasets now enable interpretable outputs for scientific imaging tasks that previously required bespoke algorithms (Achiam et al., 2023; Kirillov et al., 2023;

Radford et al., 2021; Ramesh et al., 2022). Second, commercial fine-tuning platforms have lowered barriers to domain adaptation, allowing researchers to customize foundation models without extensive AI expertise. Third, the rapid diffusion of AI into scientific workflows is outpacing critical evaluation. The consequences of this mismatch are illustrated by cases such as AlphaFold, where the scientific community has only begun systematic assessment of validity and downstream impact years after widespread adoption (Kovalevskiy et al., 2024). The current window, in which AI tools are proliferating but their effects on research practice remain open questions, is precisely when evidence-based guidance is most valuable.

1.4 Impact on Research, Society, and the Economy

Microscopy workflows are central to research across the physical and life sciences and provide an empirically rich, policy-relevant setting in which to examine AI's impact on research practice. Critical mineral research has become a strategic priority for the UK and global economies (Commission, 2023; Government, 2025; USGS, 2024), and AI integration in these workflows may influence exploration efficiency, resource assessment, and economic decision-making. Beyond the immediate domain, the competency frameworks, governance insights, and methodological tools produced by this fellowship are directly transferable to any laboratory discipline confronting AI adoption, including biomedical imaging, materials science, and environmental monitoring. The risk that AI adoption widens disparities between well-resourced and less-resourced research groups is explicitly examined, making the work relevant to UKRI's commitments to a fair and accessible research environment.

1.5 Scope and Alignment with Fellowship Objectives

This fellowship responds directly to UKRI's metascience priorities. It documents how AI adoption alters research practice in a live laboratory setting, examining changes in data collection decisions, interpretive strategies, time allocation, and the balance between exploratory and hypothesis-driven work. It analyzes epistemic and educational implications by comparing researchers at different career stages, identifying enduring skills, emerging competencies, and risks of over-reliance or skill regression. And it generates actionable evidence for research organizations and funders by quantifying resource requirements, infrastructure dependencies, governance challenges, and performance trade-offs associated with AI integration. The project focuses explicitly on how science is conducted, rather than on AI ethics or safety in the abstract, and aligns with the fellowship's objective of building systematic, evidence-based understanding of AI's impact on the research landscape.

2 Approach

2.1 Overview of Methodology

This fellowship adopts an empirical, mixed-methods metascientific approach to generate direct evidence about how AI reshapes scientific research practice. Rather than evaluating AI through technical performance metrics alone, the methodology focuses on process-level transformations: how AI affects decision-making, attention allocation, interpretive reasoning, skill development, and the division of labor between humans and machines during real research activity. The design aligns with UKRI's emphasis on understanding how AI adoption changes research culture, practice, and capability rather than on advancing AI technologies themselves.

The empirical strategy comprises three integrated phases. First, an AI assistant is configured and embedded in a working microscopy environment using existing infrastructure and open-source models, reflecting realistic adoption pathways. Second, comparative workflow studies are conducted in which researchers at different career stages perform matched tasks with and without AI assistance under controlled conditions. Third, a structured analytical synthesis integrates qualitative and quantitative evidence to address the fellowship's metascientific questions concerning research practice, training, and human-AI interaction. Throughout, the project emphasizes transparency, reproducibility, and detailed documentation to support robust inference and transferability.

2.2 Phase 1: Configuring and Embedding the AI Assistant

Microscopy is central to research across the physical and life sciences and requires sustained expert judgment rather than mechanical execution. In geoscience and critical mineral research, microscopy underpins mineral identification, textural interpretation, and reconstruction of geological processes. Decisions are made iteratively during data acquisition, not solely in post-hoc analysis, making microscopy a suitable domain for examining AI integration: it combines pattern recognition, contextual interpretation, and real-time decision-making under uncertainty. These features are not unique to geoscience, ensuring that insights from this setting transfer across disciplines.

The project focuses on characterization of gold-bearing mineral assemblages using optical and electron microscopy. Gold mineralization is a rigorous test case involving complex mineral associations, variable textures, deformation features, and alteration styles across geological settings. The domain is sufficiently established to allow expert validation yet contains ambiguity and edge cases that challenge both human and machine interpretation, enabling systematic examination of where AI augments practice and where it risks oversimplification or error. The work is conducted within the University of Liverpool's SEM-SRF to capture the constraints, incentives, and norms that shape real research practice rather than a simulated environment.

The AI assistant is fine-tuned on a curated dataset compiled from existing and newly acquired microscopy data at the SEM-SRF. Data sources include reflected and transmitted light optical microscopy, backscattered electron (BSE) and secondary electron (SE) imaging, electron backscatter diffraction (EBSD) phase and orientation maps, and energy-dispersive X-ray spectroscopy (EDS) element maps and spot analyses. These modalities represent the standard analytical toolkit in mineral characterization. The dataset is annotated using scientifically meaningful categories reflecting established research practice rather than labels optimized solely for machine performance. Expert annotators from the University of Liverpool's Earth Science Research Group (ESRG) identify minerals, textures, grain relationships, deformation features, and paragenetic associations using the conceptual frameworks applied in their own work. Annotation disagreements are documented rather than prematurely reconciled, preserving interpretive ambiguity that is central to scientific reasoning. This process also generates metascientific insight into how expertise is codified and where tacit judgment operates.

The project uses open-source vision-language models (Kimi K2.5, Qwen 3 VL 32B, or equivalent class) via commercial fine-tuning infrastructure (Fireworks AI). These models represent contemporary multimodal capabilities, including zero-shot image segmentation and region-level captioning analogous to advances in general-purpose vision foundation models (Kirillov et al., 2023; Liu et al., 2024), while remaining accessible to non-specialist research groups. Using commercial platforms mirrors pragmatic institutional adoption pathways and exposes realistic technical, financial, and organizational constraints. The objective is not maximal accuracy but a functional AI assistant capable of interacting meaningfully during microscopy workflows by suggesting candidate mineral identifications, highlighting textural features, comparing samples to reference images, proposing follow-up analyses, and indicating uncertainty.

The AI system is framed as a probabilistic assistant rather than an authority: outputs are presented with explanations and likelihood estimates to encourage critical evaluation, enabling analysis of trust calibration and responses to error. Prior to the workflow studies, baseline performance is evaluated using held-out expert-annotated test data to establish the assistant's strengths, weaknesses, and error modes under controlled conditions. Performance metrics provide contextual information but are not primary outcomes, because even imperfect AI systems can significantly alter researcher behavior, attention, and decision-making (Mosier et al., 1996; Parasuraman & Riley, 1997). Documentation of costs, technical constraints, data ownership issues, vendor dependencies, and compliance requirements constitutes a core research output, providing concrete evidence about the institutional conditions necessary for responsible AI integration.

Phase 1 delivers a validated AI assistant and annotated dataset ready for deployment in comparative workflow studies, which are the core empirical component of the fellowship.

2.3 Phase 2: Comparative Workflow Studies

The comparative workflow studies generate direct evidence about how AI changes research practice by having researchers perform matched tasks in traditional and AI-assisted environments. Participants are recruited across three career stages: early-stage PhD students (years 1-2), doctoral and postdoctoral researchers (1-4 years post-PhD), and established academics (10 or more years of experience). This stratification enables analysis of how AI effects vary with expertise and professional role, directly informing debates on skill regression, over-reliance, and appropriate AI oversight (Endsley, 2017). The target sample comprises approximately 24 participants (8 per career stage), yielding 48 sessions (each participant completes tasks in both environments), with order counterbalanced to mitigate learning effects. This design balances statistical interpretability with qualitative depth.

Tasks reflect authentic research activities, including mineral identification, textural interpretation, comparison with reference materials, and planning of further analyses. Emphasis on process fidelity ensures that observed differences reflect genuine changes in research practice rather than experimental artifacts. Sessions are comprehensively documented via screen recordings, think-aloud protocols, structured lab notes, and immediate and follow-up debriefing interviews. This multi-modal approach draws on cognitive task analysis (Crandall et al., 2006) to enable reconstruction of decision pathways, identification of critical junctures, and analysis of how AI reshapes cognitive and practical workflows. In AI-assisted sessions, the analysis focuses on when participants consult the assistant, how they interpret its suggestions, and under what conditions outputs are accepted, questioned, or rejected. Error detection and recovery are central: instances of incorrect or misleading AI suggestions are documented and responses analyzed to clarify whether effective AI use presupposes prior expertise or whether AI scaffolds novice development.

The comparative workflow data collected in Phase 2 feed directly into the integrative synthesis in Phase 3, where qualitative and quantitative evidence are combined to address the fellowship's three metascientific questions.

2.4 Phase 3: Analytical Synthesis and Metascientific Frameworks

The primary analytical output is a structured comparison of traditional and AI-assisted workflows. Observational records, interviews, and performance indicators are integrated to identify how AI alters attention allocation, sequencing of decisions, interpretive depth, and termination criteria. Key variables include timing of decisions, frequency of AI consultation, time distribution across tasks, error detection, and revision rates (Crandall et al., 2006). Thematic Analysis (Braun & Clarke, 2006) of verbal data identifies recurring patterns in reasoning, while quantitative indicators such as time to conclusion and number of AI interactions provide supporting evidence. The analysis examines trade-offs rather than assuming that speed equates to improvement. Cases where efficiency increases but interpretive depth declines, or confidence rises without accuracy gains, are explicitly examined, as are workflow inflection points where AI input changes what is noticed, how it is interpreted, or when analysis ceases. The comparative workflow framework, incorporating workflow mapping and competency identification, will be published as a transferable template for studying AI integration in other laboratory disciplines.

A central contribution is an evidence-based competency framework for AI-augmented research. This framework contrasts competencies in traditional microscopy with those emerging in AI-assisted workflows across three dimensions. Technical competencies cover interaction with AI interfaces and data management. Interpretive competencies cover evaluating outputs, recognizing failure modes, and maintaining independent judgment. Meta-cognitive competencies cover trust calibration, understanding model limitations, and determining when human expertise must override automated suggestions. Variation across career stages is explicitly analyzed to inform training design and to address when and how AI tools should be introduced in educational pathways. Outputs from both environments are evaluated using ground truth where available and expert consensus where ambiguity persists, with criteria extending beyond correctness to include interpretive richness, anomaly recognition, generation of novel insights, and appropriate expression of uncertainty. In parallel, the fellowship examines institutional and policy implications, including intellectual property and data governance considerations associated with fine-tuning models on research data in commercially sensitive domains such as critical mineral exploration, and the feasibility of AI adoption in terms of resource requirements, infrastructure dependencies, expertise needs, and vendor reliance.

Active risk management is embedded throughout. Technical risks are mitigated by focusing on meta-scientific insight rather than optimization, so that even imperfect AI performance yields scientifically valuable observations. Recruitment risks are reduced through established institutional networks within the SEM-SRF and ESRG. Ethical approval is sought at the outset, framing the study as observation of professional practice. The methodology emphasizes process-level insights to ensure robustness amid rapid technological change.

2.5 Project Timeline and Milestones

The fellowship spans 24 months across three overlapping phases (Figure 1). Early months focus on sample collection, dataset development, and AI configuration. Mid-phase activities center on comparative workflow studies. Final months prioritize integrative analysis, stakeholder engagement, and dissemination. Findings will be synthesized into concise policy briefs addressing funding, infrastructure investment, workforce development, and governance for direct use by UKRI, research councils, and institutional leaders making AI investment decisions.

Activity	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Primary Cost
Fieldwork & Sample Prep	✗								Travel / Consumables
Dataset Acquisition	✗	✗	✗						Facility Time (Data)
VLM Fine-tuning & Eval		✗	✗	✗					AI Platform (Runs)
Workflow Studies					✗	✗	✗		Facility Time (Study)
Qualitative Analysis						✗	✗	✗	Transcription Costs
Stakeholder Engagement	✗	✗	✗	✗	✗	✗	✗	✗	Engagement Travel
Synthesis & Dissemination							✗	✗	OA Publication

Figure 1: Project timeline showing major activities, their duration across eight quarters (Q1-Q8), and associated primary cost drivers.

3 Applicant Capability to Deliver

3.1 Contributions to the Generation of New Ideas, Tools, Methodologies, or Knowledge

My research integrates computational methods with traditional geoscience to address fundamental questions about rock formation and tectonic processes. A core contribution has been developing machine learning approaches that augment physics-based models (Kerswell et al., 2024) and field-based methods (Kerswell, 2026). My development of Rock Machine Learning Models (RocMLMs) (Kerswell et al., 2024) demonstrated that pretrained neural networks can emulate thermodynamic calculations with orders-of-magnitude efficiency gains while preserving scientific validity. This required rigorous data curation, validation against independent benchmarks, and transparent documentation of limitations, providing direct experience in domain-specific AI development and application. Ongoing work extends machine learning into tectonics (Kerswell, 2026), enabling new applications in traditionally field-based geoscience.

My broader publication record reflects sustained methodological innovation. Research on subduction zone processes (Kerswell et al., 2021, 2023; Kohn et al., 2018; Long et al., 2020) integrated field data, laboratory analysis, numerical simulation, and statistical modeling to evaluate plate interactions at depth. Work on metamorphic rock recovery (Kerswell et al., 2023) combined simulations with global datasets to test theoretical predictions against empirical evidence. Current research on mantle phase transformations (Kerswell et al., 2026) applies reaction kinetics to investigate non-equilibrium effects on seismic structure. Across projects, I have designed structured workflows, integrated heterogeneous datasets, quantified uncertainty, and documented assumptions, skills directly transferable to empirical analysis of AI-assisted microscopy.

I contributed to community data infrastructure through OneGeochemistry (Klöcking et al., 2023), addressing data interoperability and stewardship across geochemical sciences. My doctoral and post-doctoral research involved optical and electron microscopy, electron microprobe analysis, and mass spectrometry alongside numerical simulation and machine learning. This combination of laboratory and computational expertise supports both technical implementation and empirical evaluation of AI-assisted workflows. Research visits to ETH-Zürich and Sorbonne Université further developed skills in high-performance computing, computational fluid dynamics, and rheological modeling.

3.2 The Development of Others and Maintenance of Effective Working Relationships

I have contributed to major international collaborations including NSF OISE-1545903 (ExTerra Field Institute, $4.0M), ERC Horizon 2020 grant 882450 (Micro-scale dependent, time- and space-evolving rheologies, €2.5M), and UKRI NERC Large Grant NE/V018477/1 (Feedbacks between mineral reactions and mantle convection, £2.8M). These projects required coordinated analytical strategies, shared infrastructure, and integration of expertise across institutions in the US, France, Switzerland, and the UK.

My teaching spans undergraduate and graduate levels. As Visiting Assistant Professor at Miami University, I delivered large introductory lectures (342 students) and graduate seminars on scientific communication. Student evaluations (3.6-3.9/4.0) exceeded departmental averages. I completed Miami University's New Faculty Teaching Enhancement Program and additional pedagogical training at Boise State University. I mentored undergraduate researchers whose projects led to Geological Society of America presentations (Morrison & Kerswell, 2023; Sims & Kerswell, 2023), guiding research design, laboratory work, data analysis, and dissemination. I have established working relationships with colleagues in the University of Liverpool's SEM-SRF and ESRG, ensuring access to instrumentation and facilitating integration of AI-assisted workflows in a realistic laboratory context with an active critical mineral research focus.

3.3 Contributions to the Wider Research and Innovation Community

I have published in leading journals including the Proceedings of the National Academy of Sciences, Geochemistry Geophysics Geosystems, Journal of Geophysical Research, Geochimica et Cosmochimica Acta, and Tectonics. I provide peer review for journals such as Earth and Planetary Science Letters, Journal of Metamorphic Geology, Scientific Reports, and Gondwana Research, and for funding agencies including the German Research Foundation and the US National Science Foundation. I adopt open research practices appropriate to my field, sharing computational workflows via GitHub and the Open Science Framework where feasible. In April 2025, I co-organized and hosted the Mineralogical Society Metamorphic Studies Group meeting at Liverpool, bringing together over 50 participants across all career levels. I also regularly participate in international workshops including ASPECT Hackathons (US), Mineralogical Society of the UK and Ireland Workshops (UK), and Ada Lovelace Workshops (EU).

3.4 Contributions to Broader Research or Innovation, Users and Audiences, and Wider Societal Benefit

My research addresses applied challenges in geoscience, data infrastructure, and computational methodology relevant to resource exploration and geohazard assessment. Work on subduction heat flow (Kerswell & Kohn, 2022) informs understanding of geothermal systems and earthquake processes. Community data initiatives (Klöcking et al., 2023) required engagement with data users and facility operators, balancing technical ideals with operational realities. RocMLMs (Kerswell et al., 2024) adopted a pragmatic approach to AI, addressing computational bottlenecks while remaining integrated with physical models, an approach directly aligned with this fellowship's focus on practical impacts rather than technological novelty. Experience within UKRI-funded projects (NERC Large Grant NE/V018477/1) provides familiarity with policy contexts and strategic priorities. Collaborations involving advanced instrumentation and commercial partners have exposed issues of proprietary software, data security, and intellectual property, informing analysis of AI integration in academic environments.

3.5 Additions

My research trajectory has evolved from traditional petrology and geodynamics toward computational and AI-enabled approaches while remaining grounded in applied and fundamental science. This fellowship represents a strategic extension into metascientific investigation of questions that emerged from my personal observations of rapid AI adoption in geoscience without systematic evaluation of its effects on judgment, workflow structure, and epistemic control. I bring applied machine learning expertise, experience designing reproducible computational workflows, and familiarity with shared research facilities. I am committed to full participation in fellowship cohort activities, engagement with UKRI AI initiatives (including EPSRC AI research hubs), and attendance at the planned summer school. I will also engage constructively with the UKRI distributed peer review trial through rigorous and balanced assessment of peer applications.

4 Career Development

4.1 Independent Research Vision and Career Development Goals

This fellowship establishes the foundation for an independent research career examining how AI reshapes scientific practice. My trajectory from field-based petrology through computational geodynamics to machine learning positions me to conduct rigorous metascientific research while retaining the domain expertise required for credible analysis. The fellowship provides protected time to transition from AI practitioner to systematic investigator of AI-assisted research workflows, generating evidence-based guidance for institutions navigating technological change.

My long-term objective is to build an integrated research program bridging fundamental geoscience, computational methodology, and metascience. Rather than pursuing these in parallel, I aim to develop a group in which domain expertise informs metascientific inquiry and insights about research practice feed back into methodological innovation. Credible analysis of AI's impact requires investigators who understand both the scientific domain and the broader research environment, including institutional policies, technical infrastructure, data practices, and human workflows. This fellowship provides the critical step toward developing that integrated perspective. In the near term, the project shifts my focus from algorithm development and application (Kerswell et al., 2024; Kerswell, 2026) to empirical analysis of how AI alters research workflows. Engagement with cognitive task analysis, decision tracking, and qualitative synthesis develops core competencies for sustained metascientific research leadership that complement, rather than replace, my existing quantitative skills.

4.2 Trajectory and Skill Acquisition

By the end of the 24-month award, the empirical dataset, comparative workflow framework, and competency model will underpin an independent grant application examining AI integration across additional laboratory disciplines, targeting ESRC, NERC, or international equivalents. The fellowship will produce at least two peer-reviewed outputs: a methodological paper establishing the comparative workflow framework and an empirical paper reporting AI's effects on research practice. Engagement with Fireworks AI's commercial fine-tuning platform builds understanding of infrastructure requirements, computational costs, and deployment constraints facing research organizations. Participation in the transatlantic summer school strengthens foundations in AI architectures, metascience methods, and international research networks. Active engagement with EPSRC AI research hubs maintains currency with advances in foundation models, vision-language systems, and human-AI interaction while building collaborations across disciplinary boundaries. Networks formed through these activities and through the Metascience Fellowship cohort will position me for an independent lectureship or equivalent role combining geoscience, computational methodology, and metascientific investigation.

4.3 Mentoring Arrangements

The mentoring structure supports this interdisciplinary trajectory through two complementary advisors. Dr. Elisabetta Mariani, Reader in Earth Materials and Director of the SEM-SRF, contributes expertise in quantitative microscopy, experimental rock deformation, and critical mineral characterization. Her leadership of the SEM-SRF provides operational insight into instrumentation, workflows, user training, and infrastructure constraints, ensuring that empirical observations reflect realistic laboratory environments. Dr. David McNamara, Senior Lecturer and Head of the ESRG, provides complementary expertise in structural geology, fluid-rock interaction, and applied geoscience. His eight years with Earth Sciences New Zealand in geothermal resource assessment ground the fellowship in contexts where analytical decisions affect real-world outcomes, and as Deputy Director of the SEM-SRF he contributes perspective on facility management, technology adoption, and governance. Monthly joint meetings ensure coordinated guidance and interpretation of findings through both technical and institutional lenses.

4.4 Positive Change in the Wider Community

The fellowship contributes to fair and accessible AI adoption by explicitly examining whether AI tools widen disparities between well-resourced and less-resourced research groups. The competency framework and governance guidance produced by the fellowship will be made freely available to support institutions that lack the capacity to conduct their own evaluations. Engagement with UKRI stakeholders through policy briefs, stakeholder events, and the EPSRC AI research hubs ensures findings reach decision-makers who can act on them. I am also committed to mentoring MSc and doctoral researchers who contribute to fellowship activities, supporting the next generation of researchers in developing both domain expertise and critical AI literacy.

5 Host Organization Support

5.1 Research Environment and Infrastructure

The University of Liverpool provides an integrated environment combining advanced analytical instrumentation, high-performance computing (HPC), research software engineering, and structured research development. The fellowship is embedded in the Department of Earth, Ocean and Ecological Sciences and integrated with the SEM-SRF, a centrally supported, cross-faculty facility delivering high-resolution imaging and microanalysis for geoscience and materials research. Core instrumentation includes a Zeiss GeminiSEM 450 field emission scanning electron microscope with EDS and EBSD, optical microscopy, and dedicated sample preparation laboratories. The SEM-SRF serves doctoral researchers, postdoctoral scientists, and academic staff, providing a natural cohort for comparative workflow studies. Structured booking systems, established data management practices, and cross-disciplinary use create a realistic setting in which to examine AI integration at the levels of practice, infrastructure, and governance. Integration with the ESRG ensures access to representative sample collections and established protocols in Economic Geology, Structural Geology, and critical mineral exploration.

Computational support is provided by University of Liverpool Research IT. The Barkla2 HPC cluster supports parallel and GPU-enabled workloads for dataset preparation, AI model configuration and debugging, and image analysis. Secure storage and managed data services enable compliant handling of microscopy datasets and annotations. The Research Software Engineering team supports software architecture, optimization, reproducibility, and deployment, strengthening the sustainability of the AI assistant. Where commercial fine-tuning platforms are used, University procurement and IT security processes ensure contractual review and data governance compliance. This infrastructure enables examination of the financial, technical, and governance factors shaping AI adoption in research facilities.

5.2 Institutional Commitment and Protected Time

The University commits to full protection of fellowship time: teaching and administrative duties will be removed for the award's duration, except where directly aligned with fellowship objectives such as supervision of contributing students. This commitment is formally supported by Prof. Anthony Payne, Head of Department. Administrative support is provided by the Department and Research Support Office, covering procurement, finance, reporting, and compliance. Technical support from SEM-SRF staff, including calibration and sample preparation guidance, is available through standard operations. Office space co-located with Earth Sciences and near the SEM-SRF enables sustained interaction with users and staff, facilitating direct observation of microscopy workflows. The SEM-SRF provides [X] days of subsidized instrument time per year as an in-kind contribution (approximately £[Y]), offsetting direct facility costs claimed under FEC.

5.3 Development, Training, and Strategic Alignment

The University demonstrates sustained commitment to early career researchers through frameworks aligned with the Researcher Development Concordat. Support is delivered via The Academy and the Researcher Hub, providing career planning, networking, and professional development. The Fellows Development Program offers peer mentoring, strategic career planning, and institutional visibility to support progression toward independence. Research and Partnerships Development provides internal peer review and proposal support, while the Research Support Office oversees post-award finance and compliance. Training in research integrity, data management, and ethics governance supports rigorous handling of observational and interview data. Leadership development programs aligned with the University's Leadership Commitment Framework support progression to independent research leadership.

The fellowship aligns with institutional priorities in materials characterization, digital innovation, and interdisciplinary research. Participation in the N8 Research Partnership expands collaboration opportunities in computationally intensive research across research-intensive northern universities. The SEM-SRF's engagement with microscopy manufacturers provides insight into commercial AI tool development, supporting comparative analysis of proprietary and open-source approaches and informing discussions of procurement, sustainability, and governance.

6 Resources and Cost Justification

6.1 Overview

The total Full Economic Cost (FEC) is £259,400, with UKRI contributing £207,520 (80%) and the University of Liverpool £51,880 (20%). Direct costs include: fellow salary (£123,574), AI platform access (£16,000), local computing and data infrastructure (£11,500), microscopy facility time (£65,400), consumables (£16,000), travel and stakeholder engagement (£14,000), training (£4,000), recording equipment (£3,500), transcription and participant support (£4,000), and dissemination materials (£1,426). Institutional HPC access, research software engineering support, office space, open-access publication charges under University Publisher Agreements, and administrative services are provided in-kind.

The fellow salary is requested at 100% FTE for 24 months at Grade 8 Spine Point 36 (£47,389 per annum), with standard increments and employer on-costs. Full-time commitment is required to deliver dataset development (Months 1-9), AI fine-tuning and validation (Months 4-12), comparative workflow studies (Months 13-21), integrative analysis (Months 19-24), and stakeholder engagement. Reduced FTE would compromise coordination and empirical delivery.

6.2 AI Platform and Computing

The £16,000 allocated for commercial AI fine-tuning and inference reflects a dataset of approximately 120 GB, a large vision-language model configuration (Kimi K2.5, Qwen 3 VL 32B, or equivalent class), training duration, and inference during development and workflow sessions. Estimated allocation covers fine-tuning runs (£7,500), development and validation inference (£3,000), inference during workflow sessions (48 sessions at approximately 200 queries each; £3,500), and a retraining contingency (£2,000). Estimates are based on current GPU-backed pricing. Commercial infrastructure is technically and economically justified: it reflects realistic institutional adoption pathways, avoids capital and maintenance costs of dedicated GPU clusters, and provides documentation, version control, and support necessary for reproducibility and governance analysis. Studying AI adoption under realistic commercial conditions also enables analysis of procurement, cost transparency, contractual constraints, and governance considerations that would not arise in a purely bespoke academic deployment. Local computing (£11,500) covers a GPU-enabled workstation, secure storage expansion, and essential specialist software licenses, with intensive training runs using the commercial platform and preprocessing and analysis relying on local hardware and institutional HPC provided in-kind.

6.3 Microscopy Facility Time and Consumables

Microscopy facility time (£65,400) underpins the core empirical outcomes. Costs include training dataset acquisition (60 days at £550/day), structured workflow sessions (48 sessions at 4 hours each at £75/hour), and validation and testing time (£18,000). Although subsidized access is provided, the comparative design requires repeated, controlled instrument use beyond standard research patterns. Tasks must be sufficiently comprehensive to reveal decision pathways and interpretive reasoning, and multiple career stages are required for analytical robustness; facility time cannot be materially reduced without weakening validity. Consumables (£16,000) include mounting media, polishing compounds, carbon coating materials, and calibration standards. Standardized, high-quality preparation minimizes variability between environments and isolates AI-related effects from preparation artifacts.

6.4 Travel and Stakeholder Engagement

Travel (£14,000) supports targeted fieldwork (£6,000) to collect mineral samples with well-constrained geological context, ensuring dataset diversity and interpretive complexity. Exclusive reliance on legacy collections would limit representativeness. Stakeholder engagement and conference travel (£8,000) supports meetings with industry partners, AI providers, EPSRC AI hubs, and UKRI metascience stakeholders to ensure iterative refinement and policy relevance. UKRI-funded summer school participation is excluded from this budget.

6.5 Training and Empirical Documentation

Training (£4,000) supports development in advanced AI and ML methods (including vision-language fine-tuning and responsible deployment) and qualitative and mixed-methods research, both directly aligned with fellowship objectives. Recording equipment (£3,500) supports high-quality audio, video, and screen capture for detailed documentation of workflow sessions; process-level analysis of reasoning and interaction requires accurate capture of microscopy displays and think-aloud protocols. Participant honoraria (£2,000) compensate researchers contributing to structured studies, and professional AI transcription (£2,000) enables efficient, speaker-attributed transcription of interviews and recordings. Dissemination materials (£1,426) support policy briefs and stakeholder-facing outputs.

6.6 Value for Money

The budget is tightly focused on the fellowship's distinctive components: hands-on AI implementation in an operational facility and systematic comparative workflow analysis. The principal costs, AI platform access and microscopy time, directly enable empirical delivery and cannot be replaced by lower-cost alternatives without compromising validity. Institutional co-funding, HPC access, research software engineering support, and administrative services substantially reduce UKRI's burden. Overall, the resources represent a proportionate, strategically targeted investment to generate transferable evidence on how AI reshapes research practice, training, and governance.

7 Ethics and Responsible Research and Innovation

This fellowship examines AI integration within live microscopy workflows. Ethical considerations extend beyond data governance to responsible AI deployment, researcher autonomy, and institutional consequences of AI-augmented research. The project adopts a proactive RRI framework aligned with UKRI principles of anticipation, reflexivity, inclusion, and responsiveness.

Participants will provide informed consent covering screen capture, audio recording, think-aloud protocols, and interviews prior to data collection, for which formal ethical approval will be obtained through the University of Liverpool. The study evaluates workflow processes rather than individual performance, and this framing will be communicated clearly to participants to reduce evaluation anxiety. Participation is voluntary with the right to withdraw at any time. Data will be anonymized during transcription, securely stored, and reported in aggregate form. The design avoids deception and does not alter participants' professional authority or decision-making responsibility; AI outputs are advisory only, and final interpretive authority remains with the human researcher.

The AI assistant will be fine-tuned on microscopy data generated within the host institution and used in accordance with institutional ownership and contractual agreements. No personal participant data will be used for model training. Data provenance, annotation procedures, and model configuration will be documented to ensure transparency and reproducibility. The system will not be used in commercial decision-making during the study, and outputs will not be incorporated into reports without human verification. Risks in human-AI interaction, including automation bias, over-reliance, false confidence, and reduced vigilance, are core research questions; participants will be reminded that AI outputs may be incorrect, and errors and misclassifications will be systematically recorded. All datasets, recordings, and transcripts will be stored on secure, University-managed systems compliant with UK GDPR. Commercial AI platforms will be assessed for contractual and data protection safeguards before use.

The project explicitly evaluates cost, technical barriers, and implementation constraints affecting broader accessibility to address the risk that AI adoption advantages well-resourced groups. Ethical review will be iterative as findings emerge, with unanticipated risks addressed in consultation with the University of Liverpool's Research Ethics and Integrity team. Findings relevant to responsible AI adoption will be communicated to institutional leadership and UKRI stakeholders to inform evidence-based governance.

8 Data Management and Sharing

All data will be managed in accordance with UKRI policy and the University of Liverpool Research Data Management (RDM) framework. A formal Data Management Plan will be completed at project outset and reviewed with RDM specialists to ensure compliance with funder and legal requirements.

The fellowship will generate three primary data types. Microscopy training data will include optical and electron microscopy images (BSE, SE), EBSD phase and orientation maps, EDS elemental data, and expert annotations, with metadata recording sample provenance, preparation methods, instrument parameters, and annotation protocols. Workflow documentation will include screen recordings, think-aloud audio, interview transcripts, structured lab notes, and observational records, with metadata documenting study condition (AI-assisted versus control), task design, protocol versions, and anonymized participant characteristics (career stage only). Analytical outputs will include preprocessing scripts, statistical code, visualizations, AI configuration files, validation metrics, and, where permissible, fine-tuned model artifacts noting potential third-party platform constraints.

Data collection will follow documented protocols to ensure consistency and traceability. Annotation reliability will be assessed through structured review of a subset of samples with formal documentation of disagreements. During the active phase, all data will be stored on secure University-managed systems with controlled access and automated backup, compliant with UK GDPR and institutional information security standards. Where legally and ethically permissible, microscopy datasets and annotations will be deposited in a trusted repository with persistent identifiers and structured metadata. Anonymized qualitative data will be deposited subject to consent and disclosure risk assessment. Code will be version-controlled during development and archived with a DOI-linked release. Publications will be open-access in line with UKRI policy and covered by University Publisher Agreements. Where commercially sensitive samples are involved, data-sharing agreements will be established in advance; derived datasets, aggregated outputs, or representative subsets will be shared where possible, with embargoes applied if justified. All practices will align with FAIR principles to maximize transparency, reproducibility, and reuse.

Mentor Statement

Attachment supplied.

References

Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F., et al. (2023). Gpt-4 technical report. *arXiv Preprint arXiv:2303.08774*.

Birhane, A., Kasirzadeh, A., Leslie, D., & Wachter, S. (2023). Science in the age of large language models. *Nature Reviews Physics*, *5*(5), 277–280.

Branda, F., Ciccozzi, M., & Scarpa, F. (2025). Artificial intelligence in scientific research: Challenges, opportunities and the imperative of a human-centric synergy. *Journal of Informetrics*, *19*(4), 101727.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

Channing, G., & Ghosh, A. (2025). AI for scientific discovery is a social problem. *arXiv Preprint arXiv:2509.06580*.

Commission, E. (2023). *Study on the critical raw materials for the EU 2023*.

Crandall, B., Klein, G., & Hoffman, R. (2006). *Working minds: A practitioner's guide to cognitive task analysis*. Mit Press.

Douglas, D. (2025). Researchers' perceptions of automating scientific research. *AI & SOCIETY*, *40*(5), 4131–4144.

Endsley, M. (2017). From here to autonomy: Lessons learned from human–automation research. *Human Factors*, *59*(1), 5–27.

Ericsson, K., & Charness, N. (1994). Expert performance: Its structure and acquisition. *American Psychologist*, *49*(8), 725.

Ferrario, A., Facchini, A., & Termine, A. (2024). Experts or authorities? The strange case of the presumed epistemic superiority of artificial intelligence systems: A. Ferrario et al. *Minds and Machines*, *34*(3), 30.

Government, U. (2025). *Vision 2035: Critical minerals strategy*.

Kerswell, B. (2026). Methods in tectonics: From big data to machine learning. In *Geoscience in practice*. Geological Society of London.

Kerswell, B., & Kohn, M. J. (2022). A comparison of surface heat flow interpolations near subduction zones. In *AGU fall meeting abstracts*.

Kerswell, B., Kohn, M., & Gerya, T. (2021). Backarc lithospheric thickness and serpentine stability control slab-mantle coupling depths in subduction zones. *Geochemistry, Geophysics, Geosystems*, *22*(6), e2020GC009304.

Kerswell, B., Kohn, M., & Gerya, T. (2023). Computing rates and distributions of rock recovery in subduction zones. *Geochemistry, Geophysics, Geosystems*, *24*(5), e2022GC010834.

Kerswell, B., Cerpa, N., Tommasi, A., Godard, M., & Padrón-Navarta, J. (2024). RocMLMs: Predicting rock properties through machine learning models. *Journal of Geophysical Research: Machine Learning and Computation*, *1*(4), e2024JH000264.

Kerswell, B., Wheeler, J., Gassmöller, R., et al. (2026). Beyond equilibrium: Kinetic thresholds and rheological feedbacks create a potentially complex 410 in slab regions. *ESS Open Archive*.

Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., et al. (2023). Segment anything. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 4015–4026).

Klein, G. (2017). *Sources of power: How people make decisions*. MIT press.

Klöcking, M., Wyborn, L., Lehnert, K., Ware, B., Prent, A., Profeta, L., et al. (2023). Community recommendations for geochemical data, services and analytical capabilities in the 21st century. *Geochimica Et Cosmochimica Acta*, *351*, 192–205.

Kohn, M., Castro, A., Kerswell, B., Ranero, C., & Spear, F. (2018). Shear heating reconciles thermal models with the metamorphic rock record of subduction. *Proceedings of the National Academy of Sciences*, *115*(46), 11706–11711.

Kovalevskiy, O., Mateos-Garcia, J., & Tunyasuvunakool, K. (2024). AlphaFold two years on: Validation and impact. *Proceedings of the National Academy of Sciences*, *121*(34), e2315002121.

Lee, J., & See, K. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, *46*(1), 50–80.

Leonelli, S., & Mussgnug, A. (2025). Convenience AI.

Leontidis, G. (2024). Science in the age of ai: How artificial intelligence is changing the nature and method of scientific research.

Liu, Y., Checa, M., & Vasudevan, R. (2024). Synergizing human expertise and AI efficiency with language model for microscopy operation and automated experiment design. *Machine Learning: Science and Technology*, *5*(2), 02LT01.

Long, S., Kohn, M., Kerswell, B., Starnes, J., Larson, K., Blackford, N., & Soignard, E. (2020). Thermometry and microstructural analysis imply protracted extensional exhumation of the tso morari UHP nappe, northwestern himalaya: Implications for models of UHP exhumation. *Tectonics*, *39*(12), e2020TC006482.

Ludwig, J., & Mullainathan, S. (2024). Machine learning as a tool for hypothesis generation. *The Quarterly Journal of Economics*, *139*(2), 751–827.

Morrison, C., & Kerswell, B. (2023). Comparing PT paths of metamorphic rocks determined by quantitative and semi-quantitative approaches: A case study from the monviso ophiolite, italy. In *Geological society of america abstracts with programs. Vol. 55, no. 3*. Geological Society of America.

Mosier, K., Skitka, L., Burdick, M., & Heers, S. (1996). Automation bias, accountability, and verification behaviors. In *Proceedings of the human factors and ergonomics society annual meeting* (Vol. 40, pp. 204–208). SAGE Publications Sage CA: Los Angeles, CA.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors*, *39*(2), 230–253.

Radford, A., Kim, J., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., et al. (2021). Learning transferable visual models from natural language supervision. In *International conference on machine learning* (pp. 8748–8763). PmLR.

Ramesh, A., Dhariwal, P., Nichol, A., Chu, C., & Chen, M. (2022). Hierarchical text-conditional image generation with clip latents. *arXiv Preprint arXiv:2204.06125*, *1*(2), 3.

Resnik, D., & Hosseini, M. (2025). The ethics of using artificial intelligence in scientific research: New guidance needed for a new tool. *AI and Ethics*, *5*(2), 1499–1521.

Sims, D., & Kerswell, B. (2023). Deformation of dry high-pressure eclogites during tectonic slicing of subducted oceanic lithosphere: A case study from the monviso ophiolite, italy. In *Geological society of america abstracts with programs. Vol. 55, no. 3*. Geological Society of America.

USGS. (2024). *Mineral commodity summaries 2024*.

Yang, S., & Ma, R. (2025). Classifying epistemic relationships in human-AI interaction: An exploratory approach. *arXiv Preprint arXiv:2508.03673*.