AI-Assisted Microscopy in Geoscience

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

Kerswell B.

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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 observational 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 (e.g., Kimi K2.5, Qwen 3) 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 The Central Problem and Knowledge Gap

AI is widely heralded as a transformative force in scientific discovery, promising acceleration of data analysis, hypothesis generation, and research throughput (Wang et al., 2023). However, understanding of AI's role in scientific research remains largely speculative (Channing & Ghosh, 2025) and insufficiently grounded in *empirical evidence about how research is actually conducted with these technologies* (Chubb et al., 2022). The UKRI Metascience AI Early Career Fellowships prioritize projects that build *systematic, evidence-based understanding of AI's impact on the research landscape, researchers' day-to-day work, and institutional responses*.

Despite rapid adoption of machine learning, deep learning, and foundation models, recent evaluations of AI-augmented research highlight unresolved questions (Branda et al., 2025; Douglas, 2025; Ferrario et al., 2024; Ludwig & Mullainathan, 2024; Resnik & Hosseini, 2025; Yang & Ma, 2025). How do AI systems shape the *moment-to-moment decisions* researchers make during data acquisition and interpretation? Do they encourage exploratory pattern discovery (hypothesis generation) or primarily reinforce hypothesis testing? What competencies are required to work effectively and responsibly in AI-assisted environments? Where does human judgement remain indispensable as AI capabilities improve? These questions are both scientifically and socially consequential, bearing directly on research quality, the risk of a 'digital divide' between well-funded and less-resourced labs, and the future organization of scientific work.

Current literature tends to emphasize *algorithmic performance* (e.g., accuracy, efficiency) and *broad ethical concerns* (e.g., bias, governance). Far less attention is paid to the *micro-practices* of scientific work—the real-world tasks, interpretive judgments, and iterative decisions that constitute research practice. 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. Bridging this empirical gap is essential for advancing metascience and enabling responsible AI adoption.

1.2 Why This Work Matters Now

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; Radford et al., 2021; Ramesh et al., 2022; Wang et al., 2023). Second, commercial fine-tuning platforms have lowered barriers to domain adaptation, allowing researchers to customize foundation models without extensive AI expertise. Third, critical mineral research has become a strategic priority for the UK and global economies (Commission, 2023; Government, 2025; USGS, 2024), increasing the stakes of decisions about training, infrastructure, and workflow design in microscopy where AI tools are emerging.

Microscopy workflows therefore provide an empirically rich and policy-relevant setting for examining AI's impact on research practice.

This fellowship responds directly to UKRI objectives in three ways. First, 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. Second, 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. Third, 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. These findings provide an empirical basis for decisions about training investment, infrastructure funding, and responsible AI deployment.

1.3 Distinctiveness and Strategic Importance

This research is distinctive in several respects.

First, rather than developing new AI architectures, the project *deploys existing AI tools within traditional microscopy workflows* to generate empirical evidence about their impacts. The focus is explicitly on AI's influence on research practice and epistemic culture—*how science is conducted*—rather than on AI ethics or safety, which are addressed elsewhere.

Second, the project emphasizes *process over outcomes*. The central question is not whether AI improves accuracy or efficiency, but how its integration reshapes researchers' cognitive processes and judgement. In microscopy and critical mineral characterization, expert interpretation is embedded in iterative sequences of imaging choices, zooming strategies, and textural judgments that resist simple automation. Mapping AI's interaction with each phase of this process yields insights more generalizable than performance metrics alone.

Third, the comparative design spans researchers at different career stages. This enables analysis of not only what changes with AI adoption but *who* benefits and how. Early career researchers, mid-career scientists, and established experts may differ in trust calibration, cognitive offloading, attention allocation, and error detection when engaging with AI-assisted microscopy. Understanding these differences is critical for designing training pathways that support professional development and mitigate skill regression.

Finally, the focus on critical mineral microscopy is strategically significant. The need to characterize mineral assemblages in exploration and extraction contexts intersects directly with policy and economic priorities related to critical mineral supply chains (Commission, 2023; Government, 2025; USGS, 2024). AI integration in these workflows may influence exploration efficiency, resource assessment, and economic decision-making. The project is therefore both metascientifically relevant and economically consequential.

1.4 Expected Contributions and Advances

This fellowship advances understanding in three interconnected domains: transformation of research practice, competency development, and human–AI division of labor.

First, it will provide a *systematic characterization of how AI alters research practice*. Matched workflows with and without AI assistance will be compared to document differences in decision points, attention allocation, and interpretive strategies. This builds on cognitive science research on expertise and distributed cognition (Crandall et al., 2006; Ericsson & Charness, 1994; Hutchins, 1995; Klein, 2017), as well as human–automation research on trust calibration, situation awareness, and appropriate reliance in complex systems (Endsley, 2017; Lee & See, 2004; Mosier et al., 1996; Parasuraman & Riley, 1997) and contemporary analyses of human–AI collaboration (Beck et al., 2025; Binz et al., 2025; Daly et al., 2025; Yang & Ma, 2025).

Second, the project will develop an *evidence-based competency framework* specifying what researchers require to work effectively with AI. This framework will distinguish foundational competencies that remain essential (e.g., interpretive judgement, error recognition) from new literacies (e.g., understanding model limitations, contextualizing outputs). The results will inform higher education curricula and professional development programs.

Third, the research will clarify *where human agency remains indispensable* in AI-assisted environments. Through systematic analysis of comparative outputs, error modes, and interpretive novelty, the project will identify tasks where AI adds value and tasks requiring sustained human oversight. This contributes to broader discussions about autonomy, accountability, and the organization of research labor.

Collectively, these advances will provide funding agencies, research organizations, educators, and policymakers with robust empirical evidence to guide investment strategies, training reform, and governance frameworks for AI integration across scientific domains.

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 primarily through technical performance metrics, 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—not 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

2.2.1 Scientific Context and Rationale for Domain Selection

Microscopy is central to research across the physical and life sciences and requires sustained expert judgement 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. These features make microscopy a suitable domain for examining AI integration: it combines pattern recognition, contextual interpretation, and real-time decision-making under uncertainty.

The project focuses on characterization of gold-bearing mineral assemblages using optical and electron microscopy. Gold mineralization provides a rigorous test case: it involves 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. This enables systematic examination of where AI augments practice and where it risks oversimplification or error.

The work is conducted within the SEM-SRF, ensuring access to established workflows, instrumentation, and expert users. Embedding the study in an operational facility—rather than a simulated environment—captures the constraints, incentives, and norms that shape real research practice.

2.2.2 Data Asset Development and Annotation

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 (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 standard analytical tools 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 areas of interpretive ambiguity central to scientific reasoning. This process also generates metascientific insight into how expertise is codified and where tacit judgement operates.

2.2.3 Model Selection, Fine-Tuning, and Deployment

The project uses open-source vision-language models (Kimi K2.5 and Qwen 3) fine-tuned via commercial infrastructure (Fireworks AI). These models represent contemporary multimodal capabilities while remaining accessible to non-specialist research groups. Using commercial fine-tuning platforms mirrors pragmatic institutional adoption pathways and exposes realistic technical, financial, and organizational constraints.

Fine-tuning uses the curated microscopy dataset, with systematic documentation of data preparation requirements, computational costs, expertise demands, and encountered limitations. The objective is not maximal accuracy but a functional AI assistant capable of interacting meaningfully during microscopy workflows. The assistant performs tasks such as 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, encouraging critical evaluation. This design enables analysis of trust calibration, interpretation of AI model reasoning, and responses to error—matters central to the study of the scientific process.

Documentation of costs, technical constraints, data ownership issues, vendor dependencies, and compliance requirements constitutes a core research output. These observations provide concrete evidence about institutional conditions necessary for responsible AI integration.

2.2.4 Baseline Validation and Performance Characterization

Prior to workflow studies, baseline performance is evaluated using held-out expert-annotated test data. This establishes strengths, weaknesses, and error modes of the AI assistant under controlled conditions. AI performance metrics provide contextual information but are not primary outcomes. The analytical focus remains on how *humans interact with AI*, recognizing that even imperfect AI systems can significantly alter behavior, attention, and decision-making (Mosier et al., 1996; Parasuraman & Riley, 1997).

2.3 Phase 2: Comparative Workflow Studies

2.3.1 Study Design and Participant Recruitment

The core empirical component consists of comparative workflow studies in which researchers perform matched tasks in traditional and AI-assisted environments. Participants are recruited across career stages: early-stage PhD students (years 1–2), doctoral/postdoctoral researchers (1–4 years post-PhD), and established academics (10+ years experience). Stratification enables analysis of how AI effects vary with expertise and professional role.

The target sample comprises approximately 24 participants (8 per career stage), yielding 48 sessions (each participant completes both environments). This balances statistical interpretability with qualitative depth.

Each participant completes equivalent tasks in both environments, with order counterbalanced to mitigate learning effects. 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 artefacts.

2.3.2 Documentation of Research Practice

Sessions are comprehensively documented. Screen recordings capture visual information, tool use, and AI interactions. Participants employ think-aloud protocols to verbalize reasoning. Structured lab notes record observations and justifications. Immediate debriefing interviews probe perceived task difficulty, confidence, and AI influence. Follow-up reflective interviews compare traditional and AI-assisted experiences.

This multi-modal approach draws on cognitive task analysis (Crandall et al., 2006), adapted to scientific research. It enables reconstruction of decision pathways, identification of critical junctures, and analysis of how AI reshapes cognitive and practical workflows.

2.3.3 Analysis of Human–AI Interaction

AI-assisted sessions focus on how participants engage with the assistant. Key dimensions include timing of AI consultation, interpretation of suggestions, and conditions under which outputs are accepted, questioned, or rejected. The analysis examines whether AI is used for initial guidance or confirmation, how trust evolves, and whether monitoring outputs imposes new cognitive demands.

Error detection and recovery are central. Instances of incorrect or misleading AI suggestions are documented, and responses analyzed. Differences across experience levels clarify whether effective AI use presupposes prior expertise or whether AI scaffolds novice development. These findings directly inform debates on automation bias, skill regression, and appropriate oversight (Endsley, 2017).

2.4 Phase 3: Analytical Synthesis and Metascientific Frameworks

2.4.1 Comparative Workflow Analysis

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. 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. Particular attention is paid to workflow inflection points where AI input changes what is noticed, how it is interpreted, or when analysis ceases. Routine and ambiguous cases are compared to identify boundaries of reliable AI support.

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.

2.4.2 Competency Mapping and Training Implications

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.

Technical competencies include interaction with AI interfaces and data management. Interpretive competencies include evaluating outputs, recognizing failure modes, and maintaining independent judgement. Meta-cognitive competencies include 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. The findings provide guidance on when and how AI tools should be introduced in educational pathways, addressing risks of skill erosion and over-reliance.

2.4.3 Assessment of Research Outputs

Outputs from both environments are evaluated using ground truth where available and expert consensus where ambiguity persists. Criteria extend beyond correctness to include interpretive richness, anomaly recognition, generation of novel insights, and appropriate expression of uncertainty. This multidimensional evaluation reflects scientific epistemic standards rather than narrow performance metrics.

Comparative analysis establishes where AI enhances research quality and where it risks superficial gains. These findings inform decisions regarding task delegation, oversight, and appropriate scope of AI use in research settings.

2.4.4 Policy, Governance, and Implementation Analysis

In parallel with workflow analysis, the fellowship examines institutional and policy implications. This includes intellectual property and data governance considerations associated with fine-tuning models on research data, particularly in commercially sensitive domains such as critical mineral exploration. Existing UKRI data management frameworks are reviewed to assess adequacy for AI-augmented research and identify areas requiring clarification.

Implementation feasibility is evaluated in terms of resource requirements, infrastructure dependencies, expertise needs, and vendor reliance. This analysis assesses whether AI adoption risks widening disparities between well-resourced and less-resourced groups.

2.4.5 Risk Management and Adaptability

Active risk management is embedded throughout. Technical risks are mitigated by focusing on metascientific insight rather than optimization. Recruitment risks are reduced through established institutional networks. Ethical approval is sought early, 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.

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.

The timeline reflects methodological dependencies: workflow studies follow AI configuration; qualitative analysis follows data collection; synthesis integrates empirical findings. Stakeholder engagement occurs throughout to maintain policy relevance.

Findings will be synthesized into concise policy briefs addressing funding, infrastructure investment, workforce development, and governance. These outputs are designed for direct use by UKRI, research councils, and institutional leaders making AI investment decisions.

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. This interdisciplinary foundation provides the domain expertise and computational fluency required to investigate AI-assisted microscopy workflows systematically.

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—direct experience in domain-specific AI development. 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. This required coordination across laboratories and institutions to negotiate metadata standards, analytical provenance, and reuse practices. The experience provides insight into how computational tools interact with established research infrastructures.

My doctoral and postdoctoral 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 relevant to the proposed work.

I have consistently worked across disciplinary boundaries, translating scientific requirements into interoperable computational frameworks in collaboration with data scientists, software developers, and laboratory practitioners. International collaborations required coordinating analytical strategies across institutions and integrating complementary expertise—experience aligned with the metascientific scope of this fellowship.

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. Participation developed capacity to manage complex collaborations and align diverse methodological approaches toward shared goals.

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. This experience strengthens my ability to communicate complex technical material clearly to varied audiences.

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. These mentoring skills translate directly to engagement with facility users and researchers across career stages in the proposed fellowship.

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. Links with commercial instrument providers support informed consideration of emerging AI-enabled analytical tools and associated constraints.

International collaborations in critical mineral exploration and applied geoscience provide insight into environments where AI-assisted workflows have practical consequences, grounding the fellowship's empirical case studies.

3.3 Contributions to the Wider Research and Innovation Community

I have published in leading journals including *Proceedings of the National Academy of Sciences*, *Geochemistry Geophysics Geosystems*, *Journal of Geophysical Research*, *Geochimica et Cosmochimica Acta*, and *Tectonics*. I regularly disseminate findings at international conferences and workshops, translating computational and geoscientific advances across disciplinary communities.

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 US National Science Foundation. This service has developed experience evaluating methodological rigor across diverse scientific domains.

I adopt open research practices appropriate to my field, sharing computational workflows via GitHub and the Open Science Framework where feasible. Public repositories include RocMLM implementations, geodynamic model codes, and data analysis pipelines. The fellowship will extend these practices through release of study protocols, anonymized workflow data, and analysis code to support reproducibility.

In April 2025, I co-organized and hosted the Mineralogical Society Metamorphic Studies Group meeting at Liverpool, bringing together over 50 participants. I also participate in international workshops (e.g., ASPECT Hackathons, French Network on Subduction Zones, Ada Lovelace Workshops, ERC RhEoVOLUTION workshops), maintaining engagement with mineral science and computational geoscience developments.

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, 2026) informs understanding of geothermal systems and earthquake processes. These projects involve real-world constraints where analytical decisions have practical implications.

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 aligned with this fellowship's focus on practical impacts rather than technological novelty.

I have communicated complex scientific and computational ideas to non-specialist audiences through teaching and outreach, including mentoring student innovation initiatives. 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 practical integration of AI into research workflows. The motivation derives from my personal observations of rapid AI adoption in geoscience without systematic evaluation of its effects on judgement, workflow structure, and epistemic control.

I bring applied machine learning expertise, experience designing reproducible computational workflows, and familiarity with shared research facilities. I have worked across scientific, technical, and policy contexts, supporting both empirical and analytical components of the proposed work. My GitHub repositories document a sustained commitment to transparent and reproducible research.

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 view the fellowship as an opportunity to contribute to a community advancing rigorous understanding of AI's role in research. 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

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 in which AI is used—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, I will extend beyond conventional geoscience training to establish independent metascience capability. The fellowship shifts my focus from algorithm development (Kerswell et al., 2024; Kerswell, 2026) to empirical analysis of how AI alters research workflows. Projects such as the microscopy AI assistant and comparative workflow study develop transferable expertise in decision tracking, cognitive task analysis, and qualitative synthesis—core competencies for sustained metascientific research leadership.

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: (1) a methodological paper establishing the comparative workflow framework and (2) an empirical paper reporting AI's effects on research practice. Networks formed through EPSRC AI research hubs, the Metascience Fellowship cohort, and stakeholder engagement will position me for an independent lectureship or equivalent role combining geoscience, computational methodology, and metascientific investigation.

4.2 Mentoring Arrangements

The mentoring structure supports this interdisciplinary trajectory. Dr. Elisabetta Mariani, Reader in Earth Materials and Director of the University of Liverpool's SEM-SRF, contributes expertise in quantitative microscopy, experimental rock deformation, and critical mineral characterization—the empirical basis of the fellowship's case studies. 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. Her research on critical mineral resources and materials discovery aligns directly with the fellowship's strategic focus.

Dr. David McNamara, Senior Lecturer and Head of the University of Liverpool's ESRG, provides complementary expertise in structural geology, fluid–rock interaction, and applied geoscience. His eight years with Earth Sciences New Zealand conducting geothermal resource assessment ground the fellowship in contexts where analytical decisions affect real-world outcomes. As Deputy Director of the SEM-SRF, he contributes perspective on facility management, technology adoption, and governance. His work on geothermal systems, carbon storage, and critical resources connects the project to policy-relevant applications.

Together, this mentoring arrangement addresses identified development needs. Dr. Mariani leads on microscopy workflow integration and domain expertise; Dr. McNamara contributes applied and governance perspectives. Monthly joint meetings ensure coordinated guidance and interpretation of findings through both technical and institutional lenses.

4.3 External Training and Institutional Integration

The fellowship provides structured external development. 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.

Empirical work embedded within the University of Liverpool's SEM-SRF ensures that development occurs in authentic research contexts. Working with operational instruments, active users, and real analytical challenges requires engagement with institutional constraints, expertise development, and decision trade-offs shaping AI adoption. This embedded approach cultivates understanding of research infrastructure, user capability formation, and governance dynamics—insights inaccessible through abstract or simulation-based studies alone.

5 Host Organization Support

5.1 Research Environment, Infrastructure and Operational Support

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 will be embedded in the Department of Earth, Ocean and Ecological Sciences and integrated with the SEM-SRF.

The SEM-SRF is 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. These systems underpin mineralogical and microstructural characterization central to critical mineral exploration and Earth Materials research. Facility staff provide expertise in quantitative microscopy, crystallography, and workflow optimization. Embedding the fellowship within this operational facility ensures AI tools are evaluated under real laboratory conditions, shaped by authentic constraints, users, and institutional practices.

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 to examine AI integration at the levels of practice, infrastructure, and governance. Integration with the University's 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, model fine-tuning, 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 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.

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 (e.g., 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 colocated with Earth Sciences and near the SEM-SRF enables sustained interaction with users and staff, facilitating direct observation of microscopy workflows.

5.2 Institutional Commitment, Development 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. Guidance on intellectual property, commercial engagement, and data stewardship informs analysis of AI fine-tuning on research-generated datasets. Leadership development programs aligned with the University's Leadership Commitment Framework support progression to independent research leadership, and supervisor development training supports effective mentoring of MSc or doctoral researchers contributing to fellowship activities.

The fellowship aligns with institutional priorities in materials characterization, digital innovation, and interdisciplinary research. Established strengths in Earth Materials, Economic Geology, and Analytical Microscopy provide a strong scientific base, while emerging AI-assisted approaches position the fellowship within a strategically relevant context. Participation in the N8 Research Partnership expands collaboration opportunities in computationally intensive research across research-intensive northern universities, strengthening links to broader UK AI initiatives.

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. Institutional business engagement structures facilitate dialogue with industry and policymakers, enhancing relevance to national research infrastructure planning and responsible AI adoption.

The University provides required institutional co-funding under full economic costing, representing substantial financial commitment. Institutional infrastructure—including SEM-SRF access, HPC provision, research software engineering support, office space, library services, and administrative assistance—is provided within standard frameworks. 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. These contributions ensure fellowship funds are focused on dataset development, AI fine-tuning, empirical workflow studies, and dissemination.

Protected research time, advanced analytical and computational infrastructure, professional software engineering support, structured development programs, and strong strategic alignment together create a coherent platform for delivery. The environment enables rigorous empirical investigation of AI integration within operational microscopy workflows while supporting transition to independent research leadership in metascience and AI impacts research.

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, 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

£16,000 is allocated for commercial AI fine-tuning and inference (Fireworks AI or equivalent). Costs reflect a ~120 GB microscopy dataset, large vision-language model configuration (e.g., Kimi K2.5 or Qwen 3 VL 32B class), training duration, and inference during development and workflow sessions.

Estimated allocation: fine-tuning runs (£7,500), development/validation inference (£3,000), inference during workflow sessions (48 sessions $\times$ 200 queries) (£3,500), and 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. Building bespoke infrastructure within budget would either exceed resources or limit meaningful evaluation.

Local computing (£11,500) covers a GPU-enabled workstation, secure storage expansion, and essential specialist software licences. Intensive training runs will use the commercial platform; preprocessing and analysis will rely on local hardware and institutional HPC provided in-kind.

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.

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 $\times$ 4 hours at £75/hour), and validation/testing time (£18,000). Although subsidized access is provided, the comparative design requires repeated, controlled instrument use beyond standard research patterns.

Participants complete matched tasks under traditional and AI-assisted conditions. Tasks must be sufficiently comprehensive to reveal decision pathways and interpretive reasoning. 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. Additional consumables ensure consistent surface preparation and calibration across sessions, isolating AI-related effects from preparation artefacts.

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. Engagement ensures iterative refinement and policy relevance. UKRI-funded summer school participation is excluded.

6.5 Training and Empirical Documentation

Training (£4,000) supports development in advanced AI/ML methods (e.g., vision-language fine-tuning, responsible deployment) and qualitative/mixed-methods research. These are directly aligned with fellowship objectives.

Recording equipment (£3,500) supports high-quality audio/video capture and screen recording 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. Professional AI transcription (£2,000) enables efficient, speaker-attributed transcription of interviews and recordings. Open access publication charges (£7,500) are covered in-kind through University Publisher Agreements. 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. The allocation balances technical implementation, empirical depth, and policy-relevant dissemination while ensuring responsible stewardship of public funds.

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.

7.1 Human Participants and Observation of Practice

The study observes and records researchers performing microscopy tasks under traditional and AI-assisted conditions. Although activities reflect routine professional practice, formal ethical approval will be obtained through the University of Liverpool prior to data collection.

Participants will provide informed consent covering screen capture, audio recording, think-aloud protocols, and interviews. The study evaluates workflow processes rather than individual performance; this will be communicated clearly 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. Case examples will be anonymized to prevent identification.

The design avoids deception and does not alter participants' professional authority or decision-making responsibility. AI outputs are advisory only; final interpretive authority remains with the human researcher.

7.2 Responsible AI Development and Use

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. Where external data are involved, permissions and data-sharing agreements will be confirmed. 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 provide probabilistic and explanatory outputs rather than deterministic classifications. It will not be used in commercial decision-making during the study, and outputs will not be treated as ground truth or 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. Errors and misclassifications will be systematically recorded to identify failure modes and conditions requiring heightened oversight.

7.3 Data Governance and Security

All datasets, recordings, and transcripts will be stored on secure University-managed systems compliant with UK GDPR and institutional policies. Commercial AI platforms will be assessed for contractual and data protection safeguards. No identifiable participant data will be uploaded to external systems.

Derived datasets, code, and methodological documentation will be shared via institutional repositories where legally and commercially permissible. Where raw data are commercially sensitive, detailed metadata and protocols will be provided to support transparency.

7.4 Fairness and Institutional Implications

AI adoption may advantage well-resourced groups. The project explicitly evaluates cost, technical barriers, and implementation constraints affecting broader accessibility. Recruitment will include researchers across career stages and, where feasible, diverse backgrounds within the host institution.

7.5 Reflexive Governance

Ethical review will be iterative as findings emerge. Unanticipated risks—such as inappropriate reliance on AI outputs or governance ambiguities—will be addressed in consultation with the University of Liverpool's Research Ethics and Research Integrity team. Findings relevant to responsible AI adoption will be communicated to institutional leadership and UKRI stakeholders to inform proportionate, evidence-based governance.

8 Data Management and Sharing

8.1 Data Generation and Governance

All data will be managed in accordance with UKRI policy and the University of Liverpool Research Data Management (RDM) framework. Institutional support from Research Integrity and Library RDM services includes guidance on planning, metadata standards, repositories, licensing, and long-term preservation. 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.

1. **Microscopy training data:** optical and electron microscopy images (BSE, SE), EBSD phase and orientation maps, EDS elemental data, and expert annotations. Metadata will record sample provenance, preparation methods, instrument parameters, and annotation protocols.

2. **Workflow documentation:** screen recordings, think-aloud audio, interview transcripts, structured lab notes, and observational records. Metadata will document study condition (AI-assisted vs control), task design, protocol versions, and anonymized participant characteristics (career stage only).
3. **Analytical outputs:** preprocessing scripts, statistical code, visualizations, AI configuration files, validation metrics, and, where permissible, fine-tuned model artefacts (noting potential third-party platform constraints).

8.2 Active Management and Quality Assurance

Data collection will follow documented protocols to ensure consistency and traceability. Annotation reliability will be assessed through structured review of a subset of samples and 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.

8.3 Archiving, Sharing, and FAIR Access

Data will be prepared for archiving in the final project quarter. 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 (transcripts and documentation) 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. The default position is open sharing under permissive licences; restrictions will apply only where ethically, legally, or commercially required.

Human participant data will be collected under prior ethical approval with explicit consent for anonymized archiving and reuse. Direct identifiers will be removed and indirect identifiers minimized to reduce disclosure risk in a small specialist community. 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.

Where file sizes create technical constraints, curated representative datasets will be archived alongside complete metadata and documentation. Model configuration files, training protocols, and validation results will be shared even where redistribution of model weights is restricted. All practices will align with FAIR principles to maximize transparency, reproducibility, and reuse.

Mentor Statement

Attachment supplied.

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