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Global Community Priorities for Agentic AI in Research

Community Consultation Results

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Based on the community survey and information sessions

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Executive Summary

In November 2025, the Research Data Alliance (RDA) in collaboration with Microsoft, launched a global community consultation to explore current use of agentic AI by researchers and get their perspectives on its value throughout the research lifecycle. For this consultation, agentic AI was defined as '***artificial intelligence systems capable of autonomous operation with minimal human oversight'***. The consultation was open to all, regardless of AI expertise or experience, or geographical location. It builds upon RDA's previous collaboration with Microsoft, which had identified agentic AI as a critical capability need amongst researchers and recommended investment in automated data preparation tools.

The consultation comprised two components: four online information sessions held across different time zones and an anonymous 15-minute survey. Survey respondents evaluated 11 proposed agentic AI tools that spanned the entire research lifecycle, from planning and funding through to publication and impact reporting.

Three proposed tools emerged as clear community priorities: the **Literature Librarian**, which would search literature using natural language queries integrated with library subscriptions; the **Data Director**, designed to support research data preparation and sharing in compliance with FAIR principles; and the **Funding Finder**, which would identify relevant funding opportunities and support application processes. These top three rankings were reflected across both regional and stakeholder analyses, with the Literature Librarian, Data Director, and Funding Finder consistently appearing amongst the highest priorities.

However, it should be considered that contributions were unequal across stakeholder groups and regions, with European respondents *(n*=44) representing the largest regional cohort and researchers and scientists (*n*=33) comprising the largest stakeholder group. Overall, participants portrayed a complex, ambivalent future. Insights from this consultation will guide the next phase of work in 2026, which intends to focus on collaborative community development of an open, technology-agnostic blueprint for a priority agentic AI tool.

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1. About the Global Community Consultation

Agentic AI has the potential to transform how research is done. These systems may be able to help with many parts of the research process, from reviewing literature and generating ideas to designing experiments, analysing data, and preparing publications.[1] They may speed up research, lower costs, and make advanced research tools available to more people across all disciplines.

Within the context of this initiative, 'agentic AI' is defined as '***artificial intelligence systems that can act autonomously, reason toward specific goals, and operate independently with minimal human oversight***'. This distinguishes agentic AI from traditional AI systems that respond to direct prompts. We recognise that alternative definitions exist across the research community, and this definition served as a working framework for consultation purposes.

In November 2025, the Research Data Alliance (RDA) launched a global community consultation to identify how and where agentic AI may be able to support the research data ecosystem.[2] This built upon the RDA's previous collaboration with Microsoft, which recommended investing in automated data preparation tools and improved data standards. The collaboration also identified agentic AI as a top skilling need among researchers, as detailed in the white paper 'Data Readiness and Data-Centric AI'.[3]

Through online information sessions and an open survey[4], the consultation explored current use of agentic AI by researchers, their priorities and challenges, and how or where agentic AI could have the greatest impact in the research lifecycle. This extended Microsoft's previous engagement with over 50 research institutions within the United Kingdom that identified eleven potential agentic AI tools of use throughout the research lifecycle (**Figure 1**).

These proposed tools served as a starting point to elicit community responses and gather perspectives. It should be acknowledged that these tools do not represent an exhaustive list nor are they confirmed for technological development. For each tool, the survey asked respondents to rate its usefulness and suggest improvements or missing features. For each stage of the research lifecycle, respondents were asked to identify existing relevant tools and propose other desirable tool capabilities to support that research stage.

[1] https://arxiv.org/html/2503.08979v1
[2] https://www.rd-alliance.org/value_rda/rda-and-artificial-intelligence/global-community-priorities-for-agentic-ai-development/
[3] https://doi.org/10.15497/RDA00134
[4] https://www.rd-alliance.org/wp-content/uploads/2025/10/Agentic-AI-in-Research_-RDA-Community-Consultation-Su.pdf

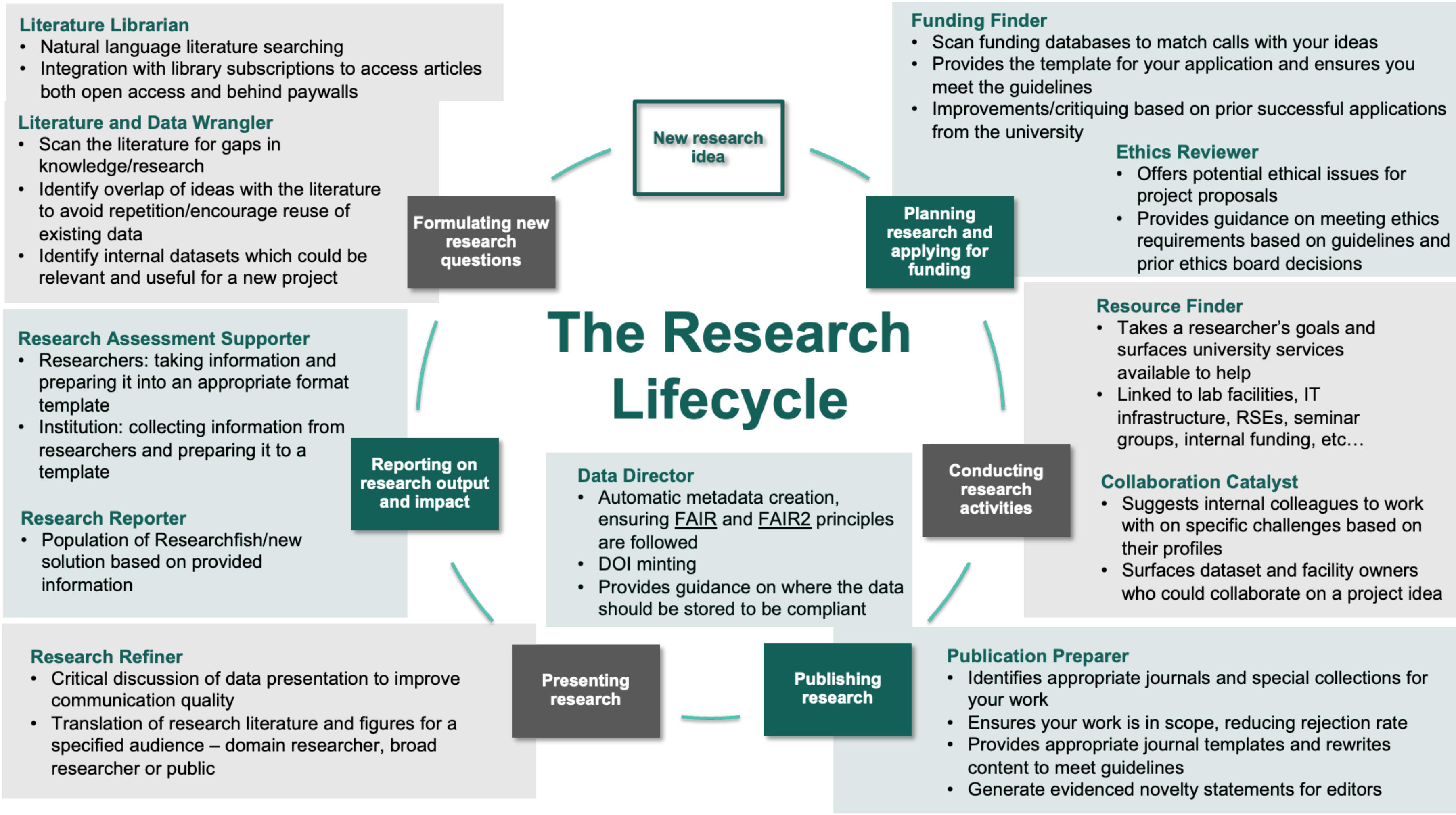

Figure 1. **Proposed agentic AI agents across the research lifecycle.** Eleven potential AI agents identified through Microsoft's engagement with UK research institutions, mapped to stages of the research lifecycle. These agents formed the basis for community prioritisation in this consultation.

1.1 Information Sessions

Four 45-minute online sessions were held via Microsoft Teams on 11th, 12th, 13th and 27th November to accommodate different time zones. Overall, the sessions attracted 190 registrants and 70 participants across all sessions. Collectively, session registrants represented 33 countries from 6 continents.

Open to all research stakeholders regardless of AI expertise, each session provided background information on agentic AI, real-world examples of agentic AI use, and a feedback session guided by Mentimeter[5] on needs, concerns, and priority areas for research impact (**Section 7.1, S5**). Information session participants were asked about their use of agentic AI in their professional roles and to rank the 11 proposed AI agents from most to least valuable.

The information sessions featured presentations from expert speakers: Assistant Professor Harang Ju (Johns Hopkins Carey Business School, United States) on collaborating with and building AI agents, Dr Moji Ghadimi (QCIF, Australia) on building a literature review agentic AI, Associate Professor Ugochi Okengwu (University of Port Harcourt, Nigeria) on the potential of agentic AI for crop image analysis, and Dr Mukkesh Kumar (A*STAR, Singapore) on agentic AI for research data platforms. Dr Ryan Payton (Microsoft, UK) also provided an overview of agentic AI in research, highlighting the eleven proposed AI agents (**Section 7.2**).

1.2 Community Survey

A 15-minute anonymous survey, open throughout November (closed on 1 December, 23:59 UTC), captured wide ranging community insights, perspectives and priorities for agentic AI in research. The survey was promoted during the RDA's 25th Plenary in the framework of International Data Week (IDW2025)[6] and disseminated via the RDA website and group posts, social media channels (LinkedIn), mailing lists, and targeted emails to potentially interested community members.

The survey was viewed 1,359 times, had 119 dropouts (respondents who started the survey but did not complete) and **83 complete responses** from **25 countries** across **5 continents**: Australia (10.8%), United States (9.6%), Netherlands (9.6%), Canada (8.4%), France (8.4%), Germany (7.2%), New Zealand (7.2%), Italy (6%), Great Britain (6%), Japan (3.6%), Spain (3.6%), Finland (2.4%), Austria (2.4%), Greece (1.2%), Indonesia (1.2%), Nigeria (1.2%), Egypt (1.2%), Poland (1.2%), Puerto Rico (1.2%), Portugal (1.2%), Sweden (1.2%), Singapore (1.2%), Slovenia (1.2%), Belgium (1.2%), South Africa (1.2%) (**Figure 2**).

[5] https://www.mentimeter.com/
[6] https://www.rd-alliance.org/plenaries/idw-2025-p25/

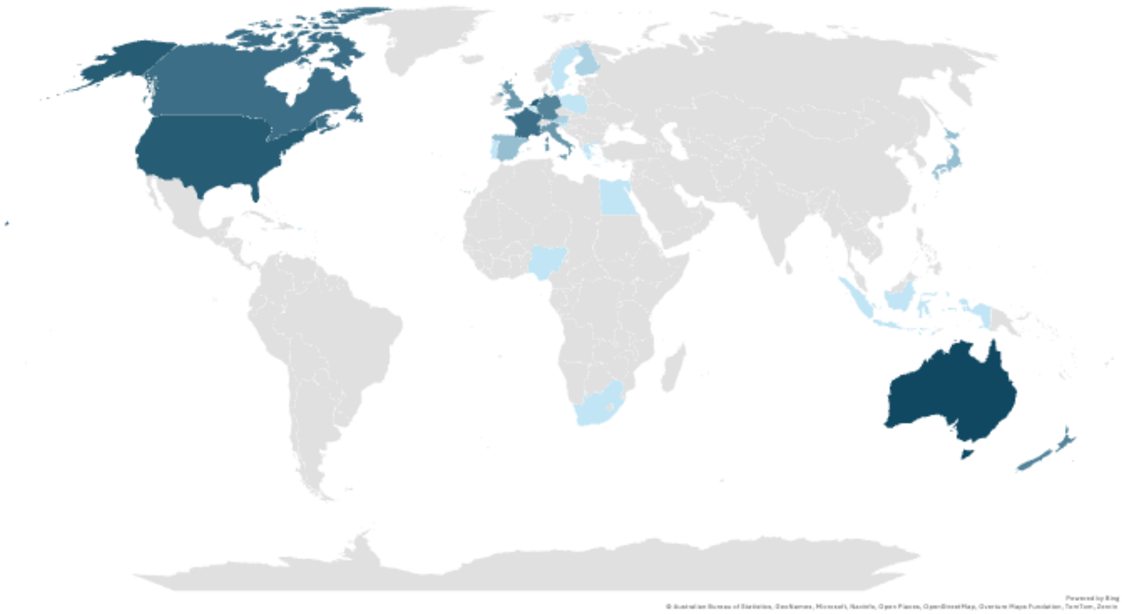

Figure 2. Survey participation by country. Geographic distribution of 83 survey respondents across 25 countries and 5 continents. Darker shading indicates higher participation rates, with Australia, United States, Netherlands, Canada, and France contributing the most responses.

While most respondents were RDA members (59%), a substantial portion were non-members (41%), indicating the survey's broad reach beyond the RDA community. As desired, the survey received responses from a range of stakeholders within the research ecosystem. We intended no AI expertise or research role to be required; every perspective was valuable regardless of familiarity with agentic AI or role in research. This consultation sought to understand diverse perspectives across the global research ecosystem the use of agentic AI in research and what stakeholders may need and want from its development. Notably, **researchers and scientists** comprised the largest single stakeholder group (39.8%) (**Figure 3**).

The ‘Other’ category (10.8%) included diverse roles such as students, data stewards, research support staff, research data specialists, open science community facilitators, programme and project officers, training managers, and an ‘academic AI agent provider for scientists’, further demonstrating the survey’s broad reach across the research ecosystem.

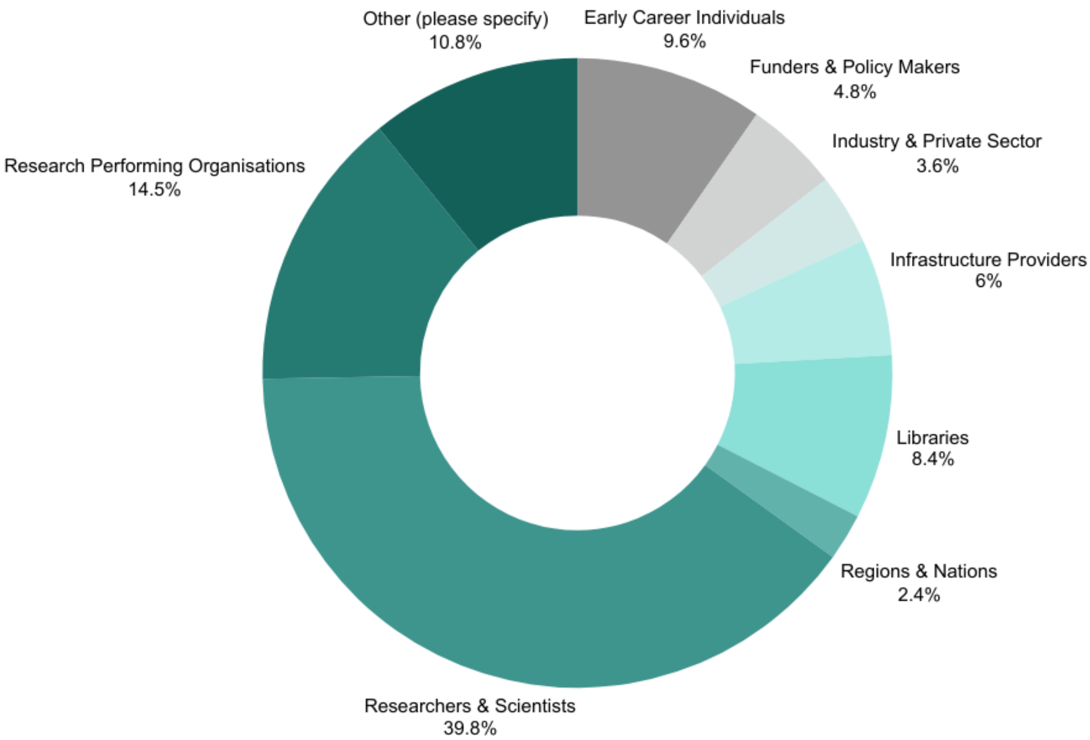

Figure 3. **Survey participation by stakeholder group.** Distribution of 83 respondents across nine stakeholder categories, with Researchers & Scientists comprising the largest group (39.8%).

In terms of their professional roles, most respondents (89.1%) had used some form of AI or machine learning (ML) tools. More than half had used both generative AI and traditional AI/ML tools (**Figure 4A**). Regarding agentic AI systems, most participants (55.4%) had not used them, while 32.5% had and 12% were unsure (**Figure 4B**).

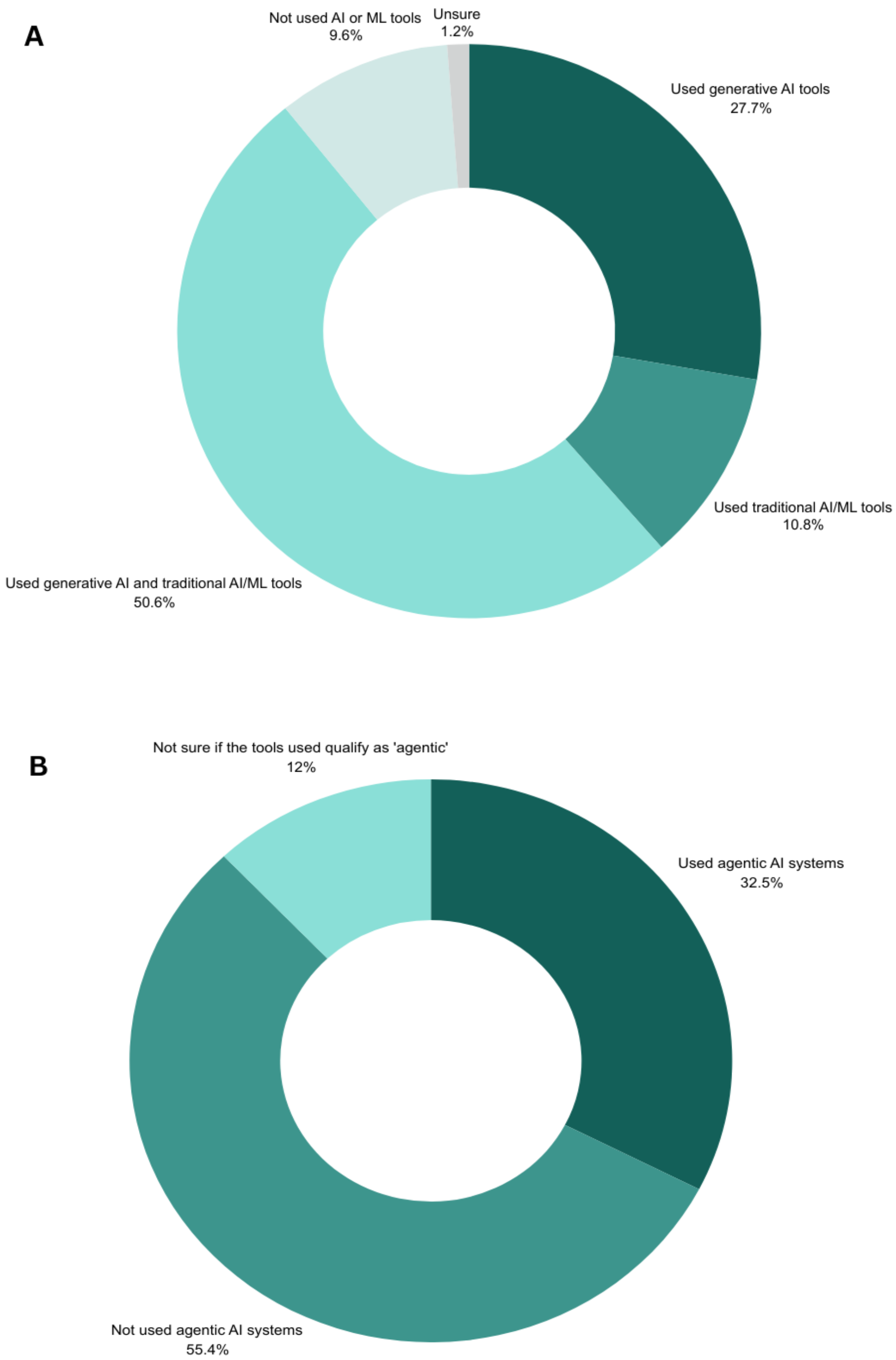

Figure 4. Survey respondents' experience with AI technologies. Distribution of 83 respondents by their professional experience with AI and machine learning tools generally (**A**) and agentic AI systems specifically (**B**).

Survey findings reveal that **conducting research activities** was the most popular application for agentic AI, selected by 50.6% of participants. This was followed closely by planning research and applying for funding, and reporting on research output and impact, both at 44.6%. Moderate interest was shown in presenting research (34.9%) and formulating new research questions (31.3%), while publishing research and other uses received the lowest response rates at 25.3% each (**Figure 5**). Respondents could select multiple options.

In the 'Other' category (25.3%), respondents mentioned diverse applications including coding and debugging, research software development, data extraction/visualisation, literature review, document analysis and summarisation, validation/verification processes, identifying research gaps and trends, multilingual tasks, and quality-checking outputs. Some respondents indicated no current or planned use of agentic AI, sharing concerns about AI maturity and trustworthiness and stating their preference to maintain their own skills.

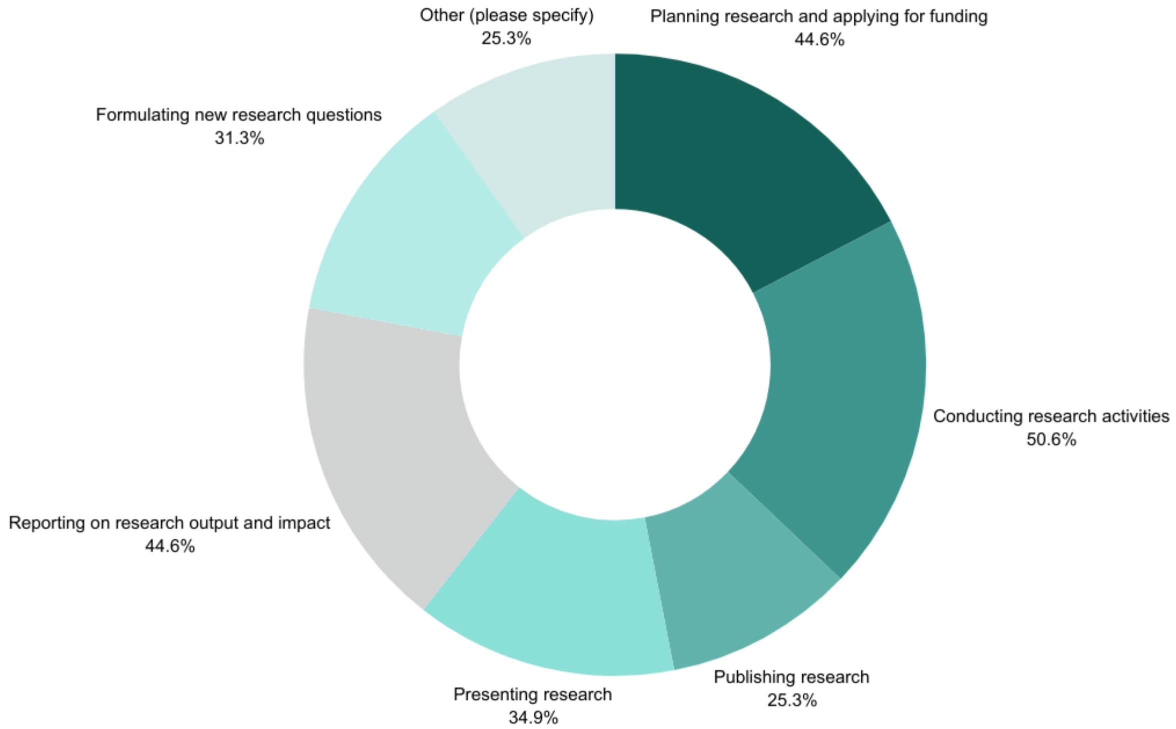

Figure 5. **Stages of the research lifecycle where respondents have used agentic AI or would find it most beneficial (*n*=83).** Respondents could select all applicable stages.

RESEARCH DATA ALLIANCE

2. Global Community Priorities for Agentic AI in Research

This section presents community priorities for agentic AI in research based on survey responses from the global research data community. Agentic AI tools detailed herein are neither exhaustive nor confirmed for development but were proposed by researchers from over 50 institutions within the United Kingdom during engagement with Microsoft, as detailed in Section 1. The information presented demonstrates tool rankings (**Section 2.1**), their application across the research lifecycle (**Sections 2.2** to **2.7**), and regional and stakeholder perspectives (**Sections 2.8** and **2.9**).

2.1 Priority AI Agents: Community Perspectives

The 11 proposed agentic AI tools were ranked according to their usefulness ratings, with respondents scoring each tool from 'very useful' to 'not useful at all'. A weighted scoring system was applied where 'very useful' received 4 points, 'somewhat useful' 3 points, 'not very useful' 2 points, and 'not useful at all' 1 point. Respondents who selected 'unsure' were excluded from the calculation as this may indicate insufficient knowledge about or experience with the tool rather than a neutral opinion. The weighted score for each tool was calculated by multiplying the number of responses in each category by their respective weights, summing these values, and dividing by the total number of valid responses (excluding 'unsure'), producing a score out of 4.0 (**Table 1**).

Table 1. Community prioritisation of proposed agentic AI agents based on weighted usefulness ratings. Tools are ranked by weighted score, calculated from survey responses (n=83) using a 4-point scale: Very useful (×4), Somewhat useful (×3), Not very useful (×2), Not useful at all (×1). 'Unsure' responses were excluded from scoring. Total weighted points are divided by valid respondents to produce the weighted score for each tool. Scores out of 4.0. Higher scores indicate greater perceived usefulness.

Rank	AI Agent Tool	Very useful (×4)	Somewhat useful (×3)	Not very useful (×2)	Not useful at all (×1)	Unsure (excluded)	Total Weighted Points	Valid Respondents	Weighted Score
1	**Literature Librarian**	40 → 160	31 → 93	1 → 2	6 → 6	5	261	78	3.35
2	**Data Director**	38 → 152	23 → 69	8 → 16	6 → 6	8	243	75	3.24
3	**Funding Finder**	40 → 160	21 → 63	6 → 12	10 → 10	6	245	77	3.18
4	**Literature and Data Wrangler**	36 → 144	21 → 63	6 → 12	13 → 13	7	232	76	3.05
5	**Research Refiner**	28 → 112	32 → 96	9 → 18	8 → 8	6	234	77	3.04
6	**Resource Finder**	30 → 120	27 → 81	11 → 22	9 → 9	6	232	77	3.01
7	**Research Reporter**	22 → 88	27 → 81	10 → 20	7 → 7	17	196	66	2.97
8	**Research Assessment Supporter**	20 → 80	23 → 69	12 → 24	5 → 5	23	178	60	2.97
9	**Collaboration Catalyst**	28 → 112	27 → 81	9 → 18	12 → 12	7	223	76	2.93
10	**Publication Preparer**	24 → 96	28 → 84	13 → 26	11 → 11	7	217	76	2.86
11	**Ethics Reviewer**	23 → 92	27 → 81	5 → 10	18 → 18	10	201	73	2.75

The **Literature Librarian** emerged as the highest-ranked tool with a weighted score of 3.35 out of 4.0, followed closely by the Data Director (3.24) and Funding Finder (3.18), while the Ethics Reviewer scored lowest at 2.75. The Research Assessment Supporter had relatively high uncertainty with 23 respondents (27.7%) selecting 'unsure', the highest among all tools (**Table 1; Section 7.1, S1**).

These findings were largely corroborated by the live ranking conducted by participants during the information sessions. The Data Director ranked first twice, the Literature and Data Wrangler appeared in the top four of all sessions. Both the Ethics Reviewer and Research Reporter consistently ranked among the least valuable tools. However, a notable discrepancy emerged with the Literature Librarian, which despite its highest survey score showed variable session performance (ranging from second to tenth place) (**Section 7.1, S5**).

Anonymous qualitative free-text survey responses were categorised by theme (positive comments, concerns/questions, general observations, and suggestions for improvements) and analysed with AI assistance (**Section 7.1, S4**).

2.1.1 Methodological Considerations

For the weighted ranking methodology used in survey data analysis, the distinction between 'very useful' and 'somewhat useful' is inherently subjective and, therefore, varies across participants. Nevertheless, weighted ranking remains the most effective method to represent the full spectrum of community perspectives, as it accounts for both the strength of preference and the diversity of opinions across stakeholder groups.

Additional caveats include methodological differences between data collection approaches. Live information session rankings were subject to time constraints and, therefore, increased cognitive load for participants. In contrast, the survey allowed time for deeper and more reflective consideration. In addition, some overlap may exist where individuals attended information sessions and completed the survey, thereby ranking tools twice.

2.2 Planning Research and Applying for Funding

The community evaluated concepts for agentic AI tools proposed to assist with research planning and funding applications.

2.2.1 Funding Finder

The Funding Finder emerged as a high priority (rank #3). This tool was proposed to identify relevant funding opportunities and support the application process by:

- Scanning funding databases and matching opportunities to research ideas
- Providing application templates and ensuring funder guidelines are met

- Suggesting improvements based on previously successful applications from an institution

2.2.1.1 Usefulness Ratings

Usefulness ratings for the Funding Finder were predominantly positive. Nearly half of respondents (48.2%) rated the tool as very useful, with an additional quarter (25.3%) considering it somewhat useful. While approximately one-fifth (19%) expressed reservations about its value, only ~7% were unsure (**Figure 6**).

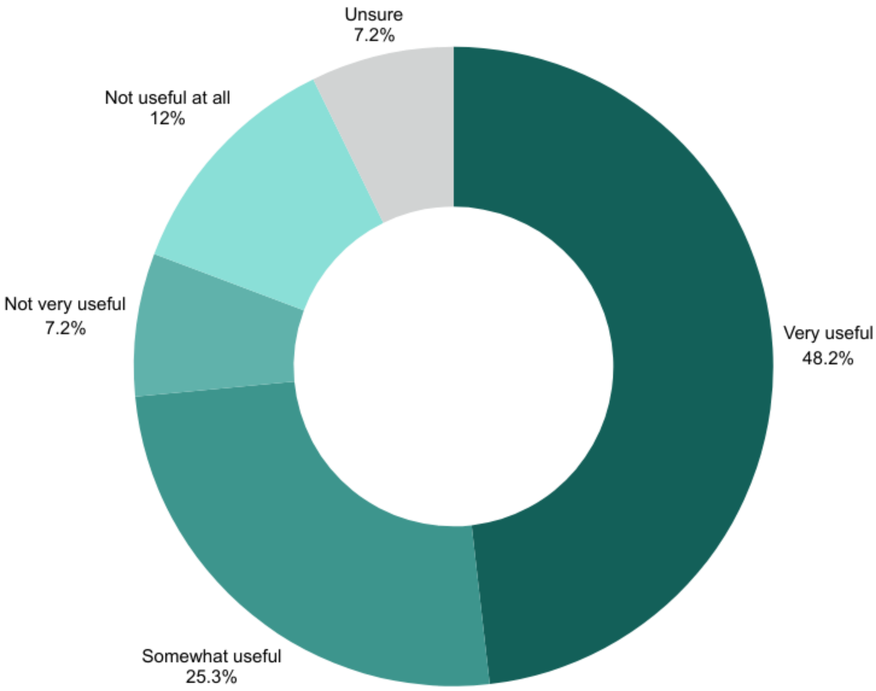

Figure 6. Community usefulness ratings for the Funding Finder (*n*=83).

2.2.1.2 Community Perspectives

Respondents identified multiple features that would make the Funding Finder tool useful. The most frequently cited benefit was automated scanning of funding databases to match opportunities with research ideas. This would save a significant amount of time spent navigating the complex funding ecosystem where opportunities are scattered across multiple sources. Beyond keyword searches, respondents valued application templates, compliance checking for funder guidelines, and notifications about new opportunities. Several emphasised that meeting administrative guidelines represents a major pain point where AI assistance would be particularly valuable. Additional desired features included identifying smaller grants with bespoke requirements, matching organisational capabilities to funder and tender guidelines, and allowing users to customise search criteria such as budget type and timing.

Substantial concerns were also raised. Many questioned whether agentic AI was necessary, suggesting that well-organised databases or traditional search engines would suffice at lower cost. Key concerns included AI hallucinations and errors requiring constant verification, lack of trust in AI accuracy, and AI's inability to handle nuance. Several found the proposal to suggest improvements based on previous funding applications particularly problematic, arguing it would enforce existing ‘buzzwords’, stifle innovative research ideas, and create a system that repeats the same formulas. Additional concerns included potential for ‘gaming the system’, funding guidelines changing during open calls through channels AI cannot access, and funding being relationship-based rather than process-based.

Recommendations included implementing the tool on the funder side to collect ideas and references and using the tool to provide guidance on data policies, assist with proposal writing and partner identification, and highlight similar previously funded projects.

2.2.2 Ethics Reviewer

The Ethics Reviewer ranked lowest among the proposed tools (rank #11). This tool was designed to identify ethical issues in research and guide users through ethical approval requirements by:

- Identifying potential ethical issues in project proposals
- Providing guidance on meeting ethics requirements based on institutional guidelines and previous ethics board decisions

2.2.2.1 Usefulness Ratings

Usefulness ratings for the Ethics Reviewer were varied. Approximately three in five respondents (~60%) rated the tool positively, with 27.7% considering it very useful and 32.5% somewhat useful. However, over a quarter (~28%) expressed reservations, rating it as not very useful or not useful at all, while 12% were unsure about its value (**Figure 7**).

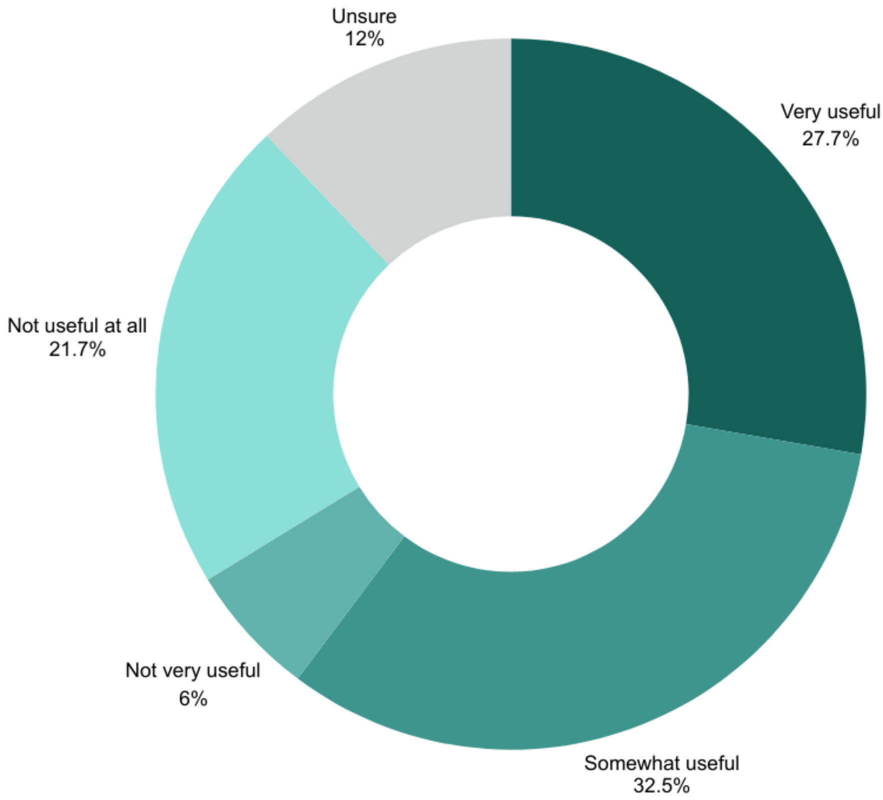

Figure 7. Community usefulness ratings for the Ethics Reviewer (*n*=83).

2.2.2.2 Community Perspectives

Respondents provided varied feedback on the potential utility of the Ethics Reviewer tool. Multiple respondents noted the tool could be useful for navigating complicated guidelines and compliance requirements, which represent significant time burdens. Several indicated the tool could help identify issues before submission to ethics boards, potentially reducing iteration time and increasing review board capacity. Respondents also highlighted that AI assistance could benefit researchers unfamiliar with ethics guidelines, help search university policies, and increase education on ethical issues. Some noted that ethics applications are often repetitive, suggesting AI could adapt previous submissions. Respondents emphasised the value of identifying potential ethical issues early and reducing administrative overhead in ethics approval processes.

In contrast, numerous respondents expressed fundamental concerns about the role of AI in the ethics review process. Many argued that the application process requires researchers to think critically about ethical implications, and automation would defeat this purpose. Respondents questioned whether AI possesses necessary sensitivity for ethical decisions, noting that ethics involves human judgment rather than probability. Concerns included AI's inability to understand meaning, potential to overlook cultural contexts, misalignment with organisational ethics frameworks, and risks of users treating the tool as a ‘box checker’ without genuine engagement in the ethical review process. Several respondents explicitly stated they would not trust AI for ethics guidance.

Respondents emphasised that any such tool should remain strictly supportive rather than acting as an ‘ethical arbiter’. Suggestions included ensuring human-in-the-loop verification, using human-written guidance, capturing jurisdictional nuances in training data, and positioning the tool as a compliance assistant rather than decision-maker.

2.2.3 Existing Relevant Tools

Respondents identified the following tools for supporting research planning and applying for funding: AutoGen, ChatGPT, ChatGPT agents, Claude Code agentic coding, commercial and university-sponsored LLMs, CrewAI, Deep research, Fundsorter, Google Scholar Lab, GrantForward, Granter.ai, Grantfinder, LangChain, Langflow, LangGraph, LLM Chat-Bot, n8n, Research Professional, RobinAi, sCite, Scientify, spinbase, and Summise.

2.2.4 Additional Capabilities

Survey respondents identified additional agentic AI capabilities they believe would be valuable for research planning and funding applications. Several participants emphasised data management planning, noting that AI could provide feedback on gaps, identify inconsistencies across documentation (including data management plans, ethics applications, protocols and grant applications), and help organise required data and methods.

Budget-related capabilities were highlighted, with requests for tools handling budget sizing, management, and expenditure constraints. Related suggestions included AI capabilities that could structure research processes into manageable steps, initiate internal approval processes, identify applications requiring special attention, and support preparation of IT infrastructure and procurement.

Further additional capabilities mentioned included mock panel reviews with digital expert reviewers, due diligence checks, contract review, data analysis, report drafting, and risk assessment. Respondents also suggested tools for tracking grant opportunities and deadlines, visualising timelines for multiple applications, identifying already-funded research in their fields, analysing peer reviewer trends, and assisting with website navigation.

Some respondents expressed concerns, including the need for risk assessment regarding AI adoption in funding applications and scepticism about AI access to relevant institutional information.

General comments indicated that AI could increase work efficiency, though one participant valued human experience over AI capabilities. Several respondents stated no additional capabilities were needed, with one noting that standard LLMs with sufficient human involvement accomplish most requirements

2.3 Conducting Research Activities

The community evaluated concepts for agentic AI tools proposed to assist with conducting research activities.

2.3.1 Resource Finder

The Resource Finder ranked midway amongst the proposed agentic AI tools (rank #6). The tool was proposed to identify available university support services based on research needs by:

- Matching research goals to relevant university services
- Connecting users with lab facilities, IT infrastructure, research software engineers (RSEs), seminar groups, and internal funding opportunities

2.3.1.1 Usefulness Ratings

Usefulness ratings for the Resource Finder were mostly positive, with around one-third (36.1%) saying it would be very useful and another one-third (32.5%) rating it as somewhat useful. Close to a quarter (~24%) found it of little or no use, while ~7% were unsure (**Figure 8**).

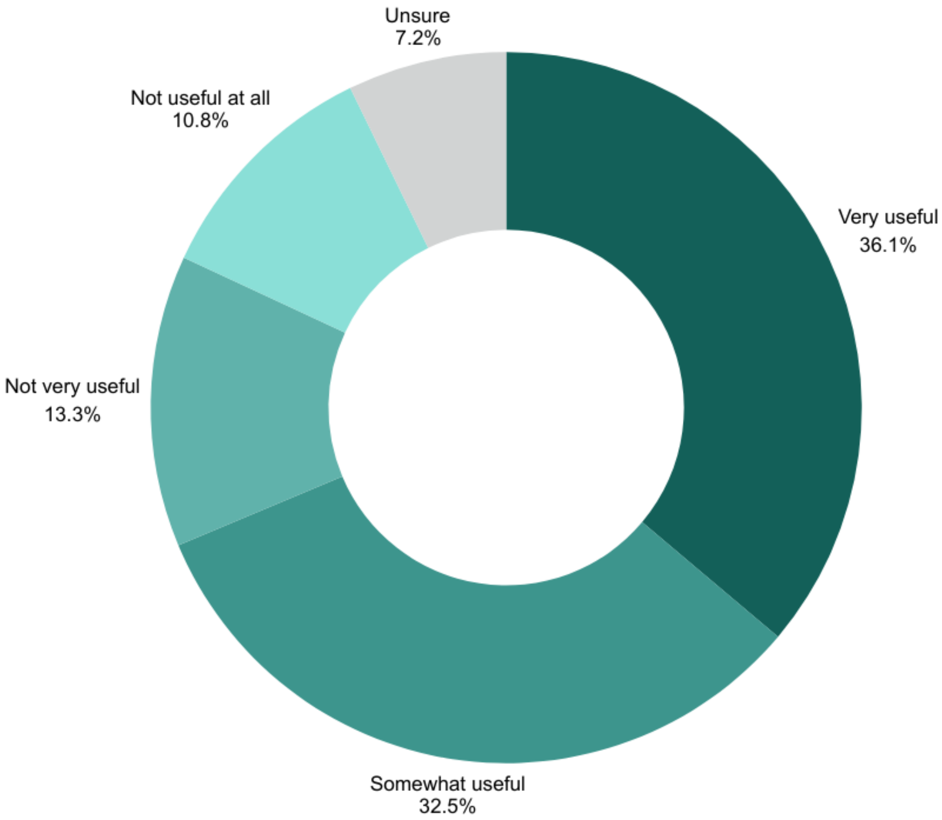

Figure 8. Community usefulness ratings for the Resource Finder (*n*=83).

2.3.1.2 Community Perspectives

Survey respondents provided varied feedback on the Resource Finder tool. Several acknowledged potential usefulness of such a tool, particularly for connecting researchers with library services and acting as a 'clearinghouse' for resources. Value was identified in discovering services unknown to researchers, especially for remote workers lacking awareness of institutional expertise. Integration with grant applications was suggested as beneficial, identifying resources at project inception. Respondents noted the tool could save time and reveal new opportunities, though some questioned whether it would meaningfully advance beyond existing search engines or integrated research environments.

Significant concerns centred on data quality, with respondents citing that this tool is only as useful as the data it can access; if this involves scraping data from the web, it would not be good quality data. Similarly, internal institutionally held data is often outdated, legacy data, reducing their value. Questions were also raised about access to data where institutions implement firewalls. Multiple respondents questioned the necessity of AI, suggesting well-built databases or direct colleague consultation would suffice. Hallucination risks were emphasised, requiring verification of all AI-generated information. Privacy concerns emerged regarding collection and processing of personal data, particularly data which might identify individual RSEs, if they are categorised as a resource. Respondents noted that researchers typically learn about institutional services through induction or peer networks, questioning whether initial lack of awareness of facilities genuinely hinders research. Additional concerns were raised about the cost-benefit ratio, noting that this tool would be little or no improvement on existing institutional resources and facilities.

Recommendations included extending coverage beyond individual institutions to national resources, enabling booking functionality for labs and RSEs rather than merely identifying services, ensuring strictly local deployment to protect sensitive information and incorporating access to documents beyond websites but documents and other digital resources to help inform the model and be able to produce quality outputs. Respondents emphasised connecting researchers with data stewards alongside RSEs and suggested practical testing before implementation.

2.3.2 Collaboration Catalyst

The Collaboration Catalyst was rated as one of the least valuable proposed agentic AI tools (rank #9). This tool was proposed to connect researchers with potential collaborators and resources within their institutions by:

- Suggesting colleagues to collaborate with based on expertise, interests, and research needs
- Identifying individuals and groups with relevant datasets, facilities, or resources for specific projects

2.3.2.1 Usefulness Ratings

Usefulness ratings for the Collaboration Catalyst were similar to those for the Resource Finder, with around one-third (33.7%) rating it as very useful and another third (32.5%) as somewhat useful, so useful for the most part. A quarter (~25%) found it not very useful or not useful at all, with 8.4% unsure (**Figure 9**).

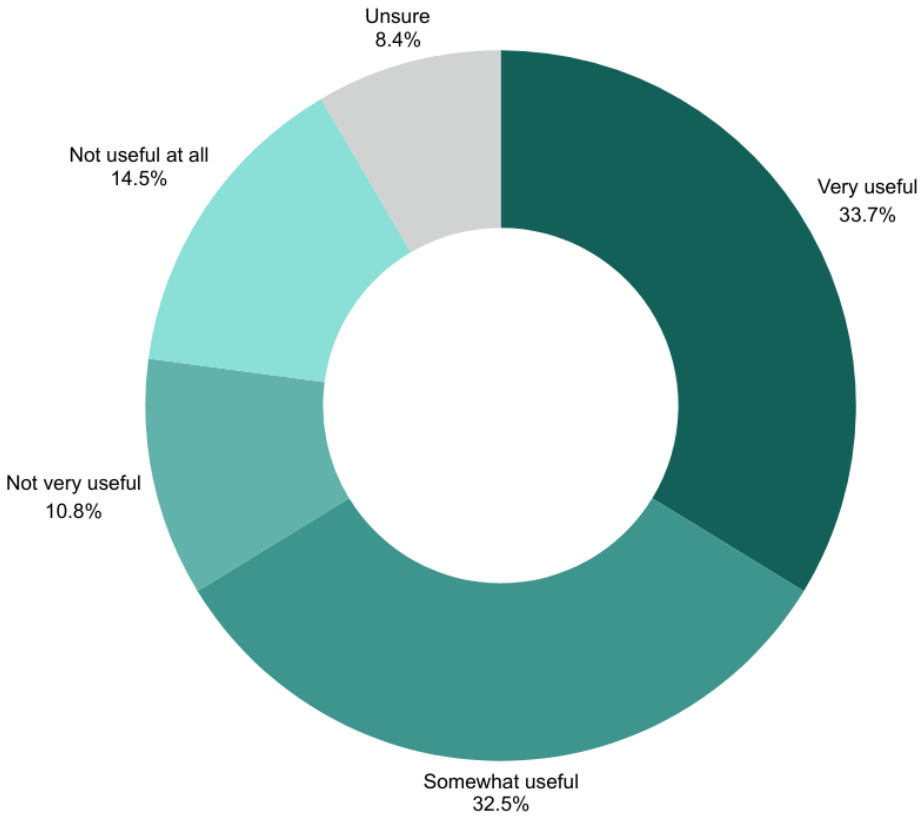

Figure 9. Community usefulness ratings for the Collaboration Catalyst (*n*=83).

2.3.2.2 Community Perspectives

Respondents noted several potential benefits of the Collaboration Catalyst tool. It could help identify cross-disciplinary collaborative possibilities, particularly valuable as research becomes increasingly interdisciplinary. They highlighted that researchers within large organisations may not know potential collaborators from other departments. Finding partners represents a significant challenge for independent researchers, and the tool could expand connections beyond existing networks. Additional suggestions included integrating the tool with resource finders and implementing it at the proposal stage of research projects.

Numerous concerns were, however, raised about the tool's effectiveness and implementation. Respondents questioned its utility within smaller institutions, suggesting it would be more valuable for cross-institutional connections. Several emphasised that successful collaborations depend on human relationships, trust, and personal interactions rather than technical compatibility. Data protection concerns were raised regarding the level of access required for such a tool. Respondents noted practical barriers including maintaining up-to-date information, achieving sufficient researcher opt-in for network effects, and potential amplification of bias favouring certain topics and researchers. Some respondents were sceptical that awareness of potential collaborators was the primary barrier, citing politics, culture and funding as more significant obstacles. Previous similar tools, such as those providing automatic reviewer suggestions, were mentioned as having become ‘spam machines’.

Recommendations included ensuring data is structured and current, operating the system locally rather than through external providers and maintaining human decision-making in establishing contacts. Another comment though, suggested such a tool could enable wider global collaboration.

2.3.3 Existing Relevant Tools

Respondents identified the following tools for supporting the conduct of research activities: AI Scientist, Biomni from Stanford, ChatGPT, Claude, Cooperative Agents for Retrieval-Augmented Generation (CoAR), Copilot, Deep Research, Gemini, Google Scholar Lab, NotebookLM, Perplexity, Research Rabbit, and Web of Science Research Intelligence. Respondents also mentioned using most LLMs generally.

2.3.4 Additional Capabilities

Survey respondents identified several additional valuable AI capabilities for supporting the conduct of various research activities. Software development and web services creation were highlighted as areas undergoing significant transformation, with expectations that researchers will increasingly undertake development work themselves. Data-related tasks featured prominently, including data wrangling, transformations, and synthesis. Data processing activities more broadly, including collection, arrangement, categorisation, annotation, visualisation and analysis, were seen as opportunities. Literature review functions and field-based research logistics, such as managing volunteer activities and population monitoring, were also identified as beneficial applications. Some respondents expressed aspirational views about AI providing valuable ideas or functioning fully autonomous in some respects, such as finding papers, reading them, deciding if they are interesting enough and showing how and why.

Important considerations and concerns were raised about reliability and explainability. For the former, one respondent emphasised that agentic AI systems must be completely dependable as researchers may lose the ability to identify errors as tasks are handed over to these systems. For the latter, the importance of transparency and reproducibility was highlighted; we risk creating a ‘black box’ situation, which in addition does not enable open data in research. Contrasting opinions emerged regarding appropriate scope: whilst some viewed autonomous capabilities as aspirational, others suggested limiting agentic systems to straightforward, well-established tasks. Concerns were expressed about offloading research to ‘black box oracles’ potentially compromising the scientific process and understanding, even if beneficial outcomes might result. Respondents noted that responsible AI guidance already lags behind current developments.

General comments revealed ambiguity about boundaries between chatbots and agentic AI, with uncertainty about trusting agents for tasks such as finding collaborators.

2.4 Publishing Research

The community evaluated concepts for agentic AI tools proposed to assist with publishing research.

2.4.1 Publication Preparer

The Publication Preparer ranked low in community prioritisation (rank #10). This tool was proposed to identify suitable journals and prepare manuscripts that meet publishing requirements by:

- Identifying appropriate journals and special collections for research
- Checking that work is in scope for target journals to reduce rejection rates
- Providing journal-specific templates and rewriting content to meet their guidelines
- Generating evidenced novelty statements for editors

2.4.1.1 Usefulness Ratings

Nearly two-thirds of respondents (~63%) rated the Publication Preparer positively, with 28.9% considering it very useful and 33.7% somewhat useful. However, nearly three in ten (~29%) expressed reservations, rating it as not very useful or not useful at all. Eight percent remained unsure (**Figure 10**).

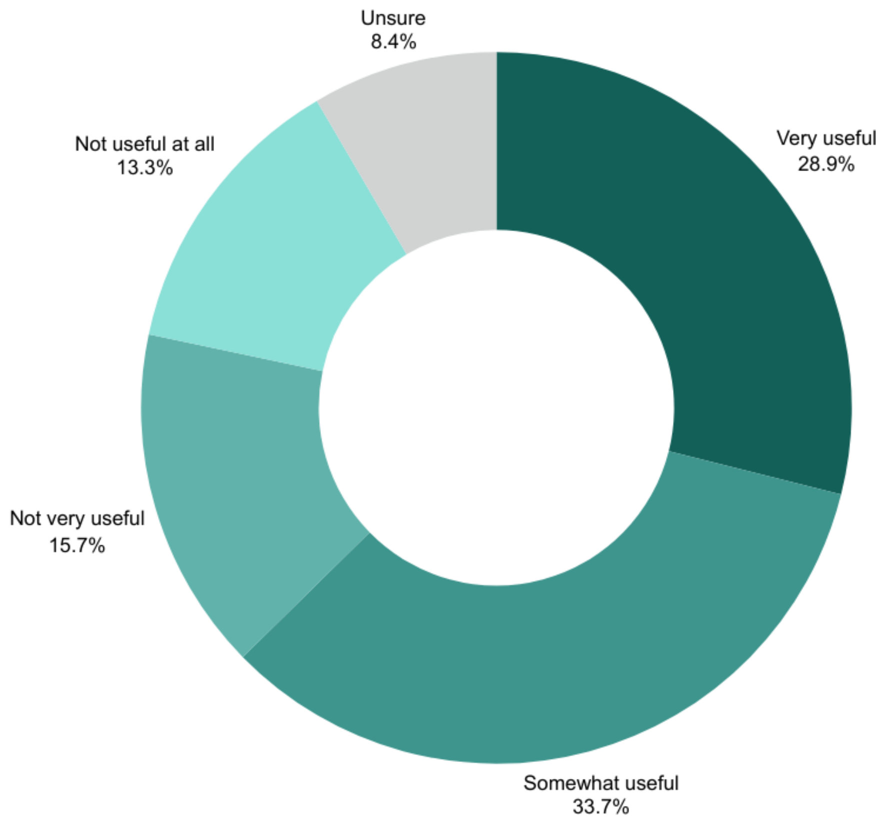

Figure 10. Community usefulness ratings for the Publication Preparer (*n*=83).

2.4.1.2 Community Perspectives

Respondents identified several potentially useful features of a Publication Preparer tool. Many found value in identifying appropriate journals, with multiple respondents stating this would be 'extremely useful' and 'useful to all researchers.' Other appreciated features included checking whether work is in scope for target journals, providing journal-specific templates, saving time on administrative tasks, proofreading support and helping with formatting. It was noted that the tool could be helpful for non-native English speakers and for finding gaps in domain-specific practices.

However, significant concerns were raised about the proposed tool's content-rewriting capabilities. Multiple respondents stated that AI rewriting is 'problematic' and expressed worry about losing personal voice and producing 'AI slop'. Respondents emphasised that novelty statements should remain human-written, with one noting they would 'reject any novelty statement that appears to be written by AI'. The risk of predatory journals being recommended was mentioned repeatedly, alongside concerns about algorithmic bias and commercial interests compromising recommendations. Additional concerns included high AI error rates, creating an 'AI loop' where AI evaluates AI-generated content, intellectual ownership issues and the potential for shifting additional work onto editors.

Respondents offered several suggestions: human oversight is essential; AI should not do the actual writing; all AI outputs must be double-checked due to hallucinations; focus should be on formatting and grammar rather than content; and community consensus is needed on acceptable AI use. Several respondents noted that researchers typically already know appropriate journals in their field. Some questioned whether the tool addresses real problems, with one stating 'the publishing system is broken' and suggesting alternative approaches are needed.

2.4.2 Data Director

The Data Director emerged as the second-highest priority tool (rank #2). This tool was proposed to support research data preparation and sharing in compliance with FAIR principles and institutional requirements by:

- Automatically creating metadata following FAIR principles
- Minting DOIs (Digital Object Identifiers) for datasets
- Recommending appropriate data repositories to ensure compliance with funder and institutional requirements

2.4.2.1 Usefulness Ratings

Usefulness ratings for the Data Director were predominantly positive. Nearly three-quarters of respondents (~74%) rated the tool positively, with 45.8% considering it very useful and 27.7% somewhat useful. Less than one-fifth (~17%) expressed reservations about its value, while 9.6% remained unsure (**Figure 11**).

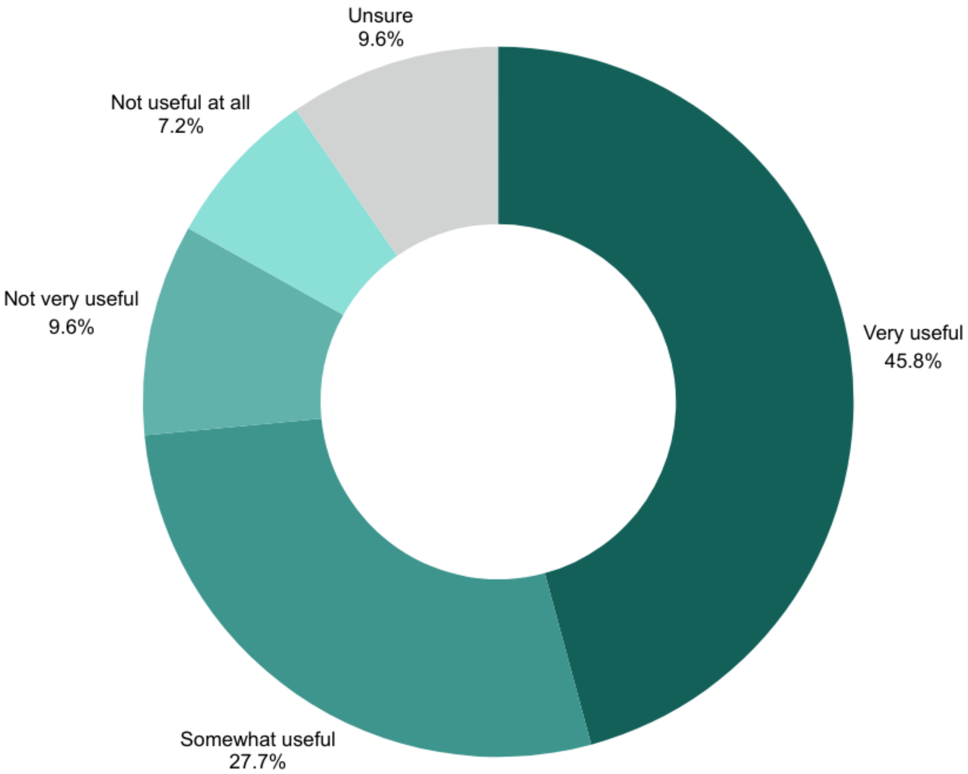

Figure 11. Community usefulness ratings for the Data Director (*n*=83).

2.4.2.2 Community Perspectives

Respondents identified several positive aspects of the Data Director tool. Multiple participants noted that automatic metadata creation following FAIR principles[7] would be valuable, citing that it could reduce human error and administrative overhead. Respondents indicated the tool could be particularly helpful for researchers at smaller research-performing organisations without adequate support services. Respondents mentioned that creating metadata is work researchers find valuable but prefer not to spend time on. They also suggested the tool could help standardise data earlier in the data process, verify manuscripts for 'FAIRness', and recommend appropriate data repositories. Some respondents noted they had seen experimental agentic AI tools that produce metadata and submit work to repositories.

Various challenges and concerns were also raised. Respondents questioned whether metadata generated by AI would be sufficiently accurate and reliable, noting that researchers need to understand data publication requirements to fact-check AI suggestions. Concerns were also expressed about transparency and the potential for AI to misrepresent data in metadata. It was noted that minting DOIs costs money, and *how* this would be funded and *by who* was questioned. Some respondents stated that existing repositories already mint DOIs and that finding appropriate repositories is a service currently provided by

[7] https://doi.org/10.1038/sdata.2016.18

data stewards and librarians within some institutions. Concerns were also raised about institutional policies being ignored if researchers follow AI recommendations without consulting organisational guidelines.

General recommendations included adding quality assurance mechanisms, automating file package generation and upload (including data, software and metadata), ensuring scientists maintain control over metadata, and improving current AI capabilities.

2.4.3 Existing Relevant Tools

Respondents identified the following tools to support the publication of research: General LLMs; ChatGPT, Claude, Copilot, Gemini, Google NotebookLM, Jenni AI, Overleaf, and SciSpace.

2.4.4 Additional Capabilities

Numerous additional AI capabilities were considered valuable for publishing research. Respondents highlighted capabilities that could enhance research quality and connectivity. One respondent proposed a ‘Socratic-style agent’ that raises questions about content based on existing literature and funding opportunities. Another emphasised the need for an AI tool to identify and map links between datasets, research papers, and other outputs, noting that hyperlinks in papers frequently do not link to valid resources and clarification of these connections would be valuable.

Practical workflow improvements were commonly mentioned. Respondents suggested support with reference formatting across papers. A language assistance tool for non-native English speakers that focuses on improving writing skills rather than generating text was also deemed useful, but that it should always be correct to avoid teaching mistakes. Other capabilities mentioned included the ability to search patents and pre-internet publications, disseminating published research through multiple channels including press releases and social media, and identifying inconsistencies between reviewer statements and article content to support editors.

Visualisation support was another area of interest, with respondents requesting tools to create plots and graphics, and to minimise time spent aligning visual elements with journal style requirements. One respondent proposed a transformative vision: AI that deconstructs publications into stand-alone insights to create a common knowledge graph.

General comments included questions about the definition of ‘publishing research’ in the context of this survey, reports of using AI tools for grammar checking and editing, and concerns about whether traditional automation should be considered agentic AI, with respondents citing concerns about researcher control and cost of such tools.

2.5 Presenting Research

The community evaluated concepts for agentic AI tools proposed to assist with presenting research.

2.5.1 Research Refiner

The Research Refiner placed midway (rank #5) amongst the proposed tools. This tool was proposed to help present research effectively to different audiences by:

- Providing critical feedback on data presentation to improve communication quality
- Translating research literature and figures for specific audiences (domain experts, general researchers, or the public)

2.5.1.1 Usefulness Ratings

Usefulness ratings for the Research Refiner were predominantly positive, with around one-third (33.7%) rating it very useful and 38.6% rating it somewhat useful. Around 20% found it not very useful or not useful at all, with ~7% unsure (**Figure 12**).

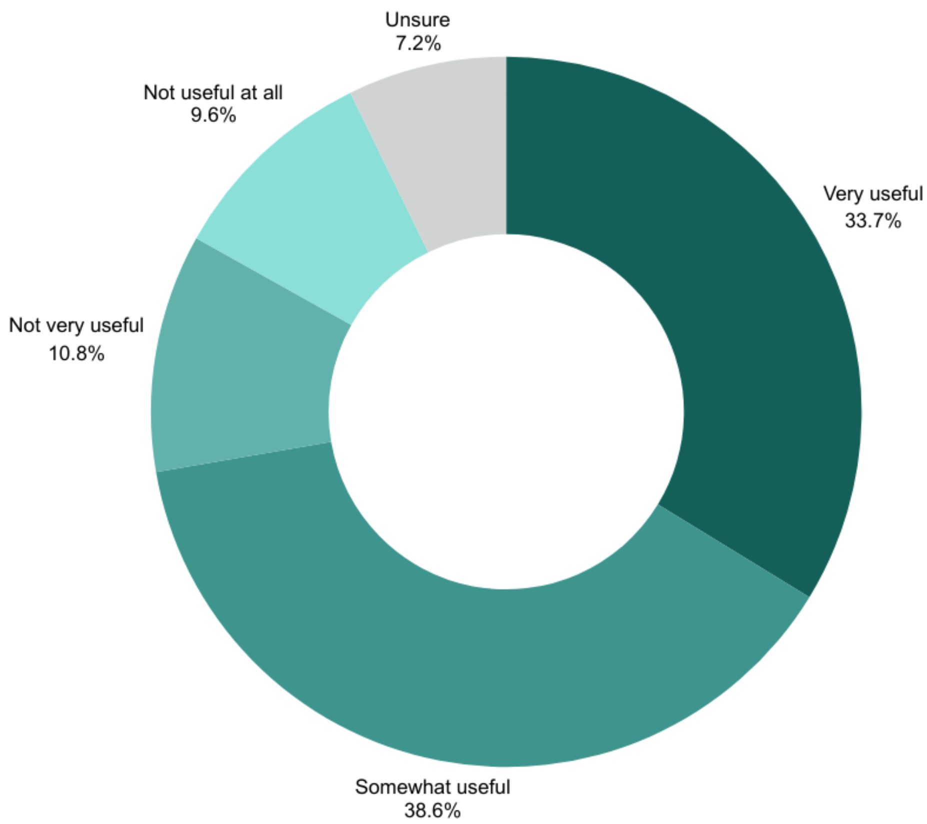

Figure 12. Community usefulness ratings for the Research Refiner (*n*=83).

2.5.1.2 Community Perspectives

Respondents identified several potential benefits of the Research Refiner tool. Multiple participants noted time-saving advantages, particularly when needing to present research in a different language. Respondents also saw potential for creating first drafts tailored to individual styles, with the tool serving as a sounding board for adjusting presentations to different audiences and for creating figures.

Substantial concerns emerged across multiple dimensions. Many participants questioned AI's trustworthiness and current capabilities for critical feedback, citing hallucinations and incorrect information as significant worries. Concerns about bland, homogenised outputs were raised. Translation of research into different languages drew specific criticism from some respondents regarding verification of correctness and ethical responsibility. Multiple respondents questioned whether agentic AI was necessary, noting existing tools like ChatGPT and Gemini already provide similar functionality. Concerns included undermining science communication as a professional role and researchers potentially following AI suggestions without professional communication skills to judge helpfulness.

Respondents suggested additional features including translation to other formats (e.g., video, podcast) and identifying knowledge translation opportunities. Several indicated they successfully use existing AI tools for stakeholder communication. Respondents emphasised that whilst AI could assist communication tasks, it cannot replace human efforts, though a couple responses highlighted its possible usefulness when communicating with nonexperts.

2.5.2 Existing Relevant Tools

Respondents identified the following tools to support the presentation of research: Beautiful AI, Canva, ChatGPT, Claude.ai, Copilot, Gemini, Google suite, Napkin.ai, NB2Slides, PresentationsAI, in addition to general LLMs.

2.5.3 Additional Capabilities

Several respondents highlighted specific AI capabilities they would find beneficial for presenting research. One respondent expressed a desire for AI to provide more suggestions for revising work. Visual and presentation-related capabilities featured in multiple responses, with requests for tools that could generate visual effects for presentation slides; prepare scientific animations; and transform data into animations to support the data-to-visualisation pipeline. One respondent specifically mentioned the value of tools that could make presentations more accessible, citing ‘digital accessibility’ as an example. Additionally, a respondent suggested that a tool capable of identifying related data or information within a specific audience sector would be useful, particularly for providing ideas to connect research results to different audiences.

Several respondents indicated that no additional capabilities were required for this stage of research. One respondent explained that researchers should undertake presentation tasks themselves, arguing that this process encourages reflection on research goals and re-evaluation of work, and should not be seen as an obstacle to be overcome using AI. Others stated that LLMs with retrieval-augmented generation (RAG) are sufficient for supporting presentation of research

2.6 Reporting on Research Output and Impact

The community evaluated concepts for agentic AI tools proposed to assist with reporting on research output and impact.

2.6.1 Research Reporter

The Research Reporter ranked in the middle of community priorities (rank #7). This tool was proposed to complete research impact reports and funder updates by:

- Automatically populating Researchfish[8] or similar reporting platforms based on research information

2.6.1.1 Usefulness Ratings

Approximately three in five respondents (~59%) rated the tool positively, with 26.5% considering it very useful and 32.5% somewhat useful. One-fifth (~20%) expressed reservations about its value, while notably, 20.5% remained unsure, one of the higher uncertainty rates among proposed tools (**Figure 13**).

[8] https://researchfish.com/

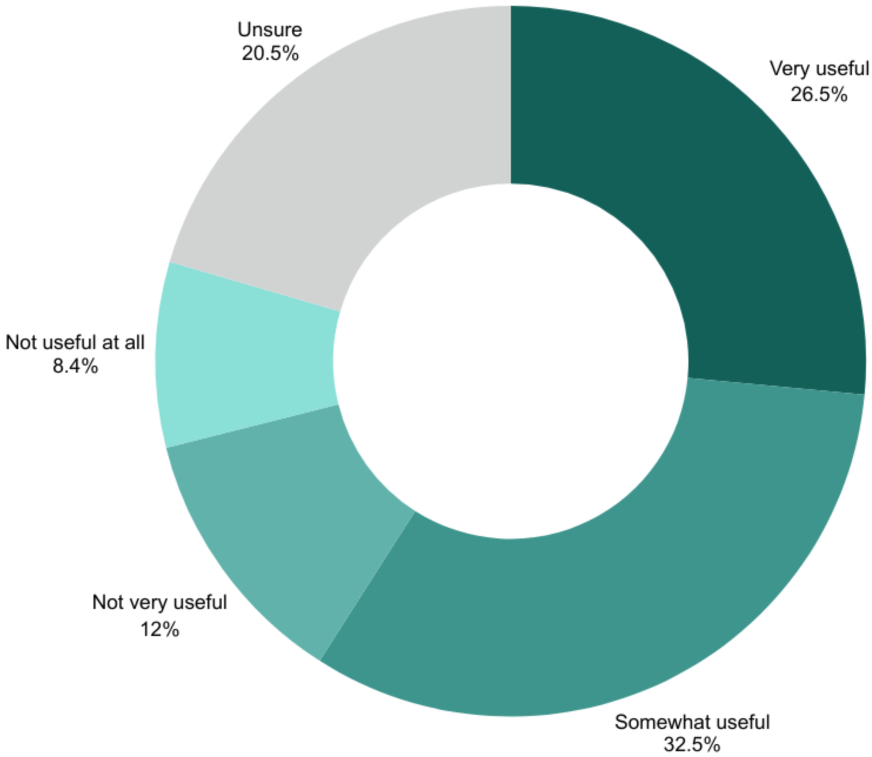

Figure 13. Community usefulness ratings for the Research Reporter (*n*=83).

2.6.1.2 Community Perspectives

The Research Reporter tool was received positively by many respondents. Many emphasised significant time-saving potential, with one describing reporting as 'the part of my job I hate the most' that 'takes up the most amount of my time.' Respondents noted that AI could automate administrative tasks, handle different report types including interim reports and ethics renewals and assist with finding citations, references and research impact evidence. Several participants indicated that AI could effectively summarise research outputs in relevant templates for funders. Respondents also mentioned that such tools could help format mandatory funder updates and aggregate research outputs.

Respondents also emphasised the need for substantial human oversight and verification, with several stating that reports 'should be done by human researchers.' Privacy and data access concerns were highlighted, as the required information is 'only partially available to the public' and resides in a researcher's personal records. Respondents expressed worry about accuracy, noting that 'the impact of errors when reporting to funders is too high to risk using agentic AI.' Ethical concerns were raised about whether researchers should write their own reports, and some questioned whether the time required to check AI-generated work might equate to the time required to create reports manually. Manipulating the system once metrics are understood, was also mentioned as a potential issue.

Recommendations included using AI to provide ideas for reporting on research output and impact, ensuring accurate business intelligence, and ensuring that researchers provide high-level content while AI fills in supplementary details from available data.

2.6.2 Research Assessment Supporter

The Research Assessment Supporter ranked eighth in community prioritisation (rank #8). This tool was proposed to help prepare research assessment submissions for national evaluation exercises by:

- Converting research information into the required assessment format and template (for researchers)
- Collecting information from multiple researchers and compiling it into standardised assessment templates (for institutions).

2.6.2.1 Usefulness Ratings

Usefulness ratings for the Research Assessment Supporter showed the most uncertainty among all proposed tools. Approximately half of respondents (~52%) rated the tool positively, with 24.1% considering it very useful and 27.7% somewhat useful. One-fifth (~20%) expressed reservations about its usefulness. Notably, 27.7% remained unsure, the highest uncertainty rate of all proposed tools (**Figure 14**).

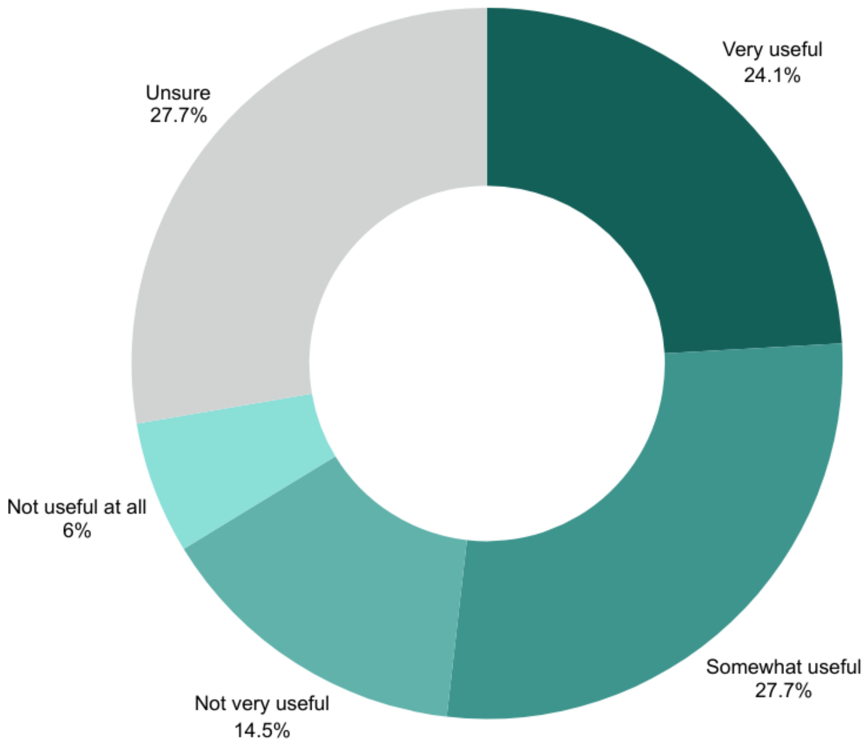

Figure 14. Community usefulness ratings for the Research Assessment Supporter (*n*=83).

2.6.2.2 Community Perspectives

Potential benefits of the Research Assessment Supporter were identified. Respondents noted the tool could be useful for creating first drafts and starting points for subsequent human review, particularly for answering questions using project description documents. Several respondents highlighted that AI could reduce administrative burden and save time, with formatting and bureaucratic tasks being well-suited for AI agents. Some respondents acknowledged that if reports are not critically read or if small mistakes do not matter, AI-generated text could be appropriate for reporting research output and impact. One respondent noted that in Australia, such assessment exercises were aborted due to being time-consuming with little impact on funding distribution, making faster processes welcome for those still required to complete them.

Significant concerns and questions were raised about the tool's implementation. Multiple respondents expressed ethical concerns about AI judging people and questioned whether AI-generated reports would be read. Respondents argued that if the tool is needed, the assessment process itself may be flawed, suggesting that well-defined information should be collected in structured databases accessible through traditional automation rather than agentic AI. Concerns included the creation of new optimisation targets, potential for ‘gaming the system’, cookie-cutter results, lack of critical reasoning and restricted access levels. Some feared an ‘AI against AI battle’ and worried that AI-generated reports would lack overarching synthesis and potentially convey unintended messages. The contentious nature of using AI for assessment was emphasised, with calls for further discussion.

Recommendations included ensuring adequate human oversight, exploring AI’s vocabulary management capabilities, noting that standard chain-of-thought LLMs with Retrieval-Augmented Generation (RAG) can already perform these tasks effectively and addressing local customisation as a pain point in existing Regulatory Information Management System (RIMS). One respondent suggested that better requirements engineering could solve underlying issues by linking systems to enable easy data transfer between databases, with DOIs assigned to each funded research project facilitating this integration.

2.6.3 Existing Relevant Tools

Respondents identified LLM Chat Bots and LLMs as general categories of tools, along with NotebookLM as a specific named tool for reporting on research output and impact.

2.6.4 Additional Capabilities

Respondents suggested additional AI capabilities including enabling more critical evaluation of research; measuring the broader impact of research beyond published articles; capabilities for identifying alternative audiences or applications for research findings; suggested templates tailored to specific research types and target audiences; and an agentic AI system that could automatically rewrite research content for particular audiences and publish it on social media platforms.

2.7 Formulating New Research Questions

The community evaluated concepts for agentic AI tools proposed to assist with formulating new research questions.

2.7.1 Literature and Data Wrangler

The Literature and Data Wrangler ranked as a valuable tool (rank #4). This tool was proposed to analyse existing research and data to identify gaps, overlaps and opportunities by:

- Scanning the literature to identify gaps in knowledge and emerging research opportunities
- Identifying overlaps between ideas and existing research to avoid duplication and encourage data reuse
- Finding relevant datasets within institutions that could support new projects

2.7.1.1 Usefulness Ratings

Usefulness ratings for the Literature and Data Wrangler were predominantly positive. Over two-thirds of respondents (~69%) rated the tool positively, with 43.4% considering it very useful and 25.3% somewhat useful. However, ~23% expressed reservations (7.2% not very useful, 15.7% not useful at all), while 8.4% remained unsure (**Figure 15**).

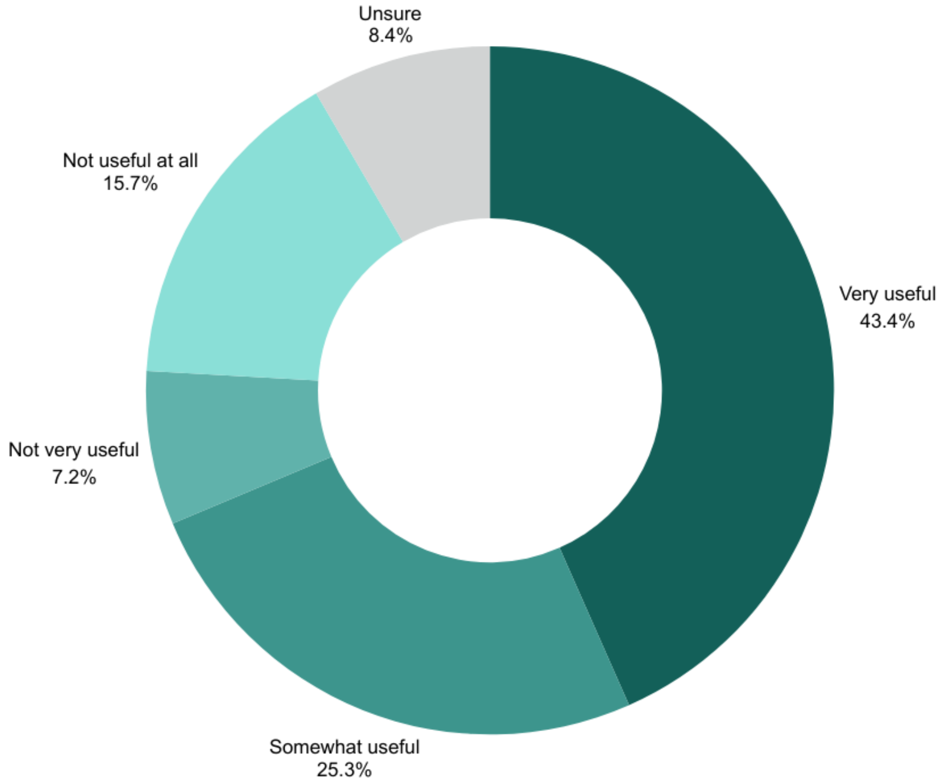

Figure 15. Community usefulness ratings for the Literature and Data Wrangler (*n*=83).

2.7.1.2 Community Perspectives

Respondents acknowledged potential benefits of the Literature and Data Wrangler tool including time-saving automation of literature searches and gap analysis. Several noted that such tools already exist to some degree and described AI as a valuable 'thought partner' that has transformed their working methods. The vast quantity of available academic literature makes AI assistance potentially beneficial, particularly for identifying datasets and avoiding duplication. Respondents suggested the tool could be directed towards priority areas such as health, climate and biosecurity, with agentic AI being well-suited for connecting related research. One respondent proposed a specific use case: diversifying literature reviews by identifying alternative researchers based on gender, regional representation and language.

Significant concerns centred on accuracy in identifying gaps in research, with respondents noting that large language models' architecture may produce unreliable results. Multiple respondents expressed doubts about AI's current capability to effectively identify research gaps, with some reporting previous failures. Trust issues emerged prominently, including concerns about bias, missing information, and the correctness of sources. Respondents questioned how the system would access non-open institutional datasets and whether training data would be sufficiently reliable. Fundamental questions arose about researchers' roles: *if literature review and idea generation are offloaded to AI, what remains for academics?* Concerns about over-reliance and the limitation of critical literature review skills were also raised.

Respondents suggested focusing on working with data rather than merely finding them. One respondent commented that novel ideas could sometimes be found in data on underrepresented populations or locations, and a tool that could identify these data would be useful. Others recommended that tools should help identify reliable references for questioning research ideas rather than producing 'average, uncritical analyses'.

2.7.2 Literature Librarian

Of the proposed tools, the Literature Librarian was ranked as the most valuable agentic AI tool for research (#1). This tool was proposed to find relevant research articles by:

- Searching literature using natural language queries (asking questions in everyday language)
- Integrating with library subscriptions to access both open access articles and those behind paywalls

2.7.2.1 Usefulness Ratings

Usefulness ratings for the Literature Librarian were overwhelmingly positive. Nearly nine in ten respondents (~87%) rated the tool positively, with 48.2% considering it very useful and 37.3% somewhat useful. Only ~8% expressed reservations about its value, while 6% remained unsure (**Figure 16**).

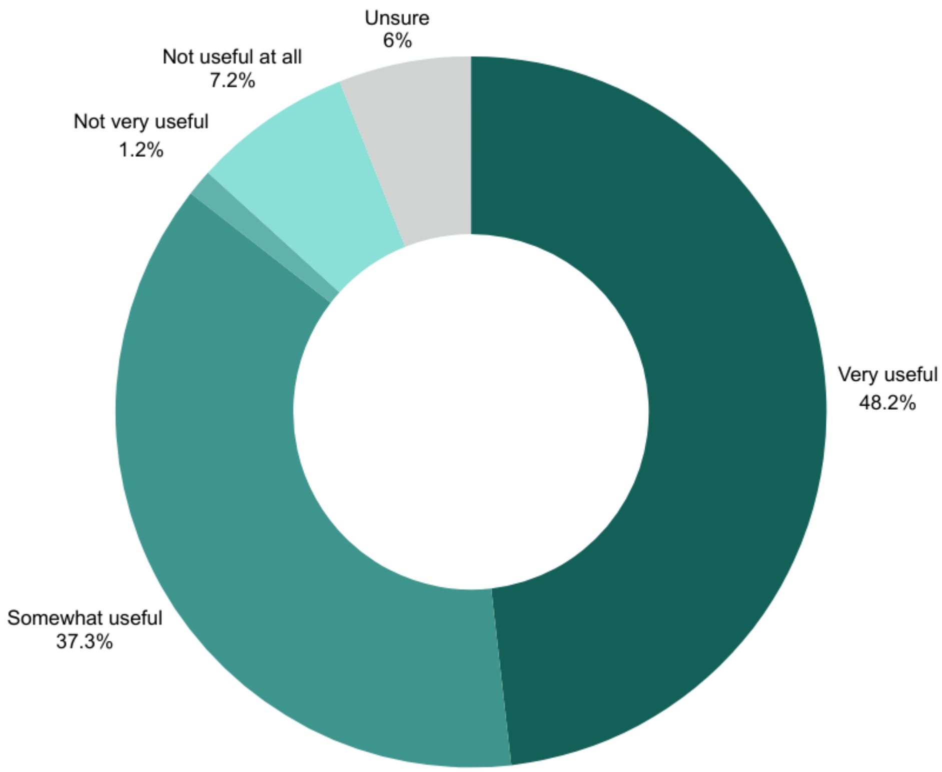

Figure 16. Community usefulness ratings for the Literature Librarian (*n*=83).

2.7.2.2 Community Perspectives

Respondents indicated that AI-based techniques such as vector embeddings (which perform semantic searches and identify contextually similar items) could enable effective ‘fuzzy’ (approximate) matching when searching databases. Several participants stated the tool would be more efficient than humans for literature searching and could work relatively well, though a manual review remains necessary. One respondent noted the usefulness of the Deep Research AI agent despite requiring human intervention. Participants suggested the tool could complement standard semantic search tools like Google Scholar and be marginally more useful than general web searches, depending on result quality. The tool was described as potentially helpful in the same way current search engines assist researchers, rather than replacing human involvement entirely.

Again, multiple respondents expressed concern about AI hallucinations and the current instability of such tools. Participants questioned whether existing library contracts with database providers would permit agentic AI access and whether campus IT protocols would allow such services. Another opinion was that such tools would be suitable only for imprecise reviews rather than nuanced searches. Concerns were raised about reproducibility of natural language queries and the need to exclude ‘AI slop’ from search results. Several participants noted that search engines already perform this function without requiring AI.

Issues regarding careful content reading and potential copyright complications with scholarly publishers were mentioned.

Respondents suggested the tool should provide summaries for papers of marginal interest whilst flagging papers requiring careful reading. Several noted that current AI tools already provide this capability and described it as an essential Research & Development task, though not unique to the research context.

2.7.3 Existing Relevant Tools

Respondents identified the following tools to support the formulation of new research questions: ChatGPT, Claude, Copilot, Deep Research, Elicit, Gemini, Google Scholar Lab, Grok, Hubmeta, Keenious, NotebookLM, Perplexity, Primo Research Assistant, Research Rabbit, Research Screener, SciSpace, Scopus, and Web of Science Research Intelligence.

2.7.4 Additional Capabilities

Respondents identified a need for AI tools that could generate executive summaries and highlight recent findings within specific research fields. One participant suggested a tool that could answer queries such as '*What's new in Seismology in the last 6 months?*' by producing an easily readable two-page summary with links to relevant sources. Related to this, another respondent proposed AI capabilities that could draw from research funding solicitations and thought pieces from stakeholder conversations.

One participant noted that AI demonstrates competence in drawing analogies across different fields, suggesting this capability could help reduce disciplinary silos and enhance interdisciplinary research. Another suggested AI tools could review researchers' own study notes and documentation, such as meeting notes, research papers and previously identified areas requiring further investigation, to identify research questions the researcher has already indicated or flagged for deeper exploration.

Some respondents indicated they had not identified or did not require additional AI capabilities beyond those already mentioned in the survey. One respondent expressed significant concern about AI formulating research questions, arguing this represents an inappropriate offloading of critical thinking.

2.8 Regional Priorities

Regional analysis of the survey results, using the same weighted scoring methodology (Section 2.1), identified regional priorities for agentic AI in research.

Survey respondents represented 25 countries across five continents, with uneven distribution: Europe (*n*=44 respondents), North America (*n*=16), Oceania (*n*=15), Asia (*n*=5), and Africa (*n*=3). Due to small sample sizes within individual countries, a continental approach was adopted to provide greater sample sizes for analysis. Asia and Africa lack sufficient data for meaningful analysis and are excluded from this comparative review.

European respondents ranked the Literature Librarian first, followed by Data Director and Research Refiner. North American respondents ranked the Collaboration Catalyst first, alongside the Resource Finder and Funding Finder (both 3.38). Oceanian respondents ranked the Funding Finder first, followed by the Data Director and Literature Librarian (**Table 2**).

Across continents, the Literature Librarian consistently performs well, prioritised in the top four tools across all continents, while the Ethics Reviewer consistently features among the least useful tools (**Section 7.1, S2**).

Table 2. **Regional variation in agentic AI agent prioritisation.** Top three and bottom three ranked tools by continent based on weighted usefulness scores. Scores calculated using the methodology: Very useful (×4), Somewhat useful (×3), Not very useful (×2), Not useful at all (×1), with 'Unsure' responses excluded. Scores out of 4.0. Higher scores indicate greater perceived usefulness.

Continent	Top 3 tools	Score	Bottom 3 tools	Score
Europe (*n*=44)	**Literature Librarian**	3.20	Ethics Reviewer	2.24
	Data Director	3.02	Publication Preparer	2.60
	Research Refiner	2.88	Collaboration Catalyst	2.68
North America (*n*=16)	**Collaboration Catalyst**	3.40	Literature and Data Wrangler	3.00
	Resource Finder	3.88	Publication Preparer	3.00
	Funding Finder	3.88	Ethics Reviewer	3.00
Oceania (*n*=15)	**Funding Finder**	3.60	Resource Finder	2.80
	Data Director	3.54	Collaboration Catalyst	2.87
	Literature Librarian	3.47	Publication Preparer	2.92

2.9 Stakeholder Priorities

Stakeholder analysis of the survey results, using the same weighted scoring methodology (Section 2.1), identified stakeholder priorities for agentic AI in research.

Survey respondents represented eight stakeholder groups with uneven distribution: researchers and scientists (*n*=33 respondents), research performing organisations (*n*=12), early career individuals (*n*=8), libraries (*n*=7), infrastructure providers (*n*=5), funders and policymakers (*n*=4), industry and private sector (*n*=3) and regions and nations (*n*=2). Stakeholder groups with five or less respondents were excluded from this analysis due to the small sample size.

Researchers and scientists ranked the Literature Librarian first, followed by Data Director and Funding Finder. Research performing organisations ranked the Data Director first, followed by the Research Assessment Supporter and Funding Finder. Early career individuals ranked the Literature Librarian first, followed by the Funding Finder and Literature and Data Wrangler. Libraries ranked the Data Director and Literature Librarian joint first, followed by the Funding Finder (**Table 3**).

Across stakeholder groups, several tools showed consistent patterns. The Funding Finder ranked in the top three for all stakeholder groups, while the Literature Librarian and Data Director each appeared in the top three for three groups. Conversely, the Publication Preparer consistently ranked among the least useful tools, appearing in the bottom three for Researchers and Scientists, Research Performing Organisations, and Libraries (**Section 7.1, S3**).

Table 3. **Stakeholder variation in agentic AI agent prioritisation.** Top three and bottom three ranked tools by stakeholder group based on weighted usefulness scores. Scores calculated using the methodology: Very useful (×4), Somewhat useful (×3), Not very useful (×2), Not useful at all (×1), with 'Unsure' responses excluded. Scores out of 4.0. Higher scores indicate greater perceived usefulness.

Stakeholder	Top 3 tools	Score	Bottom 3 tools	Score
Researchers and Scientists (*n*=33)	**Literature Librarian**	3.**30**	Ethics Reviewer	2.44
	Data Director	2.97	Resource Finder	2.68
	Funding Finder	2.94	Publication Preparer	2.78
Research Performing Organisations (*n*=12)	**Data Director**	**3.09**	Literature and Data Wrangler	2.20
	Research Assessment Supporter	3.00	Collaboration Catalyst	2.40
	Funding Finder	2.91	Publication Preparer	2.45
Early Career Individuals (*n*=8)	**Literature Librarian**	**3.88**	Research Assessment Supporter	3.00
	Funding Finder	3.83	Research Reporter	3.00
	Literature and Data Wrangler	3.75	Ethics Reviewer	3.25
Libraries (*n*=7)	**Data Director**	**3.14**	Ethics Reviewer	2.14
	Literature Librarian	**3.14**	Research Assessment Supporter	2.50
	Funding Finder	3.0	Publication Preparer	2.57

3. Conclusions and Next Steps

The community consultation identified the **Literature Librarian**, **Data Director**, and **Funding Finder** as the top three priority agentic AI tools, a finding reflected across most stakeholder groups and regions. While the quantitative rankings provide a clear hierarchy, the qualitative responses offer crucial insights into the specific features, concerns, and contexts that shape the potential value of each tool.

3.1 Interpreting the Findings

Several important considerations should be noted when interpreting these findings. Firstly, this consultation represents a snapshot in time within a rapidly evolving AI landscape, and perspectives may shift as agentic AI technologies, and their applications continue to develop.

Secondly, the consultation captured 83 responses within a limited timeframe, which, while valuable, represents only a fraction of the large and diverse global research community, with particularly small subgroups for regional and stakeholder analyses. Contribution patterns were inevitably unequal across regions and stakeholder groups.

Finally, interpreting free-text survey responses presented challenges, for example where large volumes of text required synthesis. While every effort was made to analyse responses accurately and without bias, some degree of inference was necessary to interpret participant intent and meaning.

3.2 The Future of Agentic AI in Research: Community Perspectives

When asked "What does the future of agentic AI in research look like to you?", participants during the online information sessions viewed it as transformative and inevitable, driven by innovation and opportunities. Most anticipated acceleration, increased efficiency, and AI as a supportive team member augmenting human capability (**Figure 17A**).

However, optimism was tempered by concerns. Participants' primary worries centred on transparency: understanding how models work and defending research processes. Bias and hallucinations producing false information were also concerns, raising fundamental questions about verifying results and establishing trust. Many also worried about loss of research skills and insights through reduced hands-on interaction with data, diminishing researchers' abilities to justify conclusions and develop critical judgment. Human-in-the-loop considerations were viewed as crucial for maintaining responsible oversight, particularly for ethics and governance with sensitive data. Error propagation through an automated research lifecycle was seen to pose serious risks, while unequal access, vendor lock-in, and sustainability concerns added further complexity (**Figure 17B**).

Figure 17. Community views on agentic AI opportunities and concerns. Mentimeter word clouds from information session live polling (November 2025). Responses to 'What does the future of agentic AI in research look like to you?' highlighting themes of acceleration and efficiency (**A**). Responses to 'What concerns might exist?' emphasising transparency, bias, and trust. Larger words indicate higher frequency (**B**).

3.3 Next Steps

The valuable insights from this consultation will guide the next phase of work in 2026, which will focus on collaborative community development of an open, technology-agnostic blueprint for a priority agentic AI tool. This work will be executed with the framework of the RDA and adhere to the RDA Guiding principles. Those interested in contributing to this development work are encouraged to contact the RDA Secretariat (secretariat@rda-foundation.org).

4. Acknowledgements

4.1 Organisers and Contributors

Thank you to everyone who contributed to this consultation. The expert speakers, information session participants (**Table 4**) and survey respondents who shared their honest perspectives made this global community consultation and report possible.

Special thanks to the organising team: **Hilary Hanahoe, Connie Clare** and **Curtis Sharma** from the RDA, and **Marcy Collinson** and **Ryan Payton** from Microsoft, who conceived, planned, and supported the timely delivery of this initiative. Thank you to **Trish Radotic** for providing logistical and communications assistance, and to the wider RDA Secretariat team, including **Irina Hope** and **Bridget Walker**, for their ongoing support.

Table 4. Information Session Participants. Please note only participants who provided consent have been included in this list.

First Name	Surname	Role	Organisation	Country
Ian	Atkinson	Director AI	James Cook University	Australia
Michelle	Barker	Director	Research Software Alliance (ReSA)	Australia
Ash	Bassili	CEO	myLaminin	Canada
Wendy	Beets	Business Development Manager	Fugro	Australia
Carlos	Brandt	Software Architect	EGI Foundation	Germany
Melissa	Burke	Training Manager	Australian BioCommons	Australia
Jinguang	Chai	Applied Mathematics MS Student	Columbia University	United States
Rory	Chen	DPAU manager	UNSW	Australia
Oren	Civier	Founder	TrialSafeSoft	Australia
Marcy	Collinson	Director, Worldwide Academic Research	Microsoft	United States
David	Cyrille	CRIO	Stony Brook University	United States
Steve	Diggs	Research Data Specialist	UC Office of the President	United States
Mohamed	Drira	Associate Professor	Saint Mary's University	Canada
Roberta	Ferretti	Researcher	National Research Council - Institute of Marine Engineering	Italy
Kirsty Lee	Garson	Training Coordinator	University of Cape Town	South Africa
Moji	Ghadimi	Head of AI and Quantum Algorithms	Queensland Cyber Infrastructure Foundation (QCIF)	Australia
Nina	Grau	Project officer	CODATA	France
Lars	Grønvold	Researcher	Norwegian University of Life Sciences	Norway
Hilary	Hanahoe	Secretary General	Research Data Alliance (RDA)	United Kingdom
Kim	Hartley	Program Manager	Research Software Alliance	Canada
Daniela	Hensen	Joint interim Head of Transformative Technologies	BBSRC	United Kingdom
Santosh	Ilamparuthi	Data Steward	Delft University of Technology	Netherlands
Yuyun	Ishak	Lead, Institutional Repository	Nanyang Technological University	Singapore
Harang	Ju	Assistant Professor	Johns Hopkins Carey Business School	United States
Rolanda	Julius	Researcher Development Coordinator	University of Cape Town	South Africa
Beth	Knazook	Project Manager, Research Data	Digital Repository of Ireland	Ireland
Mukkesh	Kumar	Head of Data Management Platform	A*STAR	Singapore
Pauline	Lawrey	eResearch Specialist	James Cook University	Australia
Bora	Lushaj	Research Data Steward	Erasmus University Rotterdam	Netherlands

Maria	Mirza	Scientific Project Manager	Euro-BioImaging ERIC	Germany
Darcy	Ogden	Academic Researchers Lead	Microsoft	United States
Ugochi	Okengwu	Associate Professor	University of Port Harcourt	Nigeria
Chukwuemeka	Onyeizu	Managing Director	MalionGeodata Nigeria Limited	Nigeria
Sumir	Panji	Program Manager	eLwazi Open Data Science Platform / UCT CBIO	South Africa
Ryan	Payton	Research Technology Strategist	Microsoft	United Kingdom
Sevil	Peker	Partner Manager	Sabancıdx	Turkey
Andreas	Pester	Professor AI	The British University in Egypt	Egypt
Jonathan	Petters	Associate Director, Data Management and Curation Services	Virginia Tech	United States
Daniel	Piczak	Architect	Health Support Services	Australia
Maria	Praetzellis	Associate Director, University of California Curation Center	California Digital Library	United States
Fotis	Psomopoulos	Senior Researcher	INAB / CERTH	Greece
Tovo	Rabemanantsoa	Project/IT manager	French National Research Institute for Agriculture, Food and Environment	France
Trish	Radotic	RDA Community Manager (Oceania and East Asia)	Australian Research Data Commons (ARDC)	Australia
Rodrigo	Roa	Executive Director	Data Observatory	Chile
Marco	Rorro	AI Solutions Architect	EGI Foundation	Italy
Jeyalakshmi	Sambasivam	Senior Assistant Manager	Nanyang Technological University	Singapore
James	Savage	Research Manager	Southern Institute of Technology	New Zealand
Curtis	Sharma	Communications Officer	Research Data Alliance (RDA) Europe	Belgium
Amaan	Sheikh	Grad student	Columbia University	United States
Nantha Kumar	Sivanathan	Senior Manager	A*STAR	Singapore
Emanuel	Soeding	Data Steward, Project Manager	GEOMAR	Germany
Aryamaan	Srivastava	Student	Columbia University	United States
Chiang Wee	Tan	Librarian	Nanyang Technological University	Singapore
Mui Yen	Tay	Senior Manager	Singapore Management University	Singapore
Matt	Townsend	Senior AI Specialist	Jisc	United Kingdom
Andrew	Treloar	Director, International Strategy	Australian Research Data Commons (ARDC)	Australia
Yan	Wang	Head Research Data and Software	Delft University of Technology	Netherlands
Veronica	Wang	Librarian	Singapore Management University	Singapore
Pavel	Weber	Technical Manager	Karlsruhe Institute of Technology	Germany

Anne	Wozencraft	Director, International & Global Partnerships	Health Data Research UK	United Kingdom
Mingfang	Wu	Product Manager	Australian Research Data Commons (ARDC)	Australia
Sammi	Yan	Master's student	Columbia University	United States
Qi	Zhang	Project Researcher	Research Organisation of Information and Systems	Japan

4.2 Tool Usage

Workshop registration and sessions were facilitated using Microsoft Forms[9] and Teams.[10] Mentimeter was used to capture real-time feedback from information session attendees. Survey responses were captured using QuestionPro.[11] Report charts and graphs were created using Canva.[12] In line with the RDA's Guidance on AI Tools Usage,[13] Claude Sonnet 4.5 (Pro)[14] was used for data analysis and writing assistance throughout sections of this report. The generative model was used with a privacy-preserving configuration ensuring that input and output data is not used for model training. AI-assisted data analysis and AI-generated texts have been reviewed, validated and edited as necessary by the authors for accuracy and completeness.

4.3 Disclaimer

This consultation and report were a collaborative effort between the RDA Secretariat[15] and volunteer members of the global research community, who did not receive any compensation for their involvement. All quotes and statements attributed to speakers and participants have been directly verified using transcripts and video recordings. Attribution has been made only with explicit consent, and general discussion quotes, although anonymised, have been validated against recordings. Attributed quotes were shared with their respective speakers for review and commentary prior to publication. Figures included in this paper were generated by the author (Connie Clare), while other graphics were provided by the speakers, all of which have been cleared for use. Any substantial claims presented in this report are supported by expert speaker statements as well as footnote citations from referenced sources, all verified by the authors.

5. About the RDA

The Research Data Alliance (RDA)[16] was launched as a community-driven initiative in 2013 with the vision that researchers and innovators can openly share and re-use data across

9 https://forms.office.com/
10 https://teams.live.com/free
11 https://www.questionpro.com/
12 https://www.canva.com/
13 https://www.rd-alliance.org/about/code-of-conduct/rda-guidance-on-ai-tools-usage/
14 https://claude.ai/new
15 https://www.rd-alliance.org/governance/secretariat/
16 https://www.rd-alliance.org/

technologies, disciplines, and countries to address the grand challenges of society. The RDA's mission is to build the social and technical bridges that enable that vision, accomplished through the creation, adoption and use of the social, organisational, and technical infrastructure needed to reduce barriers to data sharing and exchange.

As of December 2025, the RDA comprises a 16,000+ member-strong community of researchers, data professionals, publishers, funders and policymakers, that collaborate in working groups, interest groups and communities of practice to create recommendations and outputs. Individual membership is free of charge and open to all who share the RDA's Guiding Principles.[17] To get involved at the organisational level, explore our organisational and affiliate membership options.[18]

6. About Microsoft

Microsoft Corporation[19] is a multinational American technology company recognised for shaping the evolution of personal and enterprise computing. Founded in 1975 and headquartered in Redmond, Washington, the company initially revolutionised software accessibility through its early operating systems. Over the decades, Microsoft expanded its portfolio to encompass a broad spectrum of technologies, including productivity, software, cloud infrastructure, gaming, Artificial Intelligence and Quantum Computing.
With a longstanding emphasis on innovation and digital transformation, Microsoft continues to play a pivotal role in defining the future of the tech industry.

7. Appendices

This appendix provides supplementary materials referenced in the main report. It includes information about available data files and details of guest speakers and their presentations from the consultation information sessions.

7.1 Supplementary Data Files

Data Availability: To support transparency and enable further analysis, the following anonymised materials are publicly available:

- **S1**: Agentic AI in Research: Global Community Consultation Survey Data (*n*=83): https://doi.org/10.15497/RDA00145
- **S2**: Agentic AI in Research: Regional Analysis of Community Priorities (*n*=83): https://doi.org/10.15497/RDA00146
- **S3**: Agentic AI in Research: Stakeholder Group Analysis of Community Priorities (*n*=83): https://doi.org/10.15497/RDA00147

17 https://www.rd-alliance.org/about/
18 https://www.rd-alliance.org/membership/organisational-membership/
19 https://www.microsoft.com/

- **S4**: Agentic AI in Research: Claude.ai Prompts for Qualitative Data Analysis: https://doi.org/10.15497/RDA00148
- **S5**: Agentic AI in Research: Information Session Interactive Polling Results: https://doi.org/10.15497/RDA00149

Privacy protection: All personally identifiable information has been removed from datasets. Individual responses cannot be traced to specific participants.

Licensing: All materials are licensed under Creative Commons Attribution 4.0 International (CC BY 4.0), allowing reuse with appropriate citation of this report.

Contact: For questions about data access, interpretation, or use, please contact the RDA Secretariat at [secretariat@rda-foundation.org].

7.2 Speaker Information

7.2.1 Harang Ju: 'Collaborating with and Building AI Agents'

Dr Harang Ju is an Assistant Professor at the Johns Hopkins Carey Business School (United States). Harang's current work explores how AI agents influence team dynamics and performance. In one line of research, he examines how personality pairing between humans and AI can improve team outcomes, offering insights into the design of collaborative AI systems. In a large-scale field experiment, he evaluates how AI agents affect productivity, performance, and teamwork.

Harang presented his work on collaborating with and building AI agents. His research examines how AI agents impact workplace dynamics, particularly focusing on teamwork, communication, and productivity as these systems become increasingly common.

In the AI Agent Lab at Johns Hopkins, Harang develops AI agents that serve internal administrative, teaching, and research needs. He also founded Pairium AI,[20] a startup that commercialises personalised AI agents. His research platform, Pairit,[21] enables direct comparison between human-AI and human-human collaboration through a controlled experimental environment.

Key findings reveal that while AI agents boost productivity and text quality, they reduce image quality and output diversity. Notably, Harang's research demonstrates that personality pairing significantly matters; matching human and AI personality traits improves collaboration outcomes.[22] His work also identifies heterogeneous effects based on factors including skill

[20] https://www.pairium.ai/
[21] https://doi.org/10.48550/arXiv.2503.18238
[22] https://doi.org/10.48550/arXiv.2511.13979

level, task type, gender, language, expertise, and cognitive styles, challenging the 'one-size-fits-all' approach to AI deployment.

The participant Q&A with Harang addressed task delegation and platform capabilities. When asked about delegated tasks (80-90% to chatbots), Harang explained that humans still review most AI-generated work but rely heavily on it. Participants helped chatbots succeed through minor tweaking rather than major revisions, suggesting an effective collaborative approach. Regarding platforms for running human-AI experiments, Harang noted that while Qualtrics[23] and Empirica[24] offer some AI capabilities, they lack sophistication, which motivated his team to build their own custom platform, Pairit, that enabled their research comparing human-human versus human-AI collaboration patterns across approximately 2,300 participants and 180,000 chat messages.

View Harang's [presentation recording and slides]()

7.2.2 Moji Ghadimi: 'How to Build Your Own Literature-Review AI Agent'

Dr Moji Ghadimi leads Australia's national initiatives in artificial intelligence and quantum computing as Head of AI and Quantum Algorithms at the Queensland Cyber Infrastructure Foundation (Australia). A physicist and data scientist, he directs large-scale projects in machine learning, federated learning, and quantum-enabled optimisation across health, energy, and advanced materials. His collaborations span government, academia, and industry through partnerships with national organisations such as the ARDC, NCI, and Pawsey Supercomputing Centre.

Moji presented on building literature-review agentic AI systems for research. Based on a workshop developed for Australia's National Computing Infrastructure, he demonstrated how to create a personal AI literature review agent using Python and large language models (LLMs).

Agentic AI for literature review uses LLM-based systems to autonomously search, read, and synthesise research papers across multi-step tasks, addressing the challenge of information overload with over 100,000 papers published weekly across disciplines.

Key capabilities include searching databases, extracting structured insights, fetching relevant PDFs, and generating literature reviews with traceable references. Moji emphasised that human oversight remains essential where AI acts as an assistant rather than autonomous researcher. Applications span literature review, hypothesis generation, data analysis, and manuscript preparation. The workshop covers critical considerations including prompt engineering, ethics, intellectual property, and privacy concerns, particularly regarding

[23] https://www.qualtrics.com/
[24] https://empirica.ly/

sensitive data. Future directions include multi-agent collaboration and integration with laboratory data systems.

The participant Q&A with Moji explored how the system uses a multi-stage approach for literature review: database APIs first rank papers based on set criteria, then the LLM analyses abstracts and full texts to identify both core and tangentially related work. Regarding language support, the tool uses Groq service with various models, some supporting Arabic and other languages. It works across all research domains because it retrieves and analyses real published papers from databases rather than relying solely on AI training knowledge. Moji used llama-3.3-70b-versatile[25] and llama8b (which runs locally).[26] Regarding programming language, while currently Python-based,[27] the tool could be adapted to R[28] or developed as a web interface for non-programmers.

View Moji's [presentation recording and slides]

7.2.3 Ugochi Okengwu: 'The Prospect of Agentic AI in Crop Image Analysis'

Dr Ugochi A. Okengwu is an Associate Professor in the Computer Science Department, University of Port Harcourt (Nigeria), a scholar and researcher whose expertise spans Artificial Intelligence, Data Science, and Environmental Informatics. Her research focuses on developing AI-driven and multilingual systems for climate change awareness, environmental monitoring, and sustainable development in Africa.

Ugochi has led and contributed to several interdisciplinary projects, including Social Media Analysis of Climate Change in Africa, Tomato Leaf Disease Detection and Real-Time Data Capture Systems for Greenhouse Gas Monitoring. Ugochi's academic and professional work emphasises responsible AI, cross-regional research collaboration, and the application of intelligent systems to address societal and environmental challenges.

Ugochi presented on agentic AI in crop image analysis, using a tomato leaf disease detection mobile app as a case study.[29] With 20-40% of global crop losses caused by pests and diseases, image-based diagnosis enables early detection and management. Unlike conventional AI models that only detect and predict, agentic AI systems could perceive, reason, decide, and act autonomously, such as automatically adjusting irrigation or deploying drones for targeted spraying.

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[25] https://console.groq.com/docs/model/llama-3.3-70b-versatile
[26] https://console.groq.com/docs/model/llama-3.1-8b-instant
[27] https://www.python.org/
[28] https://www.r-project.org/
[29] https://library.ncs.org.ng/download/transfer-learning-for-tomato-leaf-disease-detection-using-convolutional-neural-networks-on-mobile-platforms/

The tomato app, developed using convolutional neural networks (CNNs), detects diseases including late blight, bacterial spot and leaf mould via smartphone cameras. Sponsored by IDRC (International Development Research Centre)[30] and managed by ACTS Africa Centre for Technology[31] under the AI4D Africa programme,[32] the app supports multiple local languages for African farmers. Agentic AI could extend this through continuous learning loops, collaborative agents coordinating irrigation and spraying, autonomous responses, and contextual reasoning combining weather and soil data. Key challenges include infrastructure limitations, data bias, multilingual support, Internet of Things (IoT) device interoperability, and ethical governance for autonomous agricultural systems.

The tomato leaf disease detection app stimulated interest among the community, with the participant Q&A with Ugochi highlighting different practical applications of AI beyond agricultural disease detection. Participants explored using generative AI and RAG (Retrieval-Augmented Generation) to improve metadata generation for large data repositories, with one noting a proposal submission for this purpose. When asked whether creating FAIR metadata is feasible when many domains lack standardised metadata, respondents suggested combining datasets with extra information through RAG could address this challenge. One participant mentioned developing a data curation chatbot to extract more complete metadata from researchers during data deposit, though the project remains in early development. Questions also addressed the app's current availability.

View Ugochi's [presentation recording and slides]()

7.2.4 Mukkesh Kumar: 'Agentic AI for Research Data Platforms'

Dr Mukkesh Kumar is the Head of Data Management Platform at A*STAR (Singapore), his interests are in data, software engineering and AI for biomedical informatics. Forging collaborations with the National University Hospital (NUH) in Value-based Healthcare Strategy, the Early Screening for Gestational Diabetes Mellitus in a Low Risk Population (EaGeR) pilot study is conducted at NUH for the real-world deployment of early pregnancy GDM predictor AI model. Working in close partnership with Singapore's Ministry of Health (MOH) and Observational Health Data Sciences and Informatics (OHDSI) global community, Mukkesh is shaping Singapore's national OMOP data standardisation and standardised data analytics strategies. Mukkesh has been mentoring the Data Managers at US Boston Children's Hospital/Harvard Medical School for multi-centre clinical research studies, building talent and capabilities in the global research ecosystem.

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[30] https://idrc-crdi.ca/en
[31] https://acts-net.org/
[32] https://ai4d.acts-net.org/ai4d-africa/

Mukkesh presented on agentic AI for research data management. He outlined the AI super-cycle progression from machine learning through generative AI to agentic AI. He explained that unlike generative AI, which creates static content, agentic AI takes autonomous actions, maintains context, and performs complex reasoning.

Mukkesh showcased the GUSTO Data Vault,[33] featuring 37 million data points, 23,000 active researchers across 69 countries, and enabling over 400 publications. A*STAR evolved from a 2024 GPT-4 literature review system to deploying the first enterprise-grade multi-agent AI system in 2025, using GPT-5 with specialised agents for general queries, topics, variables, and publications. The literature review system[34] supports the GUSTO researchers and collaborators in synthesising the GUSTO research findings and aids with the formulation of new research hypothesis, building upon the existing GUSTO findings The team won IMDA's Agentic AI Special Award for developing an AI agent managing post-surgical risk complications, becoming the first in Asia-Pacific to fine-tune OpenAI's o1 model[35] with reinforcement learning.

The participant Q&A with Mukkesh discussed technical implementation challenges of the GUSTO Data Vault. To control AI hallucinations, Mukkesh's team conducted extensive benchmarking and selected OpenAI GPT-5 for its lowest hallucination rates, supplemented by human validation and system prompting. Regarding inevitable minimal hallucinations, Mukkesh acknowledged organisations must accept some risk when deploying enterprise-wide AI systems but emphasised incorporating human-in-the-loop oversight at various stages to better manage this risk. For model stability, they're exploring open-weight alternatives while cloud API-hosted models ensure production reliability. Model outputs are evaluated using combined human and AI evaluators. Mukkesh recommended standard data models like OMOP for data catalogues to enable federated AI approaches. One participant noted declining web traffic to data catalogues as AI tools provide direct answers, raising usage measurement concerns.

View Mukkesh's [presentation recording and slides]()

7.2.5 Ryan Payton: 'Agentic AI in the Research Lifecycle'

Dr Ryan Payton is a Research Technology Strategist within the Higher Education team at Microsoft UK. Ryan presented on the evolution of AI and its application in research. He outlined the progression from basic generative AI (like ChatGPT) built on transformer models that predict text, to more sophisticated systems incorporating RAG (Retrieval-Augmented Generation) for grounding responses in specific data.

33 https://gustodatavault.sg/
34 https://askai.gustodatavault.sg/
35 https://openai.com/o1/

Using a hammer-and-nail analogy, Ryan explained how AI evolved through stages: creating tools, developing orchestration for planning, and ultimately building agentic AI systems capable of evaluating whether actions achieve desired goals and autonomously adjusting approaches. He advocated for human-in-the-loop approaches, emphasising that autonomy should be strategically deployed where AI excels while preserving human value.

Ryan presented the 11 proposed agentic AI tools identified through engagement with UK research institutions, addressing researcher and research support team pain points including finding funding, preparing publications for journal formats, accessing literature and data curation.

View Ryan's presentation recording and slides