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Short communication

Who uses AI in research, and for what? Large-scale survey evidence from Germany☆

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ABSTRACT

The integration of AI into scientific work holds significant potential to accelerate innovation. We surveyed researchers in two leading German research organizations to examine AI adoption, barriers, and perceived impact on research. Researchers are widely using AI tools – often for primary and creative tasks – and many expect the technology to be transformative for research. Effective use appears linked to both hands-on experience and engagement with learning resources. A persistent gender gap in AI use is closely associated with differences in familiarity, suggesting a potential focus for organizational efforts. Legal uncertainty and privacy concerns also emerge as major barriers, with researchers calling for clear, high-level regulatory guidance. Overall, our findings suggest directions where institutional actions might be explored to promote more equitable and effective AI adoption.

1. Introduction

The rapid advancement of artificial intelligence (AI), powered by Large Language Models (LLMs), promises transformative changes across diverse sectors and occupations (e.g., National Academies of Sciences, Engineering, and Medicine, 2024), sparking heated debates about its societal impact and future trajectory (Dwivedi et al., 2023; Goos and Savona, 2024). An important difference of AI as compared to previous waves of automation is its effect on higher income jobs and knowledge tasks (Eloundou et al., 2024). Indeed, AI tools are already in use across a variety of high-skill occupations, from journalists to accountants and legal professionals (Humlum and Vestergaard, 2025) and can offer significant productivity benefits (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023; Peng et al., 2023; Heller and Asam, 2024). While AI tools can power productivity, their effect critically depends on the adoption of the technology and user proficiency.

In this article, we look at how AI tools are used in research. When applied to this domain, the effect of AI tools can be exacerbated as they, in turn, could enable novel discoveries and foster innovation (e.g., Besiroglu et al., 2024; Agrawal et al., 2024; Cockburn et al., 2018). Yet, it is not clear how useful AI tools are perceived to be for research – a domain that is characterized by a high degree of open-ended, exploratory problems and typically involves highly qualified researchers.

To answer this question, we conducted a large-scale survey with two of the largest research associations in Europe: the Max Planck Society (MPS) and the Fraunhofer Society (FhS). The MPS and the FhS are two public research organizations in Germany, each with a distinct mission. The MPS focuses on fundamental research across a wide range of disciplines, aiming to advance scientific knowledge without immediate commercial application. In contrast, the FhS emphasizes applied research, working closely with industry to develop and transfer innovative technologies and solutions. Both are internationally renowned, publicly funded, and highly research-intensive. On average, 78% of researchers' work time is dedicated to research (Figure A2).

☆ The survey was reviewed by the Institutional Review Board of Ludwig Maximilian University of Munich (2024-1). It was approved by the Workers' Councils of the Max Planck Society and the Fraunhofer Society. We thank the presidents of the two societies – Patrick Cramer and Holger Hanselka – for supporting the study. We thank M. Schierhold and A. Kuth for implementing the survey. We also thank Buse Nur Caba, and Piper Fleming for excellent research assistance.

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A survey is uniquely beneficial for documenting AI use across the entire research process, including activities such as hypothesis generation, analysis, communication, and science management (Agrawal et al., 2024; Koehler and Sauermann, 2024; Van Quaquebeke et al., 2025). Many of these uses may critically influence research outcomes without being visible in final outputs, such as publications or code. Capturing this hidden layer of AI use complements recent efforts based on observational data, including publication records and GitHub activity (Bianchini et al., 2022; Hajkowicz et al., 2023; Dohmke et al., 2023). While survey data are self-reported, they offer a more nuanced and comprehensive view of AI use, revealing both where AI is applied and what barriers hinder its adoption.

The characteristics of our sample offer several important advantages. First, our sample allows us to consider not only established researchers who can be identified with publication data but also early-career researchers and Ph.D. students who will shape the future trajectory of scientific developments. Second, by focusing on organizations within one legal environment and academic tradition, we can limit the differences in legal and cultural context. Third, knowing key characteristics of the target population allows us to assess the representativeness of our sample and partly address concerns about selective participation by researchers already interested in the topic.

Based on our data, we explore the patterns of adoption and use of AI tools among researchers, their beliefs about the impact of the technology and opinions about its regulation. As survey data only allow us to examine associations, the documented patterns of adoption should be interpreted as descriptive. Nonetheless, our findings may help identify areas where further causal research or targeted interventions are most promising (e.g., Doshi et al., 2024).

Our findings contribute to the growing body of literature on AI adoption (e.g., Humlum and Vestergaard, 2025; Bick et al., 2024; Carvajal et al., 2024). With its focus on the use of AI among researchers, our study comes the closest to Van Noorden and Perkel (2023), who surveyed 1,659 researchers around the world in 2023 and provided initial evidence on the uptake and use of AI among researchers globally. Our study builds on their first insights, addressing some of the urgent questions set by Goos and Savona (2024).

2. Methods and sample

In June 2024, an anonymous survey was administered to all employees of the MPS and the FhS. Data collection spanned one month, with each employee able to participate only once. We chose an anonymous format to encourage uninhibited responses, given the ongoing and often polarizing public debate around the use of AI in scientific research (e.g., Wang et al., 2023; Ball, 2023). The survey was promoted by the leadership of both organizations, including two reminder emails, which likely helped increase participation among less engaged respondents.[1] We obtained 6,215 complete responses from researchers,[2] yielding a 20.5% response rate based on completed surveys.

Respondents are mainly active in informatics (24.7%), physics (24.1%), and biology (16.9%), followed by electrical (16.4%) and mechanical engineering (13.1%). 9.8% work in the social sciences. Most respondents (54.8%) work in interdisciplinary settings.[3] Two-thirds identify as male, about one-third hold a PhD, and 22.5% are aged 25–29 (Table A1 in Appendix).

The survey focused broadly on AI tools and was not limited to generative AI, yet it is feasible that respondents nevertheless focused on generative AI tools, given their prominence in public discourse.[4] Given the breadth of disciplines, the wide range of AI applications – including many that are highly specialized – and a constant stream of newly released AI tools, we chose not to elicit specific tools used by researchers. As a result, our findings reflect aggregated experiences across a diverse set of AI tools, rather than tool-specific assessments. Future work may benefit from mapping specific tools or systems to better understand how infrastructure shapes user experience.

Our sample is broadly representative of the two research organizations. Table A2 compares survey respondents to organizational populations using administrative data. In the MPS, respondents are slightly older, more likely to hold a PhD, and somewhat less likely to be female. In the FhS, respondents are slightly younger, with a modest over-representation of women. While statistically significant due to the large sample size, differences between the survey sample and the population are modest in magnitude.[5] Both organizations focus on the natural sciences and engineering. Consequently, other fields like the social sciences and humanities are underrepresented compared to the overall population of R&D personnel and researchers in the EU (Eurostat, 2025).

The survey consisted of several thematic blocks. It covered demographics, research field, and time allocation, followed by a battery on organizational climate (Matthews et al., 2022), sections on AI familiarity and use, a prompting task to assess basic prompting skills, and questions on perceived barriers, benefits, attitudes toward AI's impact on research and society, as well as AI regulation. The survey materials can be found in Supplementary materials.

To proxy the prompting ability, we used a task from Carvajal et al. (2024). The respondents were shown a picture and were asked to create a prompt to learn the name of a depicted phenomenon from an LLM (Figure A1). For the analysis, we prompted a local LLM[6] ten times for each prompt. The prompt was classified as successful if at least *one* of the ten LLM's responses mentioned the name of the phenomenon, or if the prompt mentioned uploading the picture. 19.5% of respondents who left the response field empty were excluded from this analysis.

Our survey results are descriptive: We aim to document patterns of use, perceived barriers and benefits, and attitudes toward AI tools among researchers. When interpreting our findings, it is important to note that although the survey design – particularly its anonymity and organizational endorsement – was conducive to reaching respondents who may be less interested or less engaged with AI, some degree of self-selection cannot be ruled out. The responses reflect researchers' subjective experiences and perceptions, rather than objective measures of AI effectiveness or impact. The survey was conducted in Germany, limiting cross-country variation in legal and cultural context. However, some findings – such as heightened data privacy concerns – may reflect country-specific sensitivities.

To leverage our rich data while limiting the likelihood of false positives, we use a conservative significance threshold: we report results as statistically significant only if the p-value is 0.005 or lower (Benjamin et al., 2018). In all regression analyses, we control for highest level of education, gender, age group (five-year intervals from 18–69, with

[1] Supporting this intuition, 14.6% of researchers indicate that they do not use AI tools in their research (see Fig. 2) as compared to 1.3% in the survey of Van Noorden and Perkel (2023).

[2] The number of observations varies slightly by question due to technical, non-systematic issues.

[3] Respondents could select up to three fields of research to reflect the interdisciplinarity of their work. Therefore, the reported shares sum to more than 100%.

[4] The definition was: "For the purpose of this survey, we refer to 'AI tools' as software or systems that utilize artificial intelligence and machine learning algorithms to use patterns in the data to improve their performance over time. These tools are used to analyze data, make predictions, automate tasks, and provide insights, thereby enabling machines to perform tasks that typically require human intelligence. Examples of such tools are ChatGPT, AlphaFold, Midjourney, or BERT-family models."

[5] Reweighting the sample based on age, gender, and educational attainment (share with PhD) does not meaningfully affect the interpretation or magnitude of the results.

[6] 'Llama-3.2-3B-Instruct' at a temperature of 0.2

one group for 70+), broad research field (natural sciences; engineering and technology; social sciences; medical and health sciences; humanities and arts; agricultural sciences), years of work experience, and affiliation. We refer to this set as the standard controls.

3. Results

Researchers actively use AI tools, with adoption patterns varying with roles and beliefs. In our sample, 42.4% of the researchers report being very or rather familiar with AI tools, with a further 44.0% reporting that they have used AI tools a few times. 25.9% are frequent users of AI tools and use them for their research at least once a day or more often. Only 22.2% of researchers never use AI tools for their work tasks (i.e., research, teaching, or service to the profession). 19% report that their research involves studying or developing AI. In comparison, in 2023, none reported using AI tools for research regularly (Van Noorden and Perkel, 2023), and only 17.4% reported using generative AI for any purposes at work once a week and more often. This reflects a large shift in the use of AI in research over a relatively short time span. Among the general population of highly skilled professionals in exposed occupations in Sweden, the use of ChatGPT is at 40% (Humlum and Vestergaard, 2025). Researchers' appreciation of AI tools is positively correlated with use (Table A3, column 4). Still, this relationship is correlational and may capture both selection and experience effects: researchers might use AI more because they view it as helpful, or they may grow to value it through use.

We detect strikingly persistent demographic patterns of AI familiarity and use (Fig. 1 and Table A3). First, respondents are less likely to be familiar with AI and use AI tools less frequently as age increases. Interestingly, lower familiarity and adoption among older respondents are not accompanied by greater skepticism about AI (Table A4). This pattern attenuates the concern that more senior researchers may hinder the use of AI tools among more junior ones. Second, even in our highly educated sample, familiarity and use of AI tools grow with educational attainment. Third, there is a noticeable gender gap in AI familiarity and frequency of use for research tasks (discussed in more detail below). Fourth, familiarity with AI tools is highest in social sciences and higher than, for example, in engineering and technology. The latter might reflect that advances in natural language processing have opened new horizons for the social sciences.

To provide a more nuanced view into the use of AI tools by researchers, we cluster them based on the allocation of their research tasks with k-means clustering. We identify three types of researchers: (i) 'leaders', who spend most of their time writing proposals, doing project and personnel management; (ii) 'builders', who mainly build and maintain scientific infrastructure and tools, and (iii) 'analysts', who primarily collect and analyze data, do conceptual work and prepare papers and reports (see Figure A3 for the distribution of time among tasks). On a variety of measures, leaders are more positive toward AI tools than the other two types, controlling for a battery of characteristics (Tables A5 and A6): they are more familiar with and use AI tools more frequently, expect them to be more transformative for their field, and to bring improvements ranging from skill development among researchers to higher research quality, more breakthrough research and more positive consequences for society in general. Figure A4 displays the general overview of attitudes to AI on these measures and their split by researcher type. Based on their time distribution, leaders might hold more senior managerial positions and could promote the use of AI tools in their groups.

We find that AI users and non-users differ in their attitudes: users report more optimistic views on the effects of AI on research quality, skill development, and societal impact (Table A7).[7] Users are also more likely to believe that AI tools have the potential to level the playing field across institutions rather than widen existing divides. While the overwhelming majority of researchers (69.2%) expect that AI will transform or even revolutionize their field of research in the next decade, their opinions on the effect of AI tools on society in general, are more split: 40.6% believe that AI tools offer more opportunities than risks, and 22.2% think that they pose more risks than opportunities.

Familiarity is central to the observed gender gap. Given the well-documented gender disparities in science and research (Huang et al., 2020) and the gendered patterns of technology adoption (Organisation for Economic Cooperation and Development, 2018), early gaps in AI adoption may further exacerbate existing inequalities in research visibility, productivity, and career advancement. Therefore, we consider the gender disparity in more detail.

In line with evidence from other samples (e.g., Carvajal et al., 2024; Humlum and Vestergaard, 2025; Otis et al., 2024), we also document a gender gap in familiarity with and use of AI in research tasks (Fig. 1). The granularity of our data allows us to consider a range of factors that might contribute to the gap, such as familiarity, beliefs about the effects of these tools on scientific output or society, trust in AI tools, different returns to using them, or investments in complementary skills.

To begin with, we establish that the observed gender gap in AI use for research tasks is almost entirely explained by differences in observable characteristics, with AI familiarity standing out as the dominant factor: it accounts for 71% of the explained gender gap and 99% of the total gap (Blinder–Oaxaca decomposition, Table A8).

Our results do not support the idea that women are more skeptical of AI or expect lower returns from its use. Female researchers who gained familiarity and used AI training resources report AI use at rates similar to (or even higher than) men. Consistently, among respondents who use AI tools for their work tasks, there is no significant gender difference in perceived helpfulness of AI (Table A9). Suggesting that beliefs about the returns of using the tools play a limited role, among non-users, women perceive AI tools as more helpful for research tasks than men do. Surprisingly, beliefs about the effects of AI tools – for example, on the quality of research or society in general – play only a minor role in explaining the adoption gap (Table A8).

Instead, the gender gap appears closely tied to differential engagement with resources that could allow for more efficient use of AI. When asked if they have ever consulted resources to improve their AI tool use (such as prompt engineering), 45.9% of female researchers responded that they have not and do not intend to, compared to 34.8% of men (two-sample test of proportions, $p < 0.001$). This reluctance aligns with observed behavior: women were more likely to skip the prompting task (21.4% vs. 18.1%; two-sample test of proportions, $p = 0.003$), though this difference becomes insignificant once we consider researchers who are familiar with AI tools (17.4% vs. 15.9%; two-sample test of proportions, $p = 0.18$). Likewise, while prompt success rates were lower for women overall (18.1% vs. 22.1%, two-sample test of proportions, $p = 0.005$), the gap narrows when restricted to those familiar with AI (19.5% vs. 22.2%, two-sample test of proportions, $p = 0.01$).

Reflecting different engagement patterns, women and men report different barriers to the adoption of AI tools. The most common barrier among women is a lack of knowledge (23.3%), while for men it is the lack of suitable tools (18.4%). It does not appear that women distrust the outputs produced by AI tools more than their male colleagues: 12.3% of female researchers report trust as one of the two major barriers, compared to 17.5% of male researchers (two-sample test of proportions, $p < 0.001$). The difference persists when controlling for observable characteristics.

Overall, our results indicate that familiarity with AI tools – rather than beliefs about their societal or scientific impact – is most strongly associated with lower adoption among female researchers. Therefore, raising awareness about AI tools and their applications among female

[7] As users, we define respondents who use AI tools for either research, service, or teaching at least once a month.

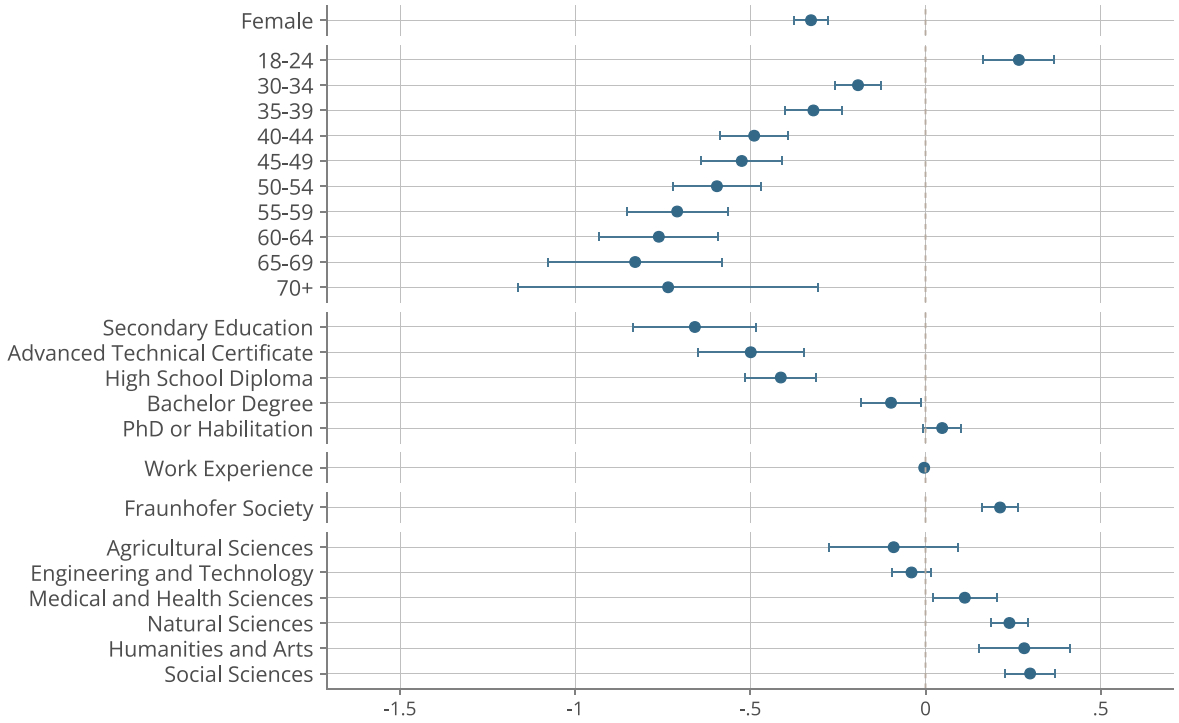

Fig. 1. Association of individual characteristics and familiarity with AI tools.
Notes. $n = 6165$. Whiskers display 95% confidence intervals.
The plot depicts coefficients of an OLS regression. The outcome variable is familiarity with AI tools measured by the question "How familiar are you with AI tools" with a six-point scale: (1) "Do not know", (2) "I do not know any AI tools", (3) "I never used AI tools but heard of them", (4) "I used AI tools a few times", (5) "Rather familiar", (6) "Very familiar". The mean of the dependent variable in the sample is at 4.4. The dashed vertical line indicates the reference group for mutually exclusive characteristics – gender (male), age group (25–29), highest education level (Master's degree), and organization (MPS).

researchers could be a promising area for further investigation in efforts to address the gender gap in AI adoption. Furthermore, our results suggest that female researchers are less likely to proactively engage with AI tools (similar to Carvajal et al., 2024). Accordingly, when considering informational measures, accounting for possible selection effects might be important (Sandvik et al., 2021).

Warranting further research, different factors may contribute to gendered adoption patterns in different populations. In the professional settings considered in our sample and that of Humlum and Vestergaard (2025), where tasks are complex and require specialized tools, familiarity appears to be the strongest inhibitor. In the educational setting of Carvajal et al. (2024), by contrast, attitudes toward AI were found to be a stronger correlate.

AI is a co-creator, not a mere assistant. AI tools are used for a variety of tasks across all stages of the research process (Fig. 2). In the early stage of ideation and conceptual development, 31.5% of researchers report using AI for literature reviews. During the implementation and analysis phase, usage is particularly high for piloting and testing (47.9%) and writing code (43.2%)—the two most frequent applications overall. In the dissemination stage, 32.9% of researchers use AI to help write research manuscripts. These patterns indicate that AI tools are becoming embedded in core research activities rather than being used only peripherally.

At the same time, researchers continue to experiment with the capabilities of AI tools. For instance, 36.9% report using AI for creative tasks unrelated to research—up from 24.9% in 2023 (Van Noorden and Perkel, 2023). Yet, this use case is no longer the most prevalent, suggesting a shift toward more targeted, goal-oriented use. Most researchers (50.6%) use AI for 2–5 tasks.

Researchers use AI tools more for the research tasks on which they spend the most time (Table A10). While part of this pattern may be mechanical – more time spent on a task increases the opportunity to use AI tools – it also suggests that these tools are primarily applied to researchers' core activities rather than to secondary tasks such as administrative communication. Notably, researchers who spend more of their research time on creative tasks (e.g., identifying research objectives, conceptual work) are more likely to use AI tools for research than researchers who spend more of their time on more routine or executive tasks (e.g., collecting data, project and personnel management), even accounting for demographic differences.

It might appear that AI tools are more suitable and helpful for creative or conceptual as opposed to executive tasks, yet the difference in perceived helpfulness is closely associated with the frequency of use: Researchers who use AI tools more frequently for certain tasks also report higher perceived helpfulness of AI for those tasks. These findings align with growing evidence that AI use in research extends beyond automation, positioning AI as a co-creator or even a manager of research processes (Koehler and Sauermann, 2024; Bianchini et al., 2022; Ivcevic and Grandinetti, 2024).

Researchers seek AI for efficiency, but many struggle with effective prompting. 50.4% of researchers report using AI to speed their work. Yet, our survey suggests that effectively using AI tools is a skill. Despite the advanced educational background and awareness of AI tools among researchers, only a fifth of them (21.0%) managed to create a successful prompt for a test task. Creating a successful prompt is positively correlated with self-reported AI familiarity and frequency of use of AI (Table A11). Relatedly, respondents who succeeded report higher helpfulness of AI tools.

Prompting itself may be a new skill: Respondents who report engaging with resources on how to use AI tools are significantly more likely to create a successful prompt (Fig. 3, $\beta = 0.59$, $p < 0.001$, based

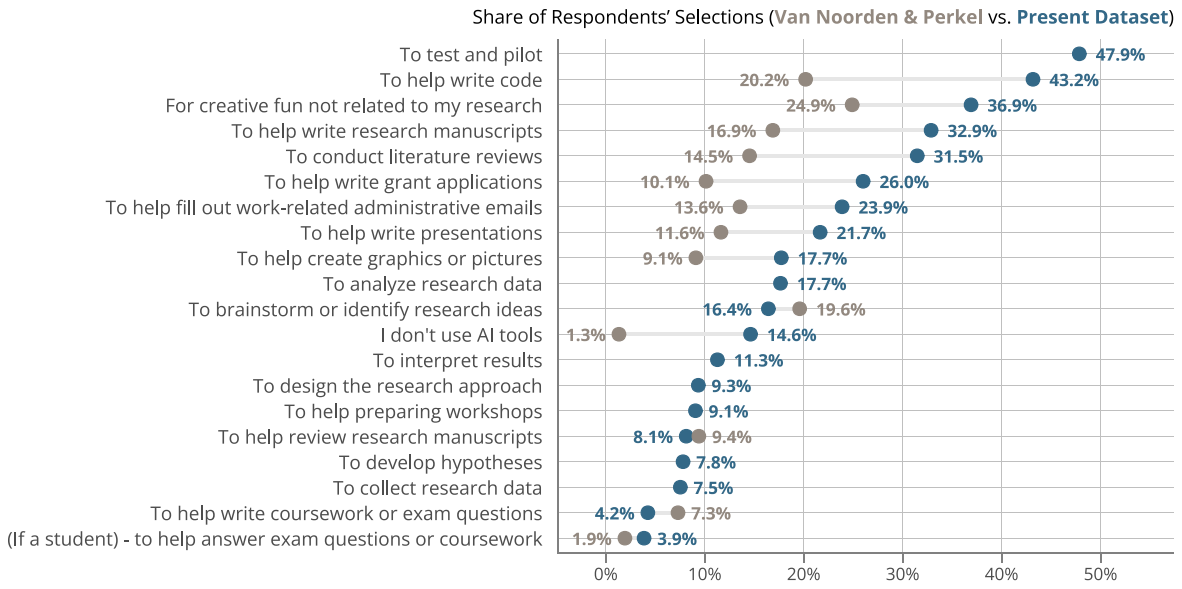

Fig. 2. "In your research, what do you use AI tools for? Select all that apply". Comparison to Van Noorden and Perkel (2023).
Notes. Some use areas were newly introduced and not comparable to the previous study.

on an OLS regression with the standard set of controls).[8] Yet, even in this group, only one out of three prompts (31.0%) generates the correct response. Recognizing prompting as a skill may itself be associated with using AI tools: Researchers who do not use AI tools more often associate them with deskilling, while users are more likely to see potential for skill development (Table A7). Note that this measure captures general perceptions of skill development and not prompting specifically.

We acknowledge that the task offers only a coarse measure of prompting ability, focused on chat-based tools and lacking the interactive features of real-world use. To mitigate this, we apply deliberately lenient success criteria – counting a single correct response out of ten – and exclude non-attempts. Despite its simplicity, the task provides a useful proxy for baseline prompting skill across a large and diverse sample.

Our results highlight that effectively using AI tools requires more than access or intention. It involves skill, which appears to come both from direct experience – learning by doing – and from structured resources. These findings point to a potential role for institutions in supporting skill development through accessible learning opportunities.

Organizations can support AI adoption. Organizational context may shape AI adoption by helping to remove key barriers and by fostering a culture and values that encourage use among its members (Hillebrand et al., 2025). First, many of the reported barriers to adoption point to potential areas where organizational structures and processes could play a supportive role (Fig. 4). The most frequently mentioned top-two barriers to more frequent AI use are legal uncertainties (17.6%), lack of knowledge (17.4%), and limited availability of suitable tools (16.6%). The legal uncertainties are particularly salient for researchers with a higher load of administrative tasks (e.g., personnel and project management).

Organizations can determine how to use AI tools through regulations. We asked respondents whether their institution regulates AI use. Perceived presence of regulations at the department, institute, or society level is associated with more frequent AI use for research.[9] Interestingly, this association differs by gender: female researchers appear less likely to use AI when they believe regulations exist (Table A12). Notably, 26% of respondents believe their research society has AI regulations — though this was not the case at the time of the survey.

Most respondents favor a high-level approach to resolving legal uncertainties: 58.7% expect regulations and guidance from supranational institutions (e.g., the EU), followed by 51.3% who look to their research societies (MPS or FhS), and 49.0% who expect it from professional associations.

Further, organizational climate and culture is associated with the use of AI tools (Table A13): While researchers' perceptions of autonomy, workload, and tolerance for failure are associated with familiarity with AI tools, only a continuous learning orientation is consistently linked to both familiarity and adoption. As shown in Figure A6, researchers who report a more positive organizational climate – measured by factors such as innovation support, openness to experimentation, and learning orientation – also tend to exhibit higher AI familiarity, more frequent use, greater perceived helpfulness, and more active engagement with learning resources.

4. Conclusion

The rapid developments in AI led to a quick adoption of new tools in the research community, rendering it an important subject of research as well as a tool for advancing it. Researchers increasingly integrate AI into their core research activities. Although opinions are divided regarding AI's long-term impact on breakthrough innovation, skill development, and research equity, there is broad agreement that the technology will profoundly transform research practice.

While our findings are correlational, they highlight areas where future causal research would be particularly valuable. Understanding how organizational capabilities, learning climates, and institutional contexts shape AI adoption – and how these factors interact with gender and age – remains crucial (Bankins et al., 2024). Future work should examine mechanisms behind observed disparities and evaluate interventions such as improved training access, supportive learning environments, and legal support. Comparative studies across organizations with different missions and infrastructures could identify the most effective conditions for inclusive adoption. Finally, longitudinal perspectives will be essential to capture how AI integration in research evolves as technologies and institutional practices continue to develop.

[8] A similar pattern appears for respondents who use AI tools more often (Figure A5).

[9] The content of the regulations is unknown.

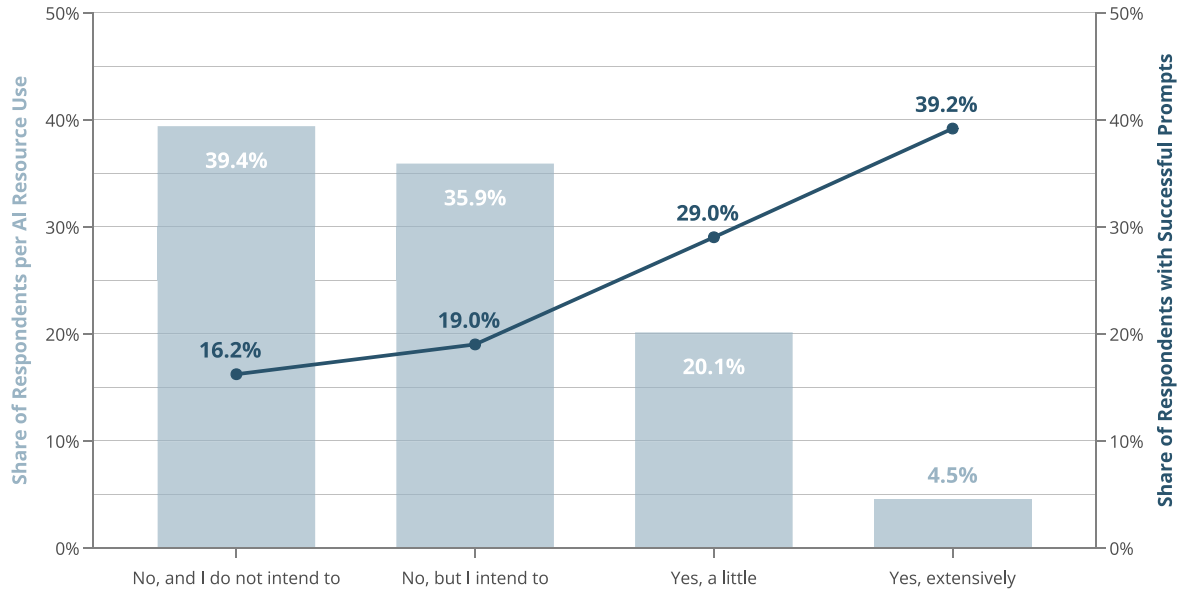

Fig. 3. Engagement with AI learning resources and prompting success.
Notes. Histogram shows responses to the question "Have you consulted any resources on how to use these tools more effectively (e.g., through prompt engineering)?" The superimposed line indicates the share of respondents in each category who crafted a successful prompt, defined as at least one correct LLM response out of 10 attempts or a mention of uploading a picture. The number of observations behind the histogram (n = 6037) differs slightly from the prompting analysis (n = 5002), as respondents who left the prompting question blank were coded as missing rather than unsuccessful, to provide a conservative estimate of prompting ability.

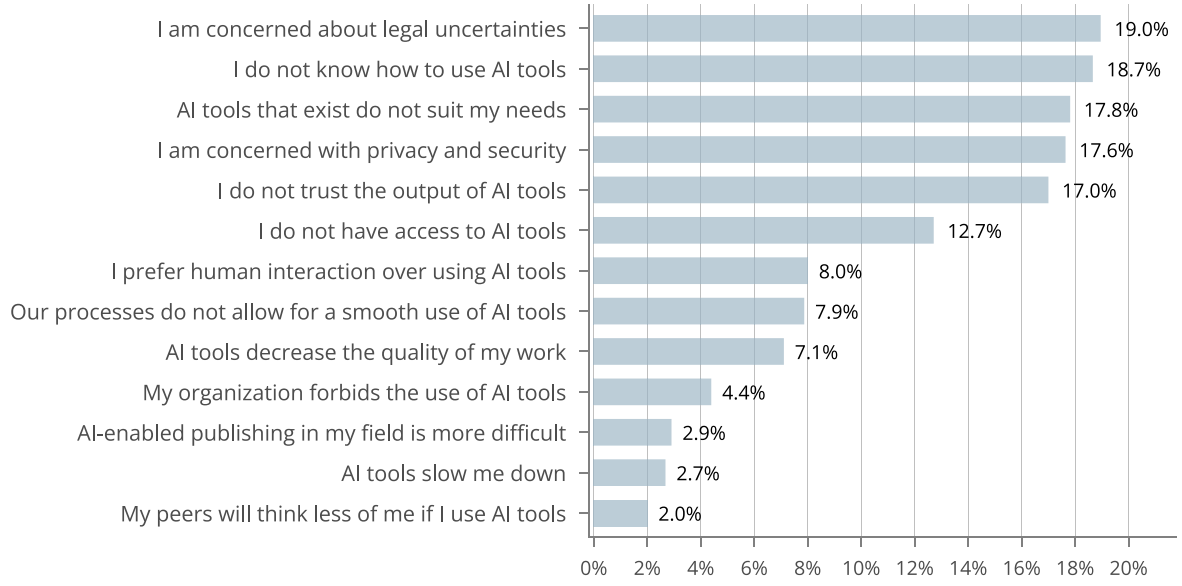

Fig. 4. Frequency of barriers cited among respondents' top two reasons for limited AI tool use.
Notes. "What prevents you from making more use of AI tools in your work? Please select and rank the most important".

CRediT authorship contribution statement

Marina Chugunova: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Dietmar Harhoff:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Katharina Hölzle:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization. **Verena Kaschub:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Sonal Malagimani:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Ulrike Morgalla:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Robert Rose:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2025.105381.

Data availability

The authors do not have permission to share data.

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