Women Experience a Compound Disadvantage When Adopting Artificial Intelligence in Scientific Research

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1 Extended Abstract

Artificial Intelligence (AI) is rapidly becoming a foundational infrastructure for scientific discovery. From drug development and protein structure prediction to climate modeling and economic forecasting, AI-enabled research holds enormous promise for advancing societal well-being [1]. Yet, as AI becomes embedded in the research process, an essential question for AI and analytics for social good arises: Who benefits from this transformation? If access to AI tools, collaborators, and recognition is unevenly distributed, AI may unintentionally amplify structural inequalities in science.

This study examines whether AI adoption in scientific research is equitably distributed and whether its benefits accrue evenly across genders. Specifically, we ask three questions. First, are women equitably represented among scientists who adopt AI in their research? Second, do women-led AI-adopting papers receive comparable gains in impact and innovation relative to men-led counterparts? Third, what collaboration structures shape the observed disparities?

To answer these questions, we analyze 175 million scientific publications from 1980 to 2024, including over 1.1 million AI-adopting papers across non-computer-science disciplines, or "domain sciences." AI-adopting papers are defined as those applying AI methods within domain sciences rather than developing AI methods themselves. To ensure measurement validity, we use four complementary identification strategies: hierarchical field classification, AI-related keyword matching, topic modeling, and a fine-tuned language-model classifier.

We measure scientific performance along three dimensions. Impact is assessed using normalized citation counts and top 1% hit rates within discipline-year cohorts [2]. Novelty is measured through atypical combinations of prior knowledge

based on journal-pair z-scores [3]. Disruptiveness is quantified using citation-network–based indices that distinguish research consolidating existing literature from work that redirects future research trajectories [4].

Our analysis first confirms that AI adoption is associated with substantial scientific advantages. However, these benefits are not equitably distributed. Women are consistently underrepresented among AI-adopting scientists relative to their overall representation in science. For example, although women account for approximately 45% of scientists in 2024, they represent only about 35% of AI adopters. The gap is more pronounced among junior and lower-productivity scientists, suggesting that early-career access to AI resources may be structurally constrained.

Disparities also extend beyond representation to returns. Among AI-adopting papers, women-led papers receive fewer normalized citations and exhibit lower novelty and disruptiveness than men-led papers. Notably, the gender gap in performance is larger for AI-adopting papers than for comparable non-AI papers. This suggests that AI adoption does not automatically level the playing field; instead, it may intensify recognition inequalities embedded in scientific institutions.

To understand the underlying mechanism, we examine collaboration patterns. In domain sciences, AI adoption often occurs through interdisciplinary collaboration between domain scientists and AI researchers, which can enhance research impact and innovation [5]. Consistent with this expectation, AI-adopting papers co-authored with AI researchers outperform those without such collaborations across all performance measures. However, women-led AI-adopting papers are less likely to involve AI researchers: only 18% of women-led papers involve AI collaborators, compared with about 31

Our analysis further reveals gender homophily in scientific collaboration as a key mechanism [6]. AI-related collaborations exhibit strong same-gender tendencies, particularly among men. Given that AI researchers are predominantly men, homophily disproportionately channels AI collaborations toward men domain scientists, thereby limiting women's access to broader AI collaboration networks. Inequality further deepens when collaborator status is considered. Women are less likely to collaborate with high-impact AI researchers, measured by prior H-index. Regression analyses show that controlling for collaborator impact substantially reduces the observed gender citation gap, indicating that unequal access to influential collaborators explains a large portion of the disparity. Interaction analyses further suggest that women benefit less from collaboration with high-status AI researchers than men do, consistent with persistent recognition inequality mechanisms [7]. These patterns remain robust in a coarsened exact matching sample that balances women-led and men-led papers on observable author-, team-, and institutional-level characteristics.

Taken together, these findings reveal a compound disadvantage in AI4Science. Women scientists are less likely to adopt AI, less likely to collaborate with AI experts and high-status AI collaborators, and less likely to receive equivalent recognition returns from such collaborations.

From a science-of-science perspective, these findings show that AI adoption is not merely a technical shift in scientific practice, but also a network-mediated process that can reshape inequality in knowledge production. Our study highlights the need for research policies that expand access to AI expertise and foster more inclusive interdisciplinary collaboration networks as AI becomes central to scientific discovery.

Keywords: science of sciences · AI4Science · artificial intelligence · computational science · gender inequality.

References

1. Wang, H., Fu, T., Du, Y., Gao, W., Huang, K., Liu, Z., et al.: Scientific discovery in the age of artificial intelligence. Nature **620**(7972), 47–60 (2023)
2. Radicchi, F., Fortunato, S., Castellano, C.: Universality of citation distributions: Toward an objective measure of scientific impact. Proceedings of the National Academy of Sciences **105**(45), 17268–17272 (2008)
3. Uzzi, B., Mukherjee, S., Stringer, M., Jones, B.: Atypical combinations and scientific impact. Science **342**(6157), 468–472 (2013)
4. Funk, R.J., Owen-Smith, J.: A dynamic network measure of technological change. Management Science **63**(3), 791–817 (2017)
5. Littmann, M., Selig, K., Cohen-Lavi, L., Frank, Y., Hönigschmid, P., Kataka, E., et al.: Validity of machine learning in biology and medicine increased through collaborations across fields of expertise. Nature Machine Intelligence **2**(1), 18–24 (2020)
6. Holman, L., Morandin, C.: Researchers collaborate with same-gendered colleagues more often than expected across the life sciences. PLOS ONE **14**(4), 1–19 (2019)
7. Ross, M.B., Glennon, B.M., Murciano-Goroff, R., Berkes, E.G., Weinberg, B.A., Lane, J.I.: Women are credited less in science than men. Nature **608**(7921), 135–145 (2022)