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The creeping normality of AI in the life sciences

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Frontiers' Commentary

The creeping normality of AI in the life sciencesIvan Jarić^{1,2*}, Pavel Pipek^{3,4}, Susan Canavan⁵, Josh A Firth^{6,7}, and Michael G Bertram^{8,9,10}

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Over the past decade, generative artificial intelligence (AI) has become increasingly embedded in the everyday work of researchers across the life sciences, particularly in the form of large language models (LLMs), driving gradual, often imperceptible, but nevertheless transformative changes in how research is performed. In many ways, the changes brought forward by LLMs match the concept of “creeping normality”—that is, a process by which a major change can be normalized and perceived as acceptable if it happens gradually through small, often subtle increments. Here, we highlight how LLMs are gradually but substantially reconfiguring thinking, collaborations, skill sets, training, expertise, and norms in the life sciences over time (Table 1).

The routine use of LLMs is bound to affect the ways in which scientists interact and collaborate. Informal collaboration networks, also referred to as the “invisible college”, are recognized as highly valuable resources for researchers, not only providing information exchange and guidance but also facilitating the development of scientific projects, ultimately improving scholarly impact (Danús *et al.* 2026). However, researchers may increasingly switch to sharing and exploring their ideas with an LLM instead of a collaborator. Furthermore, the support and affirmation provided by LLMs might also reduce motivation to seek external expertise from disparate research fields or regions, or on a particular taxonomic group, methodology, or technical approach. This is highly relevant for the life sciences because of the extent to which this research area depends on cross-sectoral collaboration, including bringing together different systems and approaches. It could lead to a greater disconnection from such informal collaborative networks and, in turn, to a reduced exposure to new ideas by promoting siloed research, ultimately reducing long-term productivity and impact. In addition, reliance of researchers on the expertise of LLMs could make some occupations, such as in-house statisticians or taxonomists, be perceived as obsolete.

Beyond collaborations, the accelerating adoption of LLMs is also likely to affect our individual information-seeking and intellectual processes. Large language models are rapidly supplanting the use of other sources of information, thereby diminishing the usage of online encyclopedias, search engines, and scientific databases. As platforms that provide feedback only to the questions one thinks of asking, LLMs may cause the process of idea generation to shift toward echo-chamber thinking, while their sycophantic tendencies can lead to

confirmation bias and reduced accuracy (Cheng *et al.* 2026; Ibrahim *et al.* 2026). Moreover, the use of LLMs may drive homogenization of scientific work (Moon *et al.* 2025), with many researchers relying on the same AI models for almost all aspects of their work process, potentially resulting in more uniform approaches, as well as homogenized thinking and language use, perhaps even enabling a narrowing of intellectual diversity and originality (Wenger and Kenett 2026). Therefore, while the use of LLMs can produce strong individual benefits to researchers through greater productivity and impact, their adoption has the potential to reshape the life sciences in undesirable ways (Hao *et al.* 2026).

The growing delegation of wider scientific tasks to LLMs also directly impacts our way of working. This includes affecting decisions on how to allocate our time to different tasks, choosing which expertise and skills to acquire, as well as influencing the decision making of early-career researchers in selecting a research field and career path. On the one hand, LLMs are already improving access to research processes and tools, particularly for researchers for whom English is not a first language, early-career researchers, those moving between disciplines, and those without adequate coding or statistical support or skills (Kusumegi *et al.* 2025). On the other hand, usage of LLMs can generate new types of inequalities and reinforce existing ones, being driven for example by different capacities to access subscription-based LLMs and versions thereof. This also intensifies the risk of deskilling in core competencies, with fundamental skills in the life sciences being outsourced to LLMs, such as literature searching and synthesis, natural-history reading and knowledge acquisition, taxonomic judgement, coding and debugging, and statistical reasoning (Melumad and Yun 2025; Messeri and Crockett 2026). In addition, adoption of AI may reduce the need and motivation for researchers to open new PhD and postdoctoral positions for certain types of work that could be outsourced to LLMs instead, further affecting training and career opportunities.

The increasing use of LLMs is also expected to drive a positive feedback loop in the acceleration of research within the life sciences. As LLMs enable researchers to generate results and manuscripts more quickly, this escalating pace will pressure the scientific community to keep up, bolstered by the “publish or perish” culture, and will advantage researchers who use LLMs most extensively, further normalizing their use and driving an intensified and accelerated research and publishing cycle.

There is a creeping normality in accountability and transparency with respect to AI in the life sciences. As AI becomes the new normal in the scientific publishing process—from drafting to coding, interpretation, presentation, and reviewing (Lu *et al.* 2026)—it will become increasingly blurry where scientific judgement is really being exercised and the extent to which hidden LLM outputs underpin scientific publishing (Naddaf and Quill 2026). Reliance on LLMs has already become the new normal for many in the community, driving a gradual but substantial transformation of scientific work. It is, therefore, critical and timely to initiate a discussion within the life sciences community as to the appropriateness of the use of LLMs at different stages of the scientific process, ranging from mundane tasks such as data collection and processing to crucial issues of informing societal questions and political decisions (Figure 1). For instance, LLMs should probably be embraced for tasks such as copyediting and proofreading (improving spelling, grammar, and text formatting), or explaining and learning coding and statistics; annotating workflows; and spotting errors, redundancies, or logical flaws in text. Use of LLMs could also be considered acceptable for more advanced tasks as long as they are underpinned by human understanding, such as direct coding, statistical support, data extraction from text, and literature synthesis, although adequate controls, verification, clear disclosure, and expert judgement will be required. To the contrary, LLM use should be considered undesirable for advanced or especially human-conscious tasks such as collaboration, conclusive data interpretation, and substantial text

generation, and particularly for independent research prioritization, peer review, funding allocation, policy recommendations, and ethical considerations. The life sciences community must urgently decide on the activities where the creeping normality of LLMs can be accepted or embraced, and where red lines and strict control measures should be imposed, in order to preserve its core scientific values.

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Table 1. An overview of the different kinds of effects of the creeping normality of AI use on the life sciences. Note that the examples provided are illustrative, rather than comprehensive.

Domain affected	Possible effects
Cognition & intellectual work	Echo chambers
	Homogenization of creativity
	Confirmation bias
Skills & training	Changing career paths
	Shifts in training priorities
	Deskilling in core competencies
Scientific norms & culture	Accelerated publication pace
	Inaccuracy tolerance
	Intensified publish-or-perish culture
Collaboration structure	Obsolescence of in-house specialists
	Fewer PhD/postdoctoral positions
	Decline in cross-area collaboration
Information generation	Displacement of curated databases
	LLMs replacing search engines & encyclopedias
	Literature review & data extraction

Figure 1. The proposed appropriateness of AI controls at different stages of the scientific process. Note that the examples provided are illustrative, rather than comprehensive. Vines drawn by Susan Canavan.

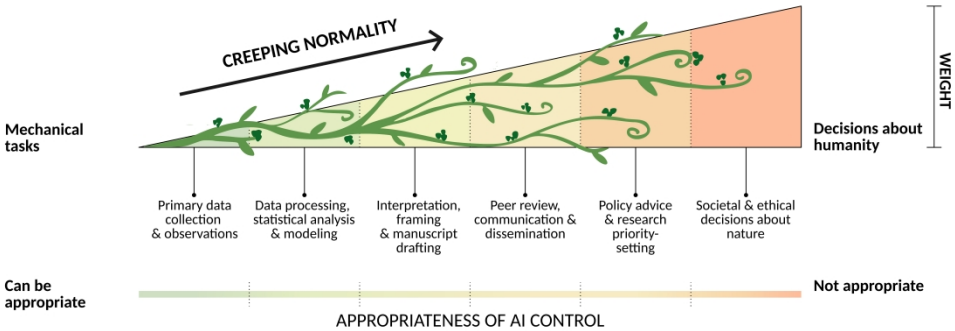


Figure 1. The proposed appropriateness of AI controls at different stages of the scientific process. Note that the examples provided are illustrative, rather than comprehensive. Vines drawn by Susan Canavan.

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