Editorial

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Push-button science

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Technological advances change not only what we can learn as scientists, but also how science is conducted. Here we explore how automation and outsourcing are affecting the act of doing science.

While we at *Nature Methods* are used to seeing fast-paced methods development, even we are impressed at the rate at which technology has advanced over the past 20 years. What was once at the very cutting edge, such as deep learning-based protein structure prediction, has now become part of the daily experimental routine. Methods not only change what we can learn about complex biological systems, they change how we do science.

Just as parents lament how they had to walk miles to and from school every day, uphill both ways, it is easy to think scientists now have it much easier than 'back in our day'. No more slab gels to sequence a gene, far fewer radioactive reagents, microscope images at the click of a button, protein structures at one's fingertips — the list could go on forever, all thanks to new technologies.

With new technologies have come new trends, especially in outsourcing and automation. For example, as technology and instruments become more sophisticated, they often become more complex and expensive. This has more and more researchers turning to core facilities for instrument access and technical expertise. Much as synchrotron facilities have been for decades, core facilities or instrument hubs and their technical staff are becoming an increasingly invaluable part of the scientific ecosystem for experiments involving mass spectrometry, light microscopy, electron microscopy, molecular imaging and beyond.

In what could perhaps be considered an ultimate realization of a core facility, in 2024 Carnegie Mellon launched the Cloud Lab, which is a remote academic laboratory focused on automating experimental workflows. The workflows, carried out by Cloud Lab staff and lab robotics, are designed in advance by researchers using a custom computer language for a range of experiments in chemistry and biology and subsequently implemented without the researcher. One can easily imagine how such a concept could improve the teaching of experimental design and make science more accessible.

In addition to work done in core facilities, many experiments are now outsourced to companies. As an example, many cutting-edge spatial transcriptomics technologies are developed in industry, and these companies conduct experiments as a service: they take user samples, run the instruments, and generate (and sometimes analyze) results. And it is not just the most expensive and complex experiments that are being done outside the lab. Beyond just gene sequencing and synthesis, tedious and mundane tasks such as plasmid construction and cloning can be completely outsourced, leaving researchers free to do more experiments and less housekeeping.

We are also already seeing how artificial intelligence (AI) is changing how scientists work. A few years ago, valuable advice for a student would be to learn to code, especially in Python or R. While this is still sage advice, more and more scientists are learning that large language models are great for writing, debugging and documenting code. Again, this change is giving researchers more time to focus on other aspects of the experimental workflow and allowing scientists without a strong background in coding to develop more sophisticated approaches.

A more general trend across the life sciences is to take humans out of the loop, even for complex experimental workflows, often with the help of AI. How much can we automate experimental workflows? Can we train deep learning models to think like human experts when it comes to experimental design and troubleshooting? Once experiments are automated, human bandwidth may no longer be a limit for throughput, improving the rate of data generation. This leaves the human expert more time for analyzing the data — perhaps also with the help of deep learning models, which we may be able to train to see things in the data a human cannot — for subsequent hypothesis generation and testing. We imagine, if implemented properly, this could greatly accelerate the pace of discovery.

What do these changes mean for science and scientists? It is easy to imagine how freeing the brightest minds from mundane tasks can allow them to focus on conceptualizing, troubleshooting and analyzing experiments. In the world of wet labs, there is the concept of 'good hands', and arguably people with these gifts are able to get through the tedious parts of experimental work quickly enough to devote their hands and minds to other things. In this sense, outsourcing and automation could be a great equalizer, prioritizing good minds as much as good hands.

But it is worth at least briefly considering whether something is lost as automation and outsourcing trends sweep through science. Over a decade ago we published an Editorial discussing the 'kit generation' of scientists relying more and more on commercial kits for experimental workflows. In it, we stressed that, while workflows may become streamlined, it is important to still understand the conceptual and practical underpinnings of methods. The same notion holds true today. Even if work is done by or with the help of experts in a core facility or outsourced completely to a company, it is crucial that researchers understand how a method works, that they can assess data quality, and that they fundamentally understand what types of conclusions can and cannot be drawn from their data.

If this last bit sounds stodgy, we do not mean it to. As editors at a technology journal, we promote new approaches, but we also know the importance of implementing them well and understanding their limitations. Most of these changes free up scientists' time, sometimes moving them away from doing, but toward more freedom to think, analyze, discover and dream. We think this is great for science.

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