Convenience AI

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Abstract: This paper considers the mundane ways in which AI is being incorporated into scientific practice today, and particularly the extent to which AI is used to automate tasks perceived to be boring, "mere routine" and inconvenient to researchers. We label such uses as instances of "Convenience AI" — that is situations where AI is applied with the primary intention to increase speed and minimize human effort. We outline how attributions of convenience to AI applications involve three key characteristics: (i) an emphasis on speed and ease of action, (ii) a comparative element, as well as (iii) a subject-dependent and subjective quality. Using examples from medical science and development economics, we highlight epistemic benefits, complications, and drawbacks of Convenience AI along these three dimensions. While the pursuit of convenience through AI can save precious time and resources as well as give rise to novel forms of inquiry, our analysis underscores how the uncritical adoption of Convenience AI for the sake of shortcutting human labour may also weaken the evidential foundations of science and generate inertia in how research is planned, set-up and conducted, with potentially damaging implications for the knowledge being produced. Critically, we argue that the consistent association of Convenience AI with the goals of productivity, efficiency, and ease, as often promoted also by companies targeting the research market for AI applications, can lower critical scrutiny of research processes and shift focus away from appreciating their broader epistemic and social implications.

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I Introduction

Debate is raging around the potential of Artificial Intelligence to boost scientific methods and facilitate discovery, with high expectations that AI will fundamentally alter the way science is done. Researchers, policymakers, and philosophers of science alike scramble to identify the implications of AI applications in efforts to foster their responsible, sustainable, and successful integration into the scientific landscape. In the words of a recent Royal Society report on "Science in the Age of AI", "now more than ever, we need to understand the extent of the transformative impact of AI on science and what scientific communities need to do to fully harness its benefits" (2024, p. 4).

Similar to other domains of AI application, current discussions of AI's impact on science centre around the extent to which this technology can supplement or even supplant human research labour. Researchers pay much attention to the transformative potential of prominent machine learning applications designed to support discovery processes, such as AlphaFold (Jumper et al., 2021) or GPT (Vaswani et al., 2023). Some even anticipate the age of fully automated science where "AI scientists" independently plan, conduct, and evaluate research without the need for human involvement (e.g., Cornelio et al., 2023; Kitano, 2021). In this paper, we look beyond spectacular pilots and speculative futures, and consider the mundane ways in which AI is being incorporated into scientific practice today – and particularly the extent to which AI is used to automate tasks perceived to be boring, "mere routine" and inconvenient to researchers. We label such uses as instances of "Convenience AI" — that is situations where AI is applied with the primary intention to increase speed and minimize human effort, without necessarily replacing humans in discovery but rather aiming to make human input more efficient, interesting, and creative.

We outline how attributions of convenience to AI applications involve three key characteristics: (i) an emphasis on speed and ease of action, (ii) a comparative element, as well as (iii) a subject-dependent and subjective quality. Using examples from medical science and development economics, we highlight epistemic benefits, complications, and drawbacks of Convenience AI along these three dimensions. While the pursuit of convenience through AI can indeed save precious time and resources as well as give rise to novel forms of inquiry, our analysis underscores how the uncritical adoption of Convenience AI for the sake of shortcutting human labour may also weaken the evidential foundations of science and generate inertia in how research is planned, set-up and conducted, with potentially damaging implications for the knowledge being produced. Critically, we argue that the consistent association of Convenience AI with the goals of productivity, efficiency, and ease, as often promoted also by companies targeting the research market for AI applications, can lower critical scrutiny of research processes and shift focus away from appreciating their broader epistemic and social implications. By doing so, our analysis also bears relevance to yet underexplored questions regarding the broader role of convenience as a value in scientific research.

Our argument proceeds in five parts. Section two introduces existing research on convenience in data-intensive biology by Ulrich Krohs, reflects on the meaning and significance of "convenience" in science and traces parallels to AI applications where convenience appears as a significant motive in research choice and design. Sections three and four present examples of Convenience AI in health care research and development economics. Section five builds on these examples by engaging both with the advantages of Convenience AI and the ways in which its uncritical adoption might put at risk the integrity and reliability of science. We conclude in section six.

II Convenience AI

Our argument takes inspiration from work on data-intensive methods in biology, where Ulrich Krohs introduced a philosophical discussion of convenience within scientific practice (2012). Around the turn of the millennium, increased scientific investment in genomic sequencing led to the development of high-throughput data acquisition methods. Highly standardized machinery, reagents, materials, and tools were redeployed globally to support the distributed nature of the sequencing effort, in pursuit of consistency across laboratories and the seamless integration of results into a unified body of evidence (Hilgartner, 2017). Further technical advances, in line with a broader kittification of biochemical research, enabled the semi-automated generation of omics data — with the expectation that the more such data were produced, the better fodder they would provide for research developments in the future (Leonelli, 2016; Stevens, 2013).[3]

Krohs argues that these developments afforded an upsurge of "convenience experimentation" – the running of experiments around preconditioned lines in a manner that is neither exploratory in an inductive, empirically-driven manner nor hypothesis-testing in relation to specific theoretical expectations, but rather is driven largely by its convenience.[4]

[3]The term omics refers to various biochemical subdisciplines, such as the study of the genome (genomics), proteins (proteomics), or metabolites (metabolomics).
[4]Others in social studies of science have provided similar arguments (e.g., Landecker, 2013; Mackenzie et al., 2013).

In other words, Krohs argued for methodological standards, habits and related technologies as motivating research directions in and of themselves, simply because of their availability and the promises related to their implementation – thereby joining a large group of science studies scholars focusing on technological lock-in and the significance of techno-scientific systems in determining how research is imagined, planned, conducted and interpreted (e.g., Fujimura, 1996; Hilgartner, 2017; Pinch & Bijker, 1984; Rheinberger, 1997).

II.1 Convenience experimentation

A key reason to identify convenience experimentation as a specific approach to research practice is to assess how this relates to other approaches. In his analysis, Krohs considers the extent to which convenience experimentation may operate as an alternative to hypothesis-driven, explanation-oriented or exploratory approaches to research, thereby focusing on the possible tensions between convenience experimentation and other forms of inquiry associated to well-trodden forms of reasoning in the philosophy of science. As an example, Krohs takes the contrast between biochemical convenience experimentation and the explanation-oriented approach of metabolic pathway analysis (MPA). In the traditional case of MPA, metabolic networks are composed of isolable pathways where regulatory functions are localized at specific steps. Experimentation and mechanistic modelling are motivated by hypotheses about biochemical reactions at these steps. Convenience experimentation, by contrast, takes place under the header of Top-Down Systems Biology (tSB). Researchers engaged in this program focus on the presence or absence of metabolites at a whole cell level and understand regulatory functions as delocalized dispositions. Krohs argues that, within tSB, convenience experimentation is neither hypothesis-testing nor commonly explanatory in a traditional sense.

Meaningfully testing a hypothesis requires the possibility of its falsification. Since tSB hypothesizes regulatory functions as delocalized dispositions emerging from the interaction of several nodes, testing these hypotheses presupposes the possibility of identifying regulations as localized metabolic kinetics instead. However, data produced through high-throughput methods employed in convenience experimentation only displays cell components in one of two states (present/absent). Failing to generate data of the resolution required to meaningfully test the primary hypothesis of delocalized regulatory functions and particular instantiations of it, Krohs argues that convenience experimentation is generally not hypothesis-testing.

Instead, the equipment used in convenience experimentation is a materialized commitment to the primary assumptions of the research project. The equipment can therefore only be used to pursue certain forms of inquiry and specific kinds of outputs, a restriction which is the consequence of the idealizations and reifications built into the technology. Yet, such constraints can remain opaque to those who are less familiar with how the equipment works and has been put together. As such, the use of such equipment leaves comparatively little room for exploring whether and how data generated through its use matches the primary hypothesis of tSB. Krohs further holds that convenience experimentation, de facto, often proceeds along highly standardized lines in a manner that poorly matches epistemic virtues closely associated to scientific exploration such as a motivation to explore alternative pathways, willingness to change perspective and challenge the status quo.[5]

Krohs emphasizes how convenience experimentation is conducted largely because of its relative ease: a form of data generation with low costs and low epistemic risk, and high perceived potential for contributing new knowledge primarily by helping to map an as-yet unexplored domain, material or problem. As he puts it, this can be "*extremely helpful in many fields of research and opens up experimental opportunities that would otherwise not be available. It is thus an important driving force of modern bio-scientific research, essential for many cutting edge projects.*" On the other hand, however, Krohs also notes how convenience experimentation "*strongly channels research. The sorts of experimental results which are at all achievable are determined to a large extent by the sort of available convenient equipment.*" (2012, p. 53)

There is of course nothing new or intrinsically wrong with specific equipment and methods catalysing research directions and determining content – this has been long documented within the history of science and technology, and theorized as a process of generative entrenchment and epistemic scaffolding (Caporael et al., 2014; Wimsatt & Griesemer, 2007). What is concerning is the fact that, precisely because convenience is the key appeal of some experimental tools and practices, researchers who adopt these methods have little incentive to question them and investigate in detail the epistemic implications of adopting them – or privileging them over other approaches. In other words, convenience experimentation can be dangerous because it can instil complacency into the use of given

[5]Krohs also argues that the abundance of data produced by semi-automated equipment and standardized research kits turns modeling from a hypothesis-driven to a data-driven endeavor, echoing broader research on big data science (Canali, 2016; Kitchin, 2014; Leonelli, 2014, 2016).

tools and lower the depth and frequency of critical scrutiny. This, in turn, can result in problematic applications festering unchecked and promising – but more laborious – alternatives being left behind – a tendency that is further strengthened by the incentive to publish as much and as quickly as possible that still underpins much of the research landscape, despite calls to abolish such “publish or perish” culture (Leonelli 2023).

This constitutes a triumph of what Kuhn called “normal science” over the search for possible anomalies, which may support the accumulation of a consistent body of knowledge, but also lead to intellectual stagnation and quasi-dogmatic belief in assumptions that may no longer be warranted by the latest findings. In the case of tSB examined by Krohs, this means forgoing traditional MPA despite its continuing usefulness towards identifying novel metabolites and related processes (Tsouka & Masoodi, 2023).

II.2 Convenience AI

Krohs’ depiction of biochemical convenience experimentation bears resemblance to science’s increasing adoption of AI tools. Akin to the introduction of standardized high-throughput data acquisition machinery into biochemical experimentation, today’s proliferation of AI applications is often linked to the opportunities they offer to save time and effort. AI promises to increase the convenience with which researchers across all domains can undertake their tasks – from operations of data cleaning to report writing. Before moving to the case of AI, however, we must first expand on Krohs’ treatment of convenience in scientific research and elaborate the definition and significance of the notion of convenience underlying our argument.

The Oxford English Dictionary (2025) defines convenience in two ways: first as “the quality of being useful, easy or suitable for somebody”; second as “the state of being able to proceed with something without difficulty.” Taken together, these definitions point toward three key features in ascribing convenience: (i) the value placed on speed and ease of action, (ii) its comparative nature, as well as (iii) its subject-dependent and subjective quality. In other words, something is convenient never simpliciter but always in comparison to an alternative and for someone.

Insofar as convenience implies saving effort, this notion is only meaningful vis-à-vis perceived alternatives: booking an expensive hotel close to a conference venue is convenient to those attending insofar as it saves time and effort *in comparison to* a cheaper hotel located much further away; using a reference manager to sort one’s citations is convenient *in comparison to* writing up a reference list from scratch; resorting to ChatGTP to research key sources on a given topic is convenient *in comparison to* asking experts or identifying reliable databases where this information can be found. Moreover, something is convenient always *to someone* in a manner that is both subject-dependent and, to some extent, subjective. What is considered convenient depends on the ease and comfort with which a task can be performed, which in turn depends on the capabilities, skill, and subjective judgement of those involved in carrying out the task. Differences not only in people's abilities but also their perception of certain tasks as, for instance, drudgerous or enjoyable shape whether they are considered convenient or not (for instance, for someone who liked to take a long walk every day, a cheaper hotel in a remote location may be more appealing than one close to the venue). Moreover, perception can be informed by background knowledge that is not always reliable, as when trusting LLMs to locate references only to discover that the results obtained were the most popular, but not necessarily the most reliable for one's research purposes.

In the case of scientific research, convenience can thus be understood as implying speed and ease of action for those involved in designing, conducting and interpreting research (activities). Pursuing convenience involves examining all the options available in terms of materials, methods, procedures and instruments to conduct a given experiment, and picking those expected to require the least effort. Convenience may be obtained through the standardization and at least partial automation of research activities – typically through tools or procedures that facilitate their performance with minimal mental and/or physical effort.

Accordingly, we shall define convenience in the context of research as *the possibility to fulfil a task with perceived ease and minimal difficulties, often through the use of a readily available tool, procedure, and/or strategy.* Underlying our definition are the three key features outlined before. First, the emphasis on saving effort. Second, the comparative nature of such assessment – where saving effort is always evaluated in relation to alternative, less comfortable courses of action and available knowledge about such alternatives. And third, the dependence of convenience on the capabilities and skills of the intended user and the subjective perception of what may count as saving effort. Prioritizing convenience thus defined means giving practical aspects of scientific practice, such as the tractability of experimental organisms, the user-friendliness of software or the efficiency of data collection, at least as important a place as more traditional aspects such as the extent to which those tools may fulfil short and long-term research goals or conform to established evidential and methodological norms within a given domain.

=The introduction of AI tools is rendering some elements of scientific practice increasingly convenient. Moreover, some AI applications are pursued and advertised precisely *by virtue of* their convenience. We label such implementations as instances of "Convenience AI," characterized along the three features of convenience previously outlined. First, Convenience AI denotes situations where AI is applied with the *primary intention to reduce human labour and effort*. The motivation underlying the promotion of Convenience AI is captured, for instance, in a recent Royal Society report: "AI tools can automate a range of time and labor-intensive tasks within the scientific workflow. Automation can lead to productivity gains for scientists" (2024, p. 26). Second, this pursuit of efficiency and easy is *relative to previous or alternative approaches*, which are explicitly discussed and critiqued by proponents of the AI solution. For instance, the machine learning-based detection of mental disorders from social media posts markets itself as providing data for large-scale psychological research more cheaply and easily than time-intensive surveys (Chancellor & De Choudhury, 2020); and virtual reality environments promise convenient social scientific research opportunities without the need for in-person experimentation (Allam et al., 2022). Lastly, since what is deemed convenient is always subject-dependent and to some degree subjective, assessments of convenience include an *explicit insistence on the value of the new solution to prospective users*. For instance, proposals to utilize AI tools for administrative tasks in the management of a lab (such as replenishing stocks or making orders) emphasize the drudgerous and uninspiring nature of such tasks, thus strengthening their perception as a waste of time to busy researchers. In the words of the Royal Society, AI tools are employed in "expediting routine scientific tasks " (Royal Society, 2024, p. 7) and "free […] researchers from tedious and repetitive tasks" (Xie et al., 2023, p. 2).

While scholarship has engaged in much detail with prominent pilot applications (e.g.. Birhane et al., 2023; Boge, 2022; Varadi & Velankar, 2023) and speculative futures of fully autonomous AI science (e.g., Bertolaso & Sterpetti, 2020; Cornelio et al., 2023; Kitano, 2021), scientists and critical examiners alike have paid comparatively little attention to implications of these more mundane ways in which AI tools are used to render more convenient activities perceived to be boring, "mere routine" and inconvenient. In what follows, we seek to remedy this situation by considering in detail the nuanced epistemic implications of these AI applications. Our case studies in medical research and development economics serve to exemplify the benefits and risks of how the pursuit of convenience through AI can shape scientific practice.

III Causal machine learning for health care and precision medicine

Medical research and related clinical applications constitute perhaps the most glaring and sophisticated example of Convenience AI being promoted widely and successfully as a substitute for human labour. An example of this comes from cancer screening and detection software, which utilize image recognition algorithms to identify abnormal/suspicious tissue growths within MRI imaging scans. Another increasingly successful case consists of machine learning techniques to analyse blood test results and locate markers for dementia, thereby facilitating early diagnosis (Schaefer et al., 2020), or drug candidates for targeted therapy, thereby supporting improved treatment (Banerjee et al., 2023). The discovery and administration of drugs constitutes a third important avenue of work, with AI informing the search for new biochemical compounds with promising therapeutic properties as well as decisions around drug dosage appropriate to specific populations or even individual patients (as long sought by the domain of precision medicine). Self-measuring devices such as wearables and a variety of health-related apps provide an additional source of relevant data, which in some cases is being harvested for predictive prevention (such as early diagnosis) among other possible uses. Last but not least, there is great potential for applications of AI-enabled data analysis to support the logistics of medical care and supplies (for instance by facilitating information flow across specialties and the restocking of biomedical labs and clinics), and for integration of health-related data with environmental and climate data, in the hope of helping tackle the health implications of climate change and related environmental emergencies (such as wildfires, floods or epidemics).

Success across these endeavours is tied to the emerging ability, which AI promises to deliver, to link and integrate disparate data sources together — which continues to be a crucial goal for the effective investigation and analysis of health conditions, related biological processes and medical treatments (Sanchez et al., 2022). The step change in utilizing AI for biomedical innovation will come from the ability to link structured and unstructured data sources, such as patient health records, and medical imaging exams (Sanchez et al, 2022). This is also what promises to support efforts to entirely automate research work in this area, for instance thanks to Robot Scientists tasked not only with replacing humans in routinized tasks but with generating discovery autonomously (Sparkes et al., 2010). Such search for autonomy is where problems in the application and reliability of AI are particularly evident, especially when connected to the quest for convenience under financial and temporal constraints (Royal Society, 2024).

We shall now review some of the challenges by relating them to the three characteristics of Convenience AI outlined in the previous section, to probe whether AI-related innovation in biomedicine is standing up to claims of increasing convenience, and what this may mean in practice.

III.1 Convenience AI as subject-dependent and subjective

We start from the third characteristic we associated to convenience AI, which we also consider to be the most relevant and problematic from an epistemic perspective. This is the idea that the value-added by AI tools is contingent upon specific forms of background knowledge and skills, which AI users and developers are expected to hold in order to use the technology safely and reliably. The question is, what may be taken to constitute reliable background knowledge to begin with. As it turns out, fact-checking in biomedicine is everything but mechanical. Identifying mistakes and bad quality data or inferences typically requires extensive and expert (non-automated, case-by-case) judgement — particularly in the case of knowledge that is derived not from highly controlled experiments, such as randomized clinical trials, but rather from observational studies, case report analysis or experiments carried out on animals or in vitro. Such cases constitute typical sources of evidence for discovery and decision-making in health care and precision medicine, and it is in the analysis of such disparate, multimodal and heterogeneous data that AI tools can truly excel (Krones et al., 2025). At the same time, expert judgement in the form of familiarity with the patient group and diseases in question continues to be indispensable towards adjudicating whether and how specific results are relevant, tenable and applicable to the situation at hand (Leonelli, 2024). The very selection of which data and knowledge may be most relevant to a given AI tool may be hugely controversial – as in the case of training data for personalized drug dosage algorithms, which is optimized for specific parts of the population depending on the data actually available to calibrate the models; or the selection and assessment of data to feed to image assessment tools (Schaekermann et al., 2020). This relates to another severe concern in the background knowledge used to develop AI tools for biomedical decision-making: that is, the massive data absences plaguing the training of AI – and particularly machine learning algorithms, given the huge imbalance in available sampling (Mittermaier et al., 2023). It is well-known that most biomedical research on humans is carried out on young men, often from a Caucasian background. In contrast, children, women and seniors, as well as diverse ethnicities and social backgrounds, are not well-represented in this space. Moreover, clinical and precision medicine – given its social prominence and controversial nature, as in the case of data on vaccination for instance - lends itself easily to the dissemination of fake or misleading data, which is itself facilitated by the spread of generative AI. This is a landscape where scientific review procedures are not always effective, given that they are underresourced, undervalued, and labour-intensive — and that attempts to automate data quality review have so far not proven very effective (Schulz et al., 2022). In fact, scientific review procedures are paradigmatic of the kind of activity which scientists would like to delegate to automated systems, and yet require human attention and judgment to be fully reliable.

Hence it is not clear that such AI applications can hold their claims to excellence once the assumptions supporting their functioning are challenged. This has serious implications for Convenience AI: It arguably underestimates the pertinence of human judgement in contextualizing and giving meaning to information (e.g. medical diagnoses for individual patients) as well as the significance and labour-intensive nature of employing multiple forms of expertise to correctly interpret AI findings.

III.2 Convenience AI as comparative

When it comes to the second characteristic of Convenience AI we have highlighted, which is its value in relation to given alternatives, we also find some problems. There is evidence that the ways in which AI tools for health care are currently financed and commercialized are not necessarily conducive to the development of tools that are good for science and for patients. In 2020, industry developed 96% of the biggest AI models and 70% of PhD students went to industry — a percentage that has likely increased by now (Ahmed et al 2023). Similarly, the hiring of academic faculty working on AI into industry has witnessed an eightfold increase between 2006 and 2020 (Ahmed et al., 2023). The result is a situation where the overall AI research agenda is increasingly aligned with commercial incentives and priorities. The commercial value of AI applications may well foster a culture of secrecy around their development, thereby severely limiting the scrutiny to which such tools are subjected (Messeri and Crockett, 2024). What matters even more for our purposes is that such culture provides strong incentives for developing good AI solutions from the engineering/computational viewpoint, which may however not be best adapted to their prospective applications within science and medicine. In other words, researchers might aim to be “good at AI” rather than “good at science.” (Royal Society, 2024). Conversely, research of high epistemic risk that not only seeks to “disrupt” workflows but might challenge existing research programs appears misaligned with the increasing emphasis on applied science and commercialization facilitated by the presence of the private sector in AI-based science funding (Royal Society, 2024, p. 35). Such tendencies become pernicious when coupled with the vast amounts of misinformation and related interest-driven campaigns surrounding biomedical and health care research and development. In this area, as long documented in relation to oncological research on the noxious health effects of tobacco smoke (Oreskes & Conway, 2010), there are significant enough economic interests to warrant lobbying and – in extreme cases – evidence fabrication to support specific outcomes and related products.

The resulting evidential landscape is uneven and confusing, a situation exacerbated by existing digital and social inequities, and leading not only to uncertainty around which data may be relevant and reliable, but also uncertainty around what criteria to use when comparing different approaches to decision-making. Such a context does not facilitate the assessment of alternatives to the proposed AI tools, the extent to which each such alternative may prove convenient, to whom and for which purpose.

III.3 Convenience AI as promoting efficiency and ease

Last but not least, there are reasons to question the claims to speed and ease of use which are most commonly associated to statements around the convenience of AI, and we highlighted above as the first characteristic of Convenience AI.

AI tools tend to uncover correlations between model input and output variables, which is not enough to detect causal relationships between interventions and outcomes in health care settings. The process is also hostage to biases and vulnerability in AI systems, including for instance spurious correlations from historic data, which may amplify existing health inequalities. The key issue is the extent to which AI tools can be (1) generalized across populations, domains and applications; and (2) relied upon to provide accurate assessment of individual patients (Miller, 2022).

Causal AI aims to address these issues and provide a reliable assessment of the applicability of the outcomes, thereby supporting early prediction, diagnosis and prevention of disease – as well as the targeted application of results. But this is as yet being tested, so assumptions of causal strength for the underlying hypotheses are not yet warranted (Sanchez et al., 2022). Also, as already mentioned above, generalization strongly depends on which kinds of data are utilized to train the system: It is not credible to generalize to populations on which there are no data, or to specific cases which are too fine-grained for predictive models to say anything statistically meaningful. There is therefore the question of how reliable AI tools actually are, given that there is very limited data availability for many of the applications so models can't be trained properly. This is particularly obvious in the case of rare diseases, but also the case in oncology and neurology given the rather partial datasets available and the difficulties in linking data across countries.

The immediate implication of this problem is that putative time- and effort-saving claims need to be evaluated against the need to manually double-check data utilized and inferences produced by these systems. This is often necessary for researchers to be able to assess the levels of bias and the potential for spurious correlations – also to tailor specific findings to the personal situation of a patient or the characteristics of a new population. But all of this takes time, which undercuts claims towards the automation levels brought on by such tools.

On top of this, consider the extent to which the application of AI tools itself requires continuous monitoring and adjustment in order to be trustworthy in producing reliable results. The coding and software used to run AI is subject to deterioration, bugs and needs to be constantly updated to comply with evolving standards within the digital ecosystem. All of this also requires a fair amount of manual work, which is one reason for the predominance of large companies in the development and marketing of AI tools – since these companies have the capacity and resilience to credibly promise long-term maintenance for AI systems.

This connects back to evaluations of how AI tools fare compared to alternative systems (claim number 2 above). Interpreting AI-produced results may take much longer than other forms of analysis, because researchers will often need to reconstruct and assess the assumptions in the models. Data also tend to be very noisy and hard to process and integrate, given the variety of sources and formats, which makes the preparation of training data for AI tools very costly. Not to speak of the enormous costs of collecting and annotating data so that they fit AI software and computational tools, which when taken into account, may counter the impression of convenience in terms of saving effort and resources.

IV AI in development economics

Development economics, as an area of substantial AI deployment in the social sciences, serves as our second example. Over the past two decades, development experts have invested greatly in harnessing AI to economize and streamline research and policy. Amongst the most prominent applications are uses of machine learning for poverty estimation. Traditional poverty data stem from costly in-person surveys (e.g., UNICEF, 2023), frequently outdated censuses (e.g., GAO, 2023), or social registries relying on proxies of questionable accuracy (Brown et al., 2016). In response to these problems, researchers have begun leveraging machine learning models trained on alternative data sources, such as mobile network records and satellite imagery (Stubbers & Holvoet, 2020). AI poverty predictions are motivated primarily by their ability to render data collection more efficient and convenient (e.g., Blumenstock et al., 2015; Burke et al., 2021; Jean et al., 2016) — a priority echoed by aid organizations seeking to adopt these tools (cf., Dixit & Gill, 2024). This drive for efficiency not merely intends to save cost and time but also promises to open up new possibilities for research and policy.

For instance, AI poverty predictions enable practitioners to collect more frequent estimates and can help assess poverty in situations where external circumstances render on-the-ground data collection difficult. Targeted uses of machine learning predictions during the recent Covid-19 pandemic provided up-to-date estimates without exposing enumerators to disproportional health risks (e.g., Aiken et al., 2022). AI poverty predictions can also offer more fine-grained poverty estimates than traditional surveying. Rather than relying on only nationally representative samples of households, easily scalable AI poverty predictions provide livelihood estimates for villages, neighbourhoods, or even individuals — enabling new avenues for research and policy. As of now, these predictions have already facilitated the individual-level targeting of cash transfers (e.g., Aiken et al., 2022) and spur novel quantitative research into the circumstances of economic deprivation when combined with other data sources. For instance, Watmough et al. (2019) leverage environmental data to understand the socioecological dimensions of poverty and Ratledge and coauthors (2022) employ machine learning poverty predictions to explore the implications of electricity grid expansions on development.

The need for timely solutions to pressing development challenges, the enticing promise of new research opportunities, and widespread AI hype (Duarte et al., 2024) have resulted in initial enthusiasm regarding AI poverty predictions. Recent years, however, have put into greater focus the limitations and complications of AI poverty estimations. In what follows, we explore AI poverty predictions as an instance of Convenience AI. Parallel to the case of precision medicine, we examine AI poverty predictions along the three dimensions of convenience to arrive at a nuanced picture of the economization of development economics through AI.

IV.1 Convenience AI as subject-dependent and subjective

We begin again with the third characteristic of convenience: an AI application is convenient *for someone* in a manner that is not only subject-dependent but also somewhat subjective.

The former underscores that developers and users must possess the right skillset and background knowledge for AI poverty predictions to be not only cost-effective and prompt but also useful and reliable. In particular, this requires practitioners to have the expertise necessary to identify important limitations of AI poverty estimations and delineate appropriate applications.

Even when the average predictive accuracy of models is high, research has shown that deep learning predictions can systematically underestimate instances of extreme poverty most relevant to development aid and research (Ratledge et al., 2022). Challenges also arise when it comes to the assessment of individual households. Household-level predictions of poverty have proven difficult with remote sensing or image data (Dar et al., 2024) and are only feasible with sensitive corporately-owned mobile network records. Even when such data is made available, estimations can be of debatable evidential value. Often predicting themselves questionably accurate proxy-means tests (C. Brown et al., 2016), machine learning estimates add an additional source of error that is often insufficiently considered and does not average out in the case of household-level predictions (Mussgnug, 2022).

Further questions exist regarding the ability of machine learning models to monitor changes in poverty over time. Some have argued that data used to train machine learning models might not contain the right features to reliably track short-term changes in livelihood outcomes (Kondmann & Zhu, 2020). Issues continue when it comes to evaluating the effects of policy interventions. Some big data sources might directly capture those policies that predictions are intended to assess, biasing estimations of the treatment effect. For instance, models trained on satellite imagery might not be able to assess the impact of infrastructural developments on poverty, since the model might use infrastructures such as roads themselves to predict a location’s wealth (Ratledge et al., 2022, p. 492).

Empirical research also reveals significant differences in accuracy depending on which poverty metrics models estimate. Asset wealth, in particular, is much more easily predicted by machine learning methods than consumption, income, or multidimensional measurements (Jean et al., 2016; Steele et al., 2017). In particular, most AI applications predict the DHS Wealth Index, which statistically aggregates variables regarding asset-ownership (Hall, Ohlsson, & Rognvaldsson, 2022, p. 3). Development experts might adopt AI poverty predictions for their efficiency and ease while failing to appreciate sufficiently how technical affordances lead machine learning models to reproduce only those poverty measurements which can be reliably estimated based on satellite or mobile phone records.

Each poverty measurement, however, embodies a particular understanding of poverty (cf. Merry, 2016). For instance, measuring monetary poverty metrics involves deciding how much of which goods a person needs. Similarly, asset-based or multidimensional measurements must determine which assets, resources, or functionings are features or determinants of economic welfare. Policy and scholarship rest on these indicators and on the understanding of poverty they endorse (Fukuda-Parr, 2013; Morgan & Bach, 2018). Existing research programs in development economics are continuously advanced through critical engagement with the conceptual and theoretical foundations that underlie poverty measurements (e.g., Sen, 1979, 1993), the inclusion of increasingly diverse perspectives through qualitative research (e.g., Narayan et al., 2000), and the development of alternative measurements (e.g., Alkire & Santos, 2010; United Nations, 1990).

In contrast, convenient AI poverty predictions of particularly expedient poverty metrics framed as "ground truth data" (e.g., Ni et al., 2021, p. 1548) are unlikely to meaningfully reassess or critically expand on existing theoretical and conceptual commitments in development economics — also since infrastructural and resource barriers shape whose voices and perspectives are reflected in the development and use of AI poverty predictions. Moreover, the relative convenience of machine learning methodologies risks disincentivizing the collection of new survey data upon which novel measurements could be designed and might threaten investment in alternative qualitative approaches to the study of economic deprivation. As a result, AI poverty prediction, as practiced today may entrench and solidify the conceptual and theoretic assumptions of commonly predicted poverty metrics (e.g., Lockhart & Jacobs, 2021) — often under the seemingly epistemically neutral pursuit of efficiency and an aura of machine objectivity (cf. Talat et al., 2021).

These limitations highlight the need to carefully delineate when AI poverty predictions can provide appropriate substitutes for survey-based poverty measurements and when they do not.[6] This also involves monitoring the robustness of AI poverty predictions over time and anticipating under which changing circumstances previous performance expectations and markers of appropriateness might be no longer warranted (cf. Freiesleben & Grote, 2023). Addressing all these considerations requires a considerable degree of technical and domain expertise. AI poverty predictions might commonly be cost-effective and prompt

[6]Better data and new methodologies might help with some of these issues but likely won't completely eliminate more fundamental technical limitations (Head et al., 2017).

but are also convenient only to those who possess this ability to use the technology safely and reliably.

As outlined, the pursuit of convenience through AI is not only subject-dependent but also somewhat subjective. The case of AI poverty predictions highlights vividly how the promotion of convenient AI applications depends on (often long-standing) framings of supplanted activities as routine and uninspiring. For instance, the work of enumerators in traditional data collection is often portrayed as monotonous and dull (ICF Macro, 2009, p. 3). Framings of surveying work as inconvenient align with an underappreciation of the skill involved and contribution made even when collecting data according to a standardized protocol (Lund et al., 2011).78 This perception of traditional surveying work to be replaced by AI leads over to the second characteristic of Convenience AI.

IV.2 Convenience AI as comparative

Attributions of convenience are always relative — AI poverty predictions are convenient *in comparison to* traditional surveying. Underlying such claims of convenience is often the implicit assumption that AI poverty prediction can seamlessly substitute for traditional survey-based poverty measurement. The previous subsection, however, has highlighted several limitations of current AI poverty predictions. Claims of substitutability must, thus, be qualified as AI poverty predictions can often have limited accuracy, underestimate extreme cases of poverty, and fail to track changes in poverty.

Moreover, current discourse on AI in development economics often fails to emphasize how the benefits of in-person surveying go beyond the mere provision of data. While on-the ground data collection requires considerable time and effort, it is also often the only in-person contact with affected communities. And, as such, it serves a number of secondary purposes critical to development economics. Surveying, as well as deliberative and participatory efforts born out of it, actively advance our understanding of deprivation, its causes, and consequences (cf. Robb, 2002). Observations of local enumerators, often themselves much closer to the lives of those surveyed than practitioners in the Global North, can feed back into economic research and future survey design whether formally through purposefully designed reflexive mechanisms or informally. This productive and fruitful engagement with the lived

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[7]Working conditions of field staff during data collection are often not only inconvenient but precarious and dangerous (ICF Macro, 2009, p. 3; Kaplan et al., 2020).
[8]Within the past two decades, development economists have put much greater emphasis and value on participatory poverty assessments (e.g., Robb, 2002)

experiences of deprived households risks getting lost if traditional data collection is substituted for expedient AI poverty predictions.

This is particularly pertinent in light of the almost exclusive development of these applications in Europe, North America, and China (Stubbers & Holvoet, 2020) as lacking technical infrastructure and expertise prevents differently resourced research communities in the Global South and affected communities from meaningfully participating in this strand of development research. Increasing the distance to affected communities, the proliferation of AI poverty predictions might also stand in the way of researchers cultivating a certain attentiveness, responsiveness, and ethics of care toward the communities that constitute their object of study (cf. Vallor, 2014).

IV.3 Convenience AI as promoting efficiency and ease

This leads to the first characteristic of convenience: AI poverty predictions promise gains in efficiency and ease. But such claims must be appropriately contextualized. This involves at least three considerations. First, we must account for additional efforts required to make up for lost secondary benefits of in-person data collection. Second, we must highlight often-underemphasized kinds of work involved in the development of AI poverty predictions. Third, we must look at what is required for AI poverty predictions to be deployed safely, reliably, and in a manner fair toward affected populations.

The previous subsection has outlined how AI poverty predictions are far from a perfect substitute for traditional data collection as practitioners risk losing out on critical secondary benefits of in-person enumeration. Amongst these are interactions with the lived realities of poverty and engagement with diverse stakeholders. Increasing designated community engagement and participatory research efforts can make up for this — and might even be more effective in involving underrepresented perspectives. However, claims of efficiency and ease must be qualified in light of the additional efforts required to compensate for the lost secondary benefits of in-person field work.

While it is undoubtedly true that AI poverty predictions can save considerable time and effort compared to in-person surveying, researchers also often underemphasize certain kinds of work involved in the development of AI applications (cf. Gray & Suri, 2019). For instance, machine learning applications commonly require considerable efforts in data cleaning and processing. Moreover, some instances of AI poverty prediction, also involve small-scale phone surveys (e.g., Aiken et al., 2022; Blumenstock et al., 2015) or in-person enumeration (Dar et al., 2024) in order to obtain estimates of poverty that can serve as training data which researchers can link to individual phone records or imagery.

This relates to the third point. Reliably, safely, and fairly developing, deploying, and using AI poverty predictions involves a great deal of care and effort. For instance, data used to train AI models, such as mobile network records or household imagery, are challenging to anonymize effectively (de Montjoye et al., 2019). Protecting the privacy of affected populations, thus, would require developers to invest time and labour into establishing robust data privacy architectures (cf. Kohli et al., 2024).

Moreover, ethical uses of poverty predictions, for instance in the targeting of humanitarian aid, arguably require the implementation of effective grievance mechanisms through which affected populations can challenge aid decisions based on AI. This is particularly critical in light of the limitations of AI poverty predictions outlined earlier. The question thus arises how the additional work that would be required to responsibly assess grievances in comparison to more accurate in-person surveys relates to the time and effort saved in data generation. This issue is further complicated as the opacity of deep learning models might affect the assessment of grievances (Boge, 2022). Explainable AI techniques might offer help but come with their own set of complications and limitations that complaint officers must be trained on.

Critically, however, it is not only administrators but also affected populations that need to be educated on emerging technologies used in international development research and aid. Affected communities' acceptance of and participation in policymaking and research depends critically on their understanding of interventions and research efforts. Absent such understanding, the use of AI technologies might undermine already fragile trust in development contexts. Thus, one might argue that affected populations should receive some amount of high-level education on how AI technologies are used in far-reaching policy and research impacting their lives. This again would require time and effort that undermines too simplistic of a cost-benefit calculus on the widespread adoption of AI poverty predictions.

V Implications of Convenience AI

The previous two sections critically interrogated AI applications aimed at economizing health care and development economics along three dimensions of convenience outlined before. In doing so, we aimed to illustrate a degree of nuanced engagement with the benefits, complications, and drawbacks of Convenience AI applications within particular contexts of scientific practice. This section, in turn, brings together and generalizes our findings — and highlights how the very promotion of AI applications around themes of convenience and ease can undermine the thoughtful and rigorous consideration of Convenience AI and its implications.

V.1 Benefits and Drawbacks of Convenience AI

Table 1:

Benefits and Drawbacks of Convenience AI

Benefits	Drawbacks
• The ability to efficiently generate and analyse more and new kinds of data	• The weakening of the empirical foundations of research and uncritical entrenchment of epistemic commitments if limitations and affordances are insufficiently accounted for
• The potential to free researchers' time and resources for new research and service work	• The deskilling of researchers in tasks replaced by AI and the distancing of researchers from their objects of study
• The reduction of unrewarded forms of scientific work such as data curation, allowing junior and early career researchers to focus on creative contributions	• The accumulation of scientific ghost work and the exacerbation of counter-productive discriminations and exclusions within and across research groups
• The potential to apply similar tools across heterogeneous data formats, thereby facilitating interoperability and integration	• The potential uncritical acceptance of general-purpose tools without checking for context-specific implications

The upshots of Convenience AI applications are undeniable. Our case studies have underscored, for instance, how Convenience AI can generate unprecedented amounts of data and offers novel analytical capabilities which can guide scientific discovery (cf. Duede, 2023). At the same time, we have outlined how the safe and reliable use of Convenience AI commonly requires meticulous design, scrutiny regarding the affordances, limitations, and complications of the technology, as well as repeated testing for their robustness. AI tools can all too easily fail, for instance, when employed under changing circumstances or when confronted with what lies beyond the often-limited applications and instances anticipated in their development. Absent such time-intensive investment in the situated reliability of Convenience AI, researchers might risk employing AI outcomes of questionable evidential value.

We wish to put a particular emphasis on how the indiscriminate adoption of convenience AI can entrench epistemic assumptions and threaten epistemic diversity, as illustrated in our case study on AI poverty predictions.[9] This issue has recently been explored by Messeri and Crocket (2024) under the fitting label of "scientific monocultures." In their use of AI, researchers can fail to recognize both the assumptions, choices, and pragmatic considerations that go into data generation, cleaning, and processing, as well as the technical affordances of AI trained on such data. Moreover, impact and funding premiums for using AI can lead researchers to rely on AI even in the presence of viable alternative approaches (Gao & Wang, 2024). This can lead to "monocultures of knowing" where AI tools, given their affordances and constraints, determine which and how research questions are explored at the expense of alternative approaches. Failing to appreciate entrenched assumptions and commitments embedded within the data AI is trained upon and treating AI outcomes as "objective" arbiters of an unmediated reality can lead to "monocultures of knowers" where particular standpoints and perspectives are (intentionally or unintentionally) prioritized. In this way, the proliferation of Convenience AI can counter recent efforts of acknowledging the situated nature of scientific knowledge production and diversify the standpoints involved in scientific research (e.g., Longino, 1990). Scientific monocultures can thus lead to researchers being unable to identify when particular uses of AI are misaligned with the research question explored (Suárez & Boem, 2022) or the long-term success of scientific programs.[10]

The issue is exacerbated by a second drawback of Convenience AI. The widespread adoption of Convenience AI can lead to the deskilling of researchers precisely in those practices of traditional data collection, experimentation, or literature engagement required to critically examine and improve AI applications (cf. Duran, 2021; Sutton et al., 2018) — practices also central to cultivating a certain ethics of care and epistemic virtues such as attentiveness, scrutiny, and humility critical to reliable scientific practice (Vallor, 2014, 2015). The crucial intersection of care cultures and scientific robustness is particularly evident in the case of health care and precision medicine considered above, where a focus on the wellbeing of individual patients needs to be combined with attention to the reliability, scalability and applicability of data and methods used to develop AI tools for medical decision-making. Deskilling might also affect the quality of future AI applications as

[9]Leonelli (2023, p. 29) defines epistemic diversity as "the condition or fact of being different or varied in ways that affect the development, understanding and/or enactment of knowledge.

[10]Notice also the close relationship between epistemic diversity and epistemic justice (Leonelli, 2023, Chapter 4; Massimi, 2021).

machine learning algorithms would have little to “learn” from without the data first generated through, for instance, skilful laboratory experimentation or field surveying.

Yet, Convenience AI applications’ promise to economize monotonous and laborious parts of scientific research might also allow researchers to invest greater time not only in more creative aspects of scientific research but also in community engagement and service work — efforts that often fall prey to repetitive research duties and administrative demands. Thus, AI applications can not only render science more efficient and convenient but also foster innovation and progress, when labour and financial resources saved on routine tasks are re-invested in other parts of scientific research (Royal Society, 2024, p. 61). The opportunity to put less time into time-consuming and laborious – but typically invisible and unrewarded – tasks such as data curation, formatting and modelling can have important social implications too, for instance by enabling junior and early career researchers usually employed for such tasks to focus on creative contributions.

At the same time, recent critical research has exposed how much anonymous and precarious labour goes into the production of commercial AI applications (Gray & Suri, 2019). Such “ghost work” is often left un- or under-accounted when AI developers praise gains in efficiency and ease facilitated by novel applications. We have illustrated this using the example of underemphasized enumeration work that can go into AI poverty predictions and highlighted how the promotion of AI applications in science often conceals the amount of data cleaning, processing that goes into rendering information “AI-ready.”

Closely related to the issue of ghost work are the ways in which Convenience AI applications might exacerbate existing power structures. The development of AI applications, in particular, often requires technical, infrastructural and financial resources only available to a small number of well-resourced research institutions, as well as commercial actors. Resources that, as our case study in development economics underscored, are also often only available in the Global North and China. This in combination with the overpowering of industry-investment in AI research might contribute to a further centralization of power in ways ultimately misaligned with a successful, diverse, and equitable scientific landscape. Even when institutions and researchers unable to afford the development of AI tools can access these technologies, the proprietary nature of industry software combined with the opacity of some AI tools might hinder much-needed scrutiny and foster the sort of uncritical reliance that is central to some of the downsides of Convenience AI outlined previously (Royal Society, 2024, p. 32).

Not least because of the costs of their development, Convenience AI applications are often intended as general-purpose technologies who can be applied to the widest possible range of problems across a variety of domains. This makes economic sense, by maximizing return on investment, and potentially facilitates interaction and integration across scientific fields of application by encouraging reliance on common standards, tools and models.

While Convenience AI applications can promise a seamless and easily scalable technological fix for wide ranges of problems, our case studies illustrated how AI applications come with highly situated complications and limitations in light of such claims of efficiency and ease must be qualified *relative to the particular task and circumstances at hand*. For instance, we have underscored how AI outputs (such as predictions of poverty metrics or diagnostic predictions) are not timeless and contextless representational objects but act as situated scaffolds whose validity and adequacy must be continuously scrutinized in light of the particular research question and needs at hand (Leonelli, 2016, 2023, p. 53). A preference for general-purpose solutions, however, leaves little space to consider cases where system-specific, specialized tools may be required to address a particular situation. Researchers are under strong pressure to adopt generalized tools better suited to large economies of scale, despite evidence that domain-specific applications are those most likely to positively support discovery (Miller, 2022; Royal Society, 2024, p. 46).

V.2 Convenience AI

This leads over to our final point. Whether Convenience AI ultimately aids or hampers scientific research depends on the conditions under which AI is adopted. If convenient solutions are adopted at speed, under strong pressure to save time and without critically evaluating the potential scientific implications for the research design and goals at hand, there is a strong risk of diminishing the benefits of Convenience AI and heightening the drawbacks.

Critically, we argue that the very framing of certain AI applications around themes of productivity, efficiency, speed, convenience, and ease can conflict with their thoughtful and rigorous situated consideration — itself a somewhat laborious exercise. Precisely because convenience is the key appeal of some AI tools, researchers who adopt these methods have little incentive to question them and investigate in detail the epistemic implications of adopting them – or privileging them over other approaches. Convenience AI can be dangerous because, motivated by speed and ease, it can instil complacency into the use of given tools and lower the depth and frequency of critical scrutiny.

The situation is compounded by the fact that perceptions of practices at risk of AI-automation as routine and uninspired can disincentivize scientists and philosophers alike from considering their transformation as worthy of critical scrutiny in the first place. This must be viewed also in light of the broader economy of scientific labour and academic reputation since what is considered dull and routine is at least partly shaped by what is regarded as worthy of academic reward and prestige. The relationship is bidirectional.

On the one hand, activities perceived to be routine are likely considered to be less prestigious. For instance, practices such as data collection and processing are occasionally presented as auxiliary to "core" scientific research, undervaluing their foundational epistemic significance, as well as the cultivated skill and practical knowledge involved (Boumans & Leonelli, 2020; Leonelli, 2016). One may interpret the promotion of AI tools for poverty data generation, for instance, as continuous with longer-standing devaluations of in-person enumeration as dull, routine, uninspiring, and inconvenient. Conversely, widespread AI hype and excitement have led to an impact premium associated with publications using AI (Gao & Wang, 2024), incentivizing researchers to rely on AI for the sake of greater visibility and employability. Such considerations may then take priority over evaluations of its suitability for the particular research question explored.

On the other hand, a lack of recognition for certain activities can contribute to their perception as uninspiring and dull. Scientists might consider as inconvenient precisely those activities that are deemed less personally profitable. Critically (and echoing our point regarding convenience made earlier), this lack in recognition and reward might further lead researchers to pay less attention toward how exactly AI tools are implemented and scrutinize their implications. In other words, if there is little incentive to personally carry out the task, there is likely also little incentive to consider in detail the nuanced and long-term consequences of its automation through Convenience AI. The dynamic is exacerbated by the fact that the very threat or act of automation can itself further devalue those activities, positioning them as unworthy of human labour and recognition in the first place (Taylor, 2018). This risks a vicious circle where activities perceived to be inconvenient and unprofitable are automated and, thereby, perceived as even less worthy of human effort and scrutiny, leading to further automation and so on.

VI Conclusion

The proliferation of AI in science, including technological milestones such as AlphaFold2 (Jumper et al., 2021), surges in the capabilities of LLMs (Vaswani et al., 2023), and recent groundbreaking investment in World Foundation Models (NVIDIA et al., 2025), promises to transform how researchers engage with existing scholarship and their objects of study. In this paper, we looked beyond spectacular pilots and speculative futures, and considered the mundane ways in which AI is being incorporated into scientific practice today – and particularly the extent to which AI is used to automate tasks perceived to be boring, "mere routine" and inconvenient to researchers. We labelled such uses as instances of "Convenience AI", that is situations where AI is applied with the primary intention to increase speed and minimize human effort, without necessarily replacing humans in discovery but aiming to make human input more efficient, interesting and creative.

We outline how attributions of convenience to AI applications involve three key characteristics: (i) an emphasis on speed and ease of action, (ii) a comparative element vis-à-vis other options, as well as (iii) a subject-dependent and subjective quality. Using examples from health care and economics, we illustrated epistemic benefits, complications, and drawbacks of Convenience AI along these three dimensions. Generalizing from these case studies, we stressed how the consistent association of Convenience AI with the goals of productivity, efficiency, and ease, as often promoted also by companies targeting the research market for AI applications, can lower critical scrutiny of research processes and shift focus away from appreciating their broader epistemic implications. This uncritical pursuit of efficiency and ease through AI can lead to research imprudently and uncritically contingent upon the values, understandings, and approaches built into or afforded by Convenience AI and lock scientists onto a path that is misaligned with the critical scrutiny and diversity of perspectives and approaches advocated for by much of today's scholarship on science (e.g., Cartwright et al., 2022; Chang, 2022; Leonelli, 2023).

Paying attention to these intersections between technology and science is ever more important at the current moment of socio-political transformation, where many of the most powerful AI providers are revoking diversity and inclusion policies, which in turn runs against basic scientific values (cf. Nature Computational Science, 2025). In a climate where critical reasoning is coming under fire even from well-established science funders and prominent AI companies are deeply entangled in current socio-political dynamics, it is ever more significant to resist the uncritical adoption of technological solutions whose user-friendliness may distract from long-term trouble ahead.

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