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AI as Systemic Risk in a Polycrisis

The Danger of Algorithmic Prediction in Unknown Environments

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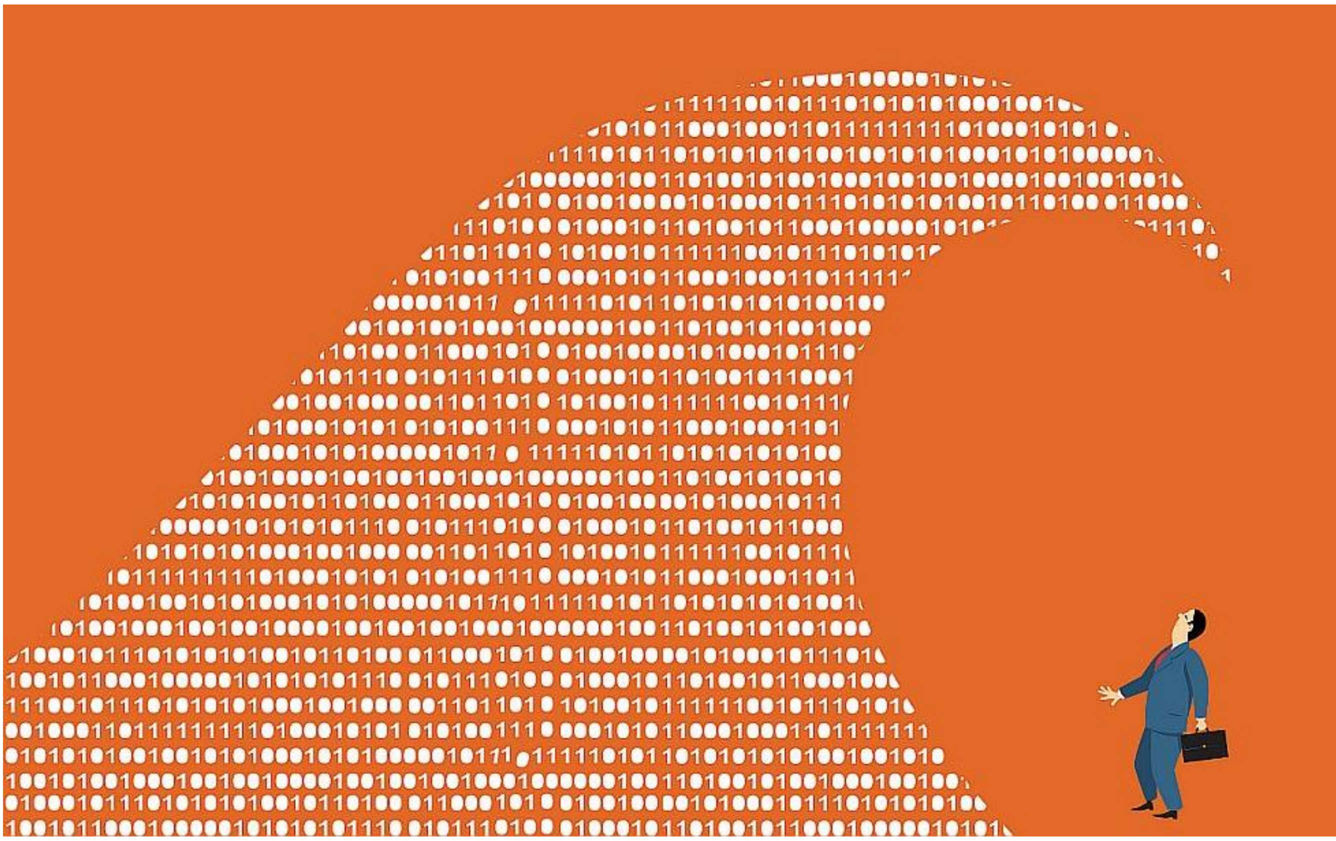

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The much-hyped power of Artificial Intelligence (AI) depends in many fields of application on the data with which it is trained. As our increasingly dynamic and interdependent world deviates from past observations used for design and training, AI systems will become less reliable. To boost European resilience, the proposed EU AI Act should be modified to account for the increased fallibility of AI systems in times of polycrisis, primarily when the public sector utilises them.

- In times of global disorder, some express the hope that predictive AI systems might cut through the noise and help, for instance, prevent the next pandemic or save resources to fight off climate change.
- However, as real-world events increasingly deviate from the data points used to make algorithmic predictions, AI systems will become less reliable and require increasing oversight. Several recent examples illustrate this worrying trend.
- Rather than fine-tuning algorithms for the current crises, policymakers should establish robust framework conditions that, while not maximising efficiency, will enable the technology-driven European economies to operate reasonably when the next crisis hits. Therefore, the Center for European Policy (cep) calls for a context-dependent classification of AI systems in the proposed AI Act and the disclosure of specific AI audit findings for peer review.

Content

1 Introduction: AI to the rescue?

The power of artificial intelligence (AI) is undoubtedly alluring, so it is not surprising that, in times of global disorder, some express the hope that algorithms might help prevent the next pandemic,[1] save resources to fight off climate change,[2] or even bring about a more equitable and inclusive future society.[3] What is often forgotten is that any AI system is fundamentally limited by the type of data with which it is trained. As a rule of thumb, modern machine learning algorithms work better when trained on large amounts of high-quality data and perform worse when the underlying data is inaccurate, incomplete, irrelevant, invalid, out of date or inconsistent.[4] What does this fundamental relationship imply for our current age of global disorder, characterised by multiple crises ranging from Russia's war against Ukraine to energy shortages, soaring inflation, and climate chaos?

As real-world events increasingly deviate from the data points used to make algorithmic predictions, AI systems will become less reliable and require increasing oversight. It is crucial to acknowledge the limitations of these systems, which arise from epistemic boundaries. Therefore, politicians and regulators alike must face the sobering reality that this technology in itself will not save us from recessions, war, or climate change. Instead, what is needed is a resilient regulatory framework, starting with the currently planned AI Act, and the type of common-sense thinking that so far only humans possess.

2 Background: black swan meets grey rhino

Realising the limited viability of quantified models in times of sudden change is a valuable starting point when reflecting on the role of AI systems in today's chaotic world. The apparent limitation of mainstream economic models during the early months of the 2007/08 financial crisis is a prime case in point: "In the face of the crisis," Jean-Claude Trichet, then president of the European Central Bank, lamented in November 2010, "we felt abandoned by conventional tools." These tools had been formulated and fine-tuned during a period of remarkably low macroeconomic volatility known as "Great Moderation"[5] – and were now overburdened by the spreading market turmoil. Without clear guidance from existing analytical frameworks, central bankers worldwide turned to historical crisis episodes to find qualitative lessons that might be learned.[6]

The observation that most of these economists ended up using analogies to the Great Depression in the 1930s,[7] illustrates that useful landmarks for guidance are few and far between when searching for lessons from the past in times of crisis. Statistics from economic history show that major financial crises are rare events: On average, crises occur every 25 years, and new recessions typically start every eight

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1 Makin, S. (2022), Could an algorithm predict the next pandemic?, Nature Outlook (26.10.2022), https://www.nature.com/articles/d41586-022-03358-4.

2 Miller, K. (2022), Building Intelligent Agents to Reach Net Zero 2050, HAI Stanford University (3.10.2022), https://hai.stanford.edu/news/building-intelligent-agents-reach-net-zero-2050.

3 Lobel, O. (2022), The Equality Machine: Harnessing Digital Technology for a Brighter, More Inclusive Future, New York: Public Affairs.

4 Pogrebivsky, S. (2021), The 6 Attributes of High-Quality Data, DataGroomr (8.7.2021), https://datagroomr.com/understand-the-6-attributes-of-high-quality-data/.

5 Bean, C. (2010), The Great Moderation, the Great Panic, and the Great Contraction, Journal of the European Economic Association 8 (2-3), pp. 289-325.

6 Eichengreen, B. (2015), Hall of mirrors: the Great Depression, the Great Recession, and the uses—and misuses—of history, Oxford: Oxford University Press.

7 Küsters, A. (2022). Applying Lessons from the Past? Exploring Historical Analogies in ECB Speeches through Text Mining, 1997-2019. International Journal of Central Banking 18 (1), pp. 277-329.

years.[8] This severely limits any empirical endeavours, including training AI systems, for instance, to predict such events. Moreover, even if data on such crises exists, it is almost by definition "dirty", as data scientists call it, meaning it lacks some information or does not measure reality as precisely as in a regular setting. Models designed or trained with "normal times" in mind might, therefore, start to fail when strong external shocks occur that signal the beginning of "abnormal times".

Due to the inherent nature of risk, this problem cannot be entirely anticipated or circumvented, a phenomenon which led the former Wall Street trader Nassim Nicholas Taleb to coin the term "black swans".[9] Black swans are unforeseen and unpredictable events with extreme consequences and, as such, can never be fully covered by our models. Besides the 2007/08 financial crisis, more recent events, like the Covid pandemic and Russia's attack on Ukraine, also fall into this category. Using AI systems to support decisionmakers in such abnormal conditions typically involves "conflicting and incomparable criteria", for example cost versus human well-being.[10] In addition, economists have used the expression "grey rhinos" to denote well-known and slow-moving risks that can amplify external shocks, such as the current high level of household indebtedness or global climate change.[11] While black swans and grey rhinos complicate any prediction, including human reasoning, the math-powered AI applications circulating nowadays are much more opaque than traditional prediction systems, typically beyond dispute or appeal, and can amplify negative feedback loops over large distances within short periods.[12] Increased use of these applications, therefore, creates new systemic risks.[13]

Things get even more complicated when several shocks hit simultaneously and establish interconnections that are not generally anticipated. The economic historian Adam Tooze has recently described the current state of the world as a "polycrisis", denoting an interaction of disparate shocks that, as a whole, is worse than the sum of its parts.[14] The picture that emerges from this brief survey is clear: the presence of multiple black swans and grey rhinos in today's polycrisis is very likely to impact the usefulness of our algorithms that are, by necessity, trained on past data, which might now become quickly outdated. This problem of training models on narrower datasets than the population they are ultimately intended to reflect is a form of so-called "data leakage", which threatens the reliability of machine learning across disciplines.[15] Even worse, evidence suggests that using predictive AI systems to cut through the noise in times of crisis might even exacerbate an already bad situation.

3 Examples: why AI tools malfunction in abnormal times

The dangers can be demonstrated by briefly turning the clock back to the early months of the Covid pandemic. As soon as the first lockdowns started, economists scrambled to get some insights into the current state of the global economy by relying on novel real-time data, as their standard measures

8 Paul, P. (2019), Modeling Financial Crises, FRBSF Economic Letter (2019-08).
9 Taleb, N. (2007), The Black Swan: The Impact of the Highly Improbable, New York: Random House.
10 Mostaghim, S. (2020), AI to the Rescue: Life-and-Death Decision-Making under Conflicting Criteria, Project website (undated), https://forschung-sachsen-anhalt.de/project/ai-rescue-life-death-decision-making-23474.
11 Marja Nykänen, M. (2022), Black swans and grey rhinos – lessons of crises on macroprudential policy, Opening remarks at the Conference on Systemic Risk Analytics, Helsinki (5.5.2022), https://www.bis.org/review/r220509c.htm.
12 O'Neil, C. (2016), Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy, New York: Crown Publishers.
13 Galaz, V. et al. (2021), Artificial intelligence, systemic risks, and sustainability, Technology in Society 67, 101741.
14 Tooze, A. (2022), Welcome to the world of the polycrisis, FT (28.10.2022), https://www.ft.com/content/498398e7-11b1-494b-9cd3-6d669dc3de33.
15 Gibney, E. (2022), Could machine learning fuel a reproducibility crisis in science?, Nature Outlook (26.7.2022), https://www.nature.com/articles/d41586-022-02035-w.

were either too slow or unreliable. Instead of waiting for official inflation and unemployment estimates, they increasingly drew on previously obscure indicators, such as mobility statistics from Apple or Google, or restaurant-booking data, to get a sense of overall economic activity.[16] While these measures managed to capture changed consumer behaviour during the pandemic, AI systems trained on data fitting the old spending patterns immediately ran into problems.

Take the case of Fair Isaac Corp (FICO), a US-based software developer whose prominent AI tools for credit and debit card fraud detection are relied upon by large banks when making lending decisions. At the beginning of the pandemic, based on past experience, these tools were expecting much more in-person than virtual shopping, a situation which eventually led to a large number of virtual transactions being flagged as problematic. This meant that the underlying algorithm recommended denying millions of legitimate purchases while consumers in lockdown eagerly tried to secure essential goods online.[17] Around the same time in China, AI-automated credit evaluation tools by big players such as Ant Group, which had continuously kept default rates as low as one per cent, likewise worked much less smoothly.[18] This was partly due to increased financial stress during the early pandemic. However, the new problems probably also reflected the fact that Ant's scores were based not only on traditional factors like credit history but also used much broader criteria, such as a user's hobbies and purchasing preferences – in other words, behavioural measures that experienced dramatic changes due to self-isolation.

In other crisis contexts, such as health or climate change, which tend to resemble "grey rhino" risks more than "black swans", the problem is not the sudden change in critical indicators but the gap in high-quality data that weakens algorithmic prediction. Due to challenges regarding the size and composition of the data used to train AI models for healthcare, the latter are not as accurate at predicting diseases as reports typically suggest.[19] Similarly, since countries vary in the quality and quantity of meteorological and other geographical data collected, climate risk prediction models for certain areas might be erroneous.[20] Typically, those small, low-income communities that face the greatest financial losses and risk in a world of climate change[21] lack the type of high-quality climate data required for training early warning systems with the capacity to respond quickly. For instance, energy researchers criticise the fact that current data-driven plans for combatting climate change fail due to their lack of Africa-specific data and models.[22] This divide between the data haves and the data have-nots hinders collaborative action[23] and may reinforce inequality between communities as an AI system will tailor its recommendations to areas where it can draw on a larger amount of data.

16 The Economist (2020), Why real-time economic data need to be treated with caution (23.7.2020), https://www.economist.com/finance-and-economics/2020/07/23/why-real-time-economic-data-need-to-be-treated-with-caution.

17 Dave, P. (2022), When the AI goes haywire, bring on the humans, Reuters (13.10.2022), https://www.reuters.com/technology/when-ai-goes-haywire-bring-humans-2022-10-13/.

18 Chorzempa, M. (2022), The Cashless Revolution: China's Reinvention of Money and the End of America's Domination of Finance and Technology, New York: Public Affairs, pp. 98f., 103.

19 Berisha, V. / Julie Liss, J. (2022), AI in Medicine Is Overhyped, Scientific American (19.10.2022), https://www.scientificamerican.com/article/ai-in-medicine-is-overhyped/.

20 Center for Data Innovation (2022), How Does the Data Divide Impact Global Policy Challenges?, Online Panel Discussion (7.12.2022), https://datainnovation.org/2022/12/how-does-the-data-divide-impact-global-policy-challenges/.

21 Naddaf, M. (2022), Climate change is costing trillions – and low-income countries are paying the price, Nature News (7.11.2022), https://www.nature.com/articles/d41586-022-03573-z.

22 Mutiso, R. (2022), Net-zero plans exclude Africa, Nature World View (2.11.2022), https://www.nature.com/articles/d41586-022-03475-0.

23 Diebold, G. (2022), Data Divide or Digital Divide? Or Both?, ISE Magazine (7.11.2022), https://www.isemag.com/industry-trends-and-research/article/14284950/data-divide-or-digital-divide-or-both.

In fact, experts are increasingly coming to realise that using predictive analytics in situations of complexity, disorder or insufficient data might even reinforce underlying negative trends. For instance, in order to handle the fallout from its opioid crisis, the US relies on a prominent drug addiction risk algorithm that, as researchers have now documented,[24] seems to be worsening the situation. The underlying AI-based screening tools of patients are inherently flawed as they cannot handle complex constructs like human health and, therefore, often deny treatment to those patients who are most vulnerable or represent medically complex cases. Realising the potential of these automated systems to turn into "weapons of math destruction"[25] has far-reaching consequences when thinking about regulation: "If predictive analytics are partly creating the reality they purport to predict," as Carissa Véliz, a researcher at the University of Oxford, recently concluded, "then they are partly responsible for the negative trends we are experiencing in the digital age, from increasing inequality to polarisation, misinformation, and harm to children and teenagers".[26] The current polycrisis will exacerbate these fundamental problems behind algorithmic predictions.

A final example from the security field illustrates this worrying insight. A recent study published by the European Union Agency for Fundamental Rights criticises the increased use of AI systems for predictive policing.[27] Again, the problem with AI-based tools – in this case for law enforcement – is that they typically rely on historical and thus potentially out-dated and biased data, with the AI learning the emerging patterns. The resulting "feedback loops" are particularly damaging in a polycrisis. For example, a lower police presence in an area will usually result in fewer criminal charges, leading to the area being even less policed in the future, as the AI recommends allocating resources to other sites that it deems more critical. This, in turn, makes the specific area more vulnerable to external shocks, such as attacks on critical infrastructure or terrorism, since the AI model only incorporates data on past criminal charges and cannot think strategically about other relevant aspects, such as the location of a frequently visited train station or a critical energy supplier. The same problem can be detected for predictive AI systems used in migration, asylum and border control, which become increasingly relevant in times of climate change-induced human mobility but whose incorrect assessments "have significant consequences for the preparedness of Member States, but also for the likelihood that individuals can access international protection".[28] In other words, the utility of AI-based prediction tools is limited to narrow domains – focusing, for instance, on finance, the environment, medicine or security – to the exclusion of all others. As Martin Wolf noted, thinking about the world in intellectual silos may be efficient in a reasonably stable world, but it will inevitably fail in a polycrisis.[29]

4 Outlook: how to mitigate the risks of false algorithmic prediction

To some extent, gathering new data, increasing global data-sharing, and mandating common data standards can improve geographical and chronological coverage, thereby leading to better

[24] Szalavitz, M. (2021), The Pain Was Unbearable. So Why Did Doctors Turn Her Away?, Wired (11.8.2021), https://www.wired.com/story/opioid-drug-addiction-algorithm-chronic-pain/.

[25] O'Neil, C. (2016), Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy, New York: Crown Publishers.

[26] Véliz, C. (2021), If AI Is Predicting Your Future, Are You Still Free?, Wired (27.12.2021), https://www.wired.com/story/algorithmic-prophecies-undermine-free-will/.

[27] FRA (2022), Bias in algorithms – Artificial intelligence and discrimination, Luxembourg: Publications Office of the European Union, https://fra.europa.eu/en/publication/2022/bias-algorithm.

[28] Access Now et al. (2022), Open Letter: The EU AI Act must protect people on the move, https://edri.org/wp-content/uploads/2022/12/Open-letter_EU-AI-Act_migration_December-2022.pdf, p. 3.

[29] Wolf, M. (2022), How to think about policy in a polycrisis, FT (29.11.2022), https://www.ft.com/content/a1918fec-2c8f-4051-ad78-c300b0fc9adb.

quantitative models. Another possible avenue might be reinforcement learning, which does not depend on external datasets but on information created during training. Some researchers hope to develop more resilient AI systems based on a type of statistical reasoning known as “sequential planning under uncertainty”.[30] However, these alternatives offer no panacea since all datasets are imperfect in some way and “black swans” might still occur at any time. Moreover, the increasing speed and growing inter-connectivity of crises mean it is practically impossible to keep data updated with sufficient frequency. Tellingly, even those experts who hope that machine learning might help identify the most dangerous viruses concede that predictive tools cannot prevent the next pandemic.[31] Similarly, experts suggest that there are “no silver bullets” for producing reliable, clinical AI models.[32]

Ultimately, answering the question of whether our models can ever hope to act upon an increasingly complex world boils down to whether we are just teaching algorithms to reiterate things they already know or whether they are capable of learning entirely new principles – a question that is still hotly debated among computer scientists and philosophers, and will probably not be solved any time soon. Given this insecurity and ambivalence, one should not entrust much-hyped algorithms with solving the current crises or providing resilience. Instead, one must take a more nuanced approach. The best defence against the risks of algorithmic prediction in times of global disorder is to maintain a simple and robust regulatory landscape. The rules must not be so detailed and all-encompassing that innovative start-ups cannot emerge in the first place. Instead, they should define framework conditions so that the market can separate sensible from non-sensible AI-based prediction tools in the long term without these applications being able to cause society-wide damage in the short term.

This robust regulatory framework should include mandating more corporate teams to review AI performance in order to avoid problems such as those reported by FICO. While the EU’s new AI law will require some monitoring, much needs to be done: a McKinsey survey among 1,843 firms in 2021 suggests that most are not regularly monitoring AI-based programs after launching them.[33] Even firms with responsible AI teams do not invest enough, with people working in the field suffering as a result.[34] Firms should be legally obliged to publish their AI audits, which would further incentivise the spending of more resources on investigating AI harms. While these audits have been suggested to increase algorithmic accountability, their proper implementation necessitates regulatory guidance on sufficient standards and common practices.[35] As the EU’s currently planned AI Act and AI liability law will mandate firms to document how they are mitigating harms, clearly defined standards and more human and technical resources are needed to avoid further “burnout” in the auditing sector, which would potentially exacerbate, rather than mitigate, AI harm. One possible solution might be to mandate the disclosure of critical components of audit findings for peer review.[36]

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30 Miller, K. (2022), Building Intelligent Agents to Reach Net Zero 2050, HAI Stanford University (3.10.2022), https://hai.stanford.edu/news/building-intelligent-agents-reach-net-zero-2050.

31 Makin, S. (2022), Could an algorithm predict the next pandemic?, Nature Outlook (26.10.2022), https://www.nature.com/articles/d41586-022-03358-4.

32 Berisha, V. / Julie Liss, J. (2022), AI in Medicine Is Overhyped, Scientific American (19.10.2022), https://www.scientificamerican.com/article/ai-in-medicine-is-overhyped/.

33 McKinsey Analytics (2021), The state of AI in 2021 (December).

34 Heikkilä, M. (2022), Responsible AI has a burnout problem, MIT Technology Review (28.10.2022), https://www.technologyreview.com/2022/10/28/1062332/responsible-ai-has-a-burnout-problem/.

35 Costanza-Chock, S. / Raji, I. / Buolamwini, J. (2022), Who Audits the Auditors? Recommendations from a Field Scan of the Algorithmic Auditing Ecosystem, ACM Conference on Fairness, Accountability, and Transparency, pp. 1571–1583.

36 Costanza-Chock, S. / Raji, I. / Buolamwini, J. (2022), Who Audits the Auditors? Recommendations from a Field Scan of the Algorithmic Auditing Ecosystem, ACM Conference on Fairness, Accountability, and Transparency, p. 1579.

A crucial starting point for adaptation will be next year's trilogue negotiations between the European Commission, Council and Parliament on the AI Act, which is the European flagship initiative for regulating machine learning systems in the digital age. Its rules should be modified to account for the increased fallibility of AI systems in times of polycrisis. In general, the unpredictability of "black swan" and "grey rhino" events suggests that a purely risk-based approach might not be sufficient as we cannot know the overall risk of a given system. However, if one accepts the current draft's risk-based approach as a given, incorporating the dangers arising in times of polycrisis could be done by classifying a higher proportion of AI-driven systems as "high-risk" whenever the current economic or political climate suggests that their training data might be out of touch with reality. High-risk systems within the meaning of the AI Act are those that can have a significant impact on the life chances of a user, and are thus required to certify, inter alia, high-quality training data, adequate human oversight, and testing for accuracy and robustness. The most recent compromise text for the AI Act lists eight concrete types of systems that fall into this category, such as automated systems for vocational training or law enforcement.[37] However, a context-sensitive classification scheme would allow for the inclusion of more AI systems into this regulatory regime in times of polycrisis, thus ensuring that these systems have to meet higher data and robustness standards. For instance, one could mandate that all AI applications falling into the category of "systems with limited risk", which in normal times necessitates only rudimentary transparency obligations, would have to fulfil the additional obligations for "high-risk" systems when current external shocks, such as warfare, pandemic, or loss of critical infrastructure, increase the likelihood of erroneous decisions by pre-trained models. While large undertakings or the public sector could comparatively easily hire more lawyers or computer scientists to implement the requirements for high-risk systems, smaller companies or start-ups lack these possibilities, which must be taken into account.

The European Council's negotiating position on the AI Act, adopted on December 6, 2022, is, therefore, a step in the wrong direction, as it seeks to relax requirements for high-risk systems.[38] Concerning the classification of AI systems as high-risk, the compromise proposal now includes an additional horizontal layer to ensure that AI systems that are unlikely to cause severe violations of health, safety or fundamental rights (because their output is only ancillary to an action or decision) are exempted. While this is welcome in principle as it will relieve the burden on innovative start-ups, the horizontal regulation should additionally take into account whether the expected risks would change in times of external shocks or multiple crises. Art. 6(3) in the draft AI Act should thus be worded in such a way as to exempt those systems where the outcome is entirely immaterial concerning the action or decision to be taken and, therefore, unlikely to lead to a significant risk to health, safety or fundamental rights, *even in the context of a polycrisis*, i.e. multiple and simultaneous external shocks. For start-ups, it is particularly problematic that the envisioned horizontal requirements are not to be issued until at least one year after the AI Act goes into effect.[39] Therefore, the cep requests that the European Parliament,

[37] The version from 25 November 2022 can be found here: https://data.consilium.europa.eu/doc/document/ST-14954-2022-INIT/de/pdf. Siehe auch: Kullas, M. / Harta, L. (2021), Europäisches Gesetz über Künstliche Intelligenz Kurzfassung, cepAnalyse zu COM2021 206 (13.12.2021), https://www.cep.eu/eu-themen/details/cep/europaeisches-gesetz-ueber-kuenstliche-intelligenz-cepanalyse-zu-com2021-206.html.

[38] Stierle, S. (2022), Schwierige Trilog-Verhandlungen im neuen Jahr, Tagesspiegel Background (7.12.2022), https://background.tagesspiegel.de/digitalisierung/schwierige-trilog-verhandlungen-im-neuen-jahr.

[39] Gorzala, J. (2022), AI Act der EU: KI-Regulierung im Anmarsch, Der Brutkasten (7.12.2022), https://brutkasten.com/ai-act-der-eu-ki-regulierung-im-anmarsch/.

in its positioning expected in early 2023, should focus on the additional risks of algorithmic prediction arising in crises and call for faster implementation of the horizontal rule.

Another avenue for considering the polycrisis effects in the AI Act is offered by the envisaged registration of AI systems. According to the Commission's original draft, providers of high-risk AI systems should have to register their systems in an EU database when they enter the market. Several civil society organisations have pointed out that a meaningful transparency regime should additionally provide information on the actual use of these systems in practice.[40] This is particularly necessary in times of polycrisis, as the examples described above show that there can be significantly higher risks associated with algorithmic prediction in abnormal, highly dynamic situations compared to a static risk assessment based on the mere business description of a company. Again, particularly stringent transparency obligations should not hinder innovative start-ups but should be formulated particularly for those AI systems used by dominant undertakings or public authorities, as these have the most potentially far-reaching impact in the event of a "black swan" with society-wide dimensions, such as the onset of warfare. Therefore, the cep welcomes that the AI Act has been revised to indicate that certain users of high-risk AI systems that are public authorities, institutions, or other entities will also be required to register with the EU database of high-risk AI systems.

Overall, it is important to emphasise that the proposed regulatory changes regarding AI audits and the EU AI Act are not intended to restrict the application of AI to well-defined, controlled environments, as this could diminish crucial learning effects. Rather, the goal is to find "robust rules" that enable exactly this: safe application to a complex system, as today's polycrisis undoubtedly is. Once lawmakers have defined regulatory framework conditions in such a way that using AI-based systems for economic or political decision-making cannot cause society-wide damage in the short term, the market can separate sensible from non-sensible AI-based prediction tools in the long term.

5 Conclusion: the need for robust rules

Overall, rather than fine-tuning algorithms for the current crises, European policymakers and regulators should establish general rules of the game that, while not maximising efficiency, will enable increasingly technology-driven economies to operate reasonably if and when the world enters the next crisis. In general, the unpredictability of "black swan" and "grey rhino" events suggests that a purely risk-based approach, as proposed in the EU AI Act, might not be sufficient as we cannot know the overall risk of a given system. However, if one accepts the current draft's risk-based approach, incorporating the dangers arising in times of polycrisis could be done by classifying a higher proportion of AI-driven systems as "high-risk" whenever the current economic or political climate suggests that their training data might be out of touch with reality. Most importantly, political leaders, entrepreneurs and journalists, who enthusiastically embrace the potential of modern algorithms, must better understand and communicate their potential for harm in the event that their performance degrades in a polycrisis.

[40] Aszódi, N. (2022), Wie die Regierung bei den Risiken von KI wegschaut, Tagesspiegel Background (6.12.2022), https://background.tagesspiegel.de/digitalisierung/wie-die-regierung-bei-den-risiken-von-ki-wegschaut.

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