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The Digital Divining Rod: How AI Contributes to a more Resilient Supply of Raw Materials

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Europe's transformation to a digitalised and sustainable economy requires a secure supply of rare metals such as lithium and cobalt. Diversifying sources of supply is the order of the day. However, information about new raw material deposits is still driven by chance and patchy. This cepInput argues that using AI in reconnaissance and surveillance will improve the information base and should therefore be encouraged.

- The use of AI in resource exploration **significantly increases cost efficiency and search speed and may reduce the consequential social costs of mining**.
- The **promotion of AI-based exploration technologies** should therefore be an essential component of the EU's forthcoming Critical Raw Materials Act. At the same time, the **EU data regulations** must ensure that high-quality data is used for training the underlying systems, and that interdependency effects are monitored by "humans in the loop".
- In the interests of sustainability, algorithms should also evaluate **information on the likely environmental effects of** commercial exploitation. In addition, the funded technologies should be used to **build a recycling economy for critical metals** in Europe.

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1 Motivation

Beneath the earth's surface are a multitude of mineral resources, many of which may be of use in the future. Some minerals have only been mined in small quantities in the past but are becoming increasingly crucial in the future. These include the rare metals needed for the production of batteries (lithium, cobalt), wind turbines (rare earths) and electronic displays (indium). Such minerals are indispensable for Europe's transformation to a digitalised and sustainable economy. Currently, however, extraction and smelting are concentrated in a few non-EU countries such as China, Australia and South Africa. Procuring these minerals is, therefore, subject to multiple risks with regard to price development, security of supply and environmental impact.[1] This supply structure also creates strategic dependencies for Europe, which must be critically evaluated in the current geopolitical context.

One possible way out is to explore new raw material deposits inside or outside the EU. So far, however, there has also been a clear global divide in exploration activities: Canada, Australia, the United States and China are perceived as the most critical regions due to their size and importance for the mining industry, with more than half of the global exploration budget for metals in 2021 being assigned to these regions.[2] So far, in terms of volume, Europe has not played a significant role in the regional evaluations and is not even recorded separately as a region in the available analyses. Although there have recently been isolated large-scale discoveries in Europe, in Sweden[3] and Norway[4], this has yet to be backed up by a systematic exploration strategy. Recent price trends have further impeded incentive: The comparatively low metal prices of recent years, which bottomed out in 2016, caused the capital markets for metals to dry up and forced companies to focus on safer but less rewarding work near existing mines. The resulting decline in discoveries has become an increasingly acute threat to supply security in the face of soaring demand for battery metals such as lithium and cobalt.

One way to increase the yield may be an increased focus on so-called "greenfield" exploration, i.e. the exploration of previously largely unexplored geological terrain away from known deposits.[5] However, the high level of uncertainty regarding the results of conventional exploration methods - combined with considerable capital expenditure - represents a major incentive barrier. Better analytical methods are therefore needed so that the chances of success of an exploration can be assessed in advance. This raises the question of whether exploration and exploitation processes can be optimised using the latest artificial intelligence (AI) methods, which have already revolutionised many other industries, such as mobility and e-commerce.[6]

This **cepInput** analyses the potential and the requirements for using AI in the exploration and monitoring of critical metal deposits. Section 2 looks at the current information deficits regarding the existence of resources and reserves, both in terms of geological deposits and the wealth of resources contained in end products that is currently lying dormant. Section 3 describes in detail how new AI approaches could make the discovery and extraction of critical minerals more efficient in the future

1 Wolf, A. (2022). Europe's handling of the raw materials of the future. cepInput No.11/2022.
2 S&P Global Market Intelligence (2022). World Exploration Trends. PDAC Special Edition April 2022, p. 13.
3 CNBC (2023). Sweden finds Europe's largest deposit of rare earth metals, which could become 'more important than oil and gas'.
4 CNN (2023). Norway discovers huge trove of metals, minerals and rare earths on its seabed.
5 S&P Global Market Intelligence (2022). World Exploration Trends. PDAC Special Edition April 2022, p. 13.
6 Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243

and provides several concrete examples from the non-European start-up scene whose valuable experience should now be transferred to Europe. At the same time, this section also points out the technical and regulatory imponderables that are currently still in place and goes on to analyse, from an economic perspective, the extent to which AI-based methods should be eligible for support. Section 4 discusses the role of AI in European raw material policy to date and substantiates its eligibility for support. On this basis, in Section 5, we conclude by formulating some concrete policy recommendations for the European Commission (EU) that may help to ensure that the continent does not miss the shift towards machine-driven mining and exploration. Section 6 provides a summary of the core findings.

2 Information deficits regarding raw material deposits

2.1 Geological deposits

Publicly accessible primary data on the geographical distribution of raw material deposits are primarily provided by national statistical authorities. However, the recording criteria and demarcations are not standardised internationally. The U.S. Geological Survey (USGS) has established itself as a source for country comparisons, incorporating information from authorities in other countries as well as its own research results from non-official sources. The USGS distinguishes between reserves and resources. Reserves are defined by the USGS as identified deposits that can be economically extracted under current conditions. Resources also include identified deposits that are not currently economic and deposits that are assumed to exist based on geological indicators.[7] The current extent of a country's raw material reserves, therefore, depends not only on the physical availability of the deposits but also on the state of technical development and the price situation on the raw material markets. The total stock of resources is also subject to significant fluctuations due to exploration activities as well as the correction of estimates. Information sources relating to raw material deposits in the EU area are also patchy and sometimes inconsistent.[8] This also applies to deposits in marine areas that Member States have licences to explore.[9]

Geologists have traditionally searched for mineral deposits by painstakingly collecting field data and then analysing it by hand. Conventional methods thus rely exclusively on human interpretation but also often fail. Although billions of dollars are invested in exploration, only a handful of new deposits are discovered each year: Miners commonly state that only one out of about a hundred exploratory wells brings anything to light.[10] The number of discoveries has already been declining since the turn of the millennium.[11] Lack of investment in new mines also indicates that the conventional approach will not be able to cope with the demand that has been proliferating in recent years, particularly as a result of the need for a climate-neutral transformation of the global economy. The indexed metal price is

[7] USGS (2020). Appendices - Mineral Commodity Summaries 2020. US Geological Survey. https://pubs.usgs.gov/periodicals/mcs2020/mcs2020-appendixes.pdf.

[8] Lewicka, E., Guzik, K., & Galos, K. (2021). On the possibilities of critical raw materials production from the EU's primary sources. Resources, 10(5), S. 50.

[9] Lusty, P. A., & Murton, B. J. (2018). Deep-ocean mineral deposits: metal resources and windows into earth processes. Elements: An International Magazine of Mineralogy, Geochemistry, and Petrology, 14(5), 301-306.

[10] Beiser, V. (2022). These Algorithms Are Hunting for an EV Battery Mother Lode. WIRED (12.12.2022). https://www.wired.com/story/these-mining-algorithms-are-hunting-for-an-ev-battery-mother-lode/

[11] For figures see: Davies, S. (2020). Assessment of Methodologies to Predict Potential Mineral Endowment on Entering an Immature Exploration Space, using the Western Australian Sandstone Orogenic Gold District as a Natural Laboratory. Doctoral Thesis, The University of Western Australia.

now back above its 2012 peak, and exploration budgets have increased by 35% from $8.35 billion in 2020 to $11.24 billion in 2021. Nevertheless, the 2021 global exploration budget is only 50% of the 2012 peak.[12] Significantly, the share of greenfield exploration in the total budget is close to a record low at 26%, down from 41% in 2007.[13] Drilling's high error rate and low chance of success in the face of growing demand and inadequate funds, together mean that more efficient exploration methods can - and must - play an essential role in the future if the global community is to achieve its ambitious climate and digitalisation goals.

2.2 Urban Mining

The problems which exist in the mining of future raw materials have drawn attention to alternative sources. With increasing industrial use, the wealth of raw materials lying dormant in everyday products is becoming more and more attractive. The term "urban mining" describes strategies to make this treasure trove economically viable through waste management and reprocessing. The advantages of such so-called "anthropogenic" raw material deposits are apparent. They can be developed without the environmental risks associated with mining and are independent of price fluctuations and supply risks on the world markets.[14] Moreover, anthropogenic deposits are concentrated in urban areas and thus principally near production facilities. The EU's dependence on a small number of producing countries would thus be reduced by increased mining in cities.

At the same time, however, establishing the necessary recycling chains represents a significant technical and organisational challenge. As in conventional mining, the first requirement is to get an overview of the size of existing deposits. This is particularly difficult for future raw materials, which are often fixed inside durable consumer goods such as mobile phones. Since a large part of the life cycle takes place in the realm of the consumer, material flows and changes in local stocks are difficult to estimate. Constant changes in material intensity due to short innovation cycles further complicate the evaluation.[15] Across Europe, however, the volumes are quite significant. The *Urban Mine Platform* made calculations to this effect in 2018. For example, it estimates the amount of lithium in European batteries at around 13,000 tonnes and the amount of cobalt at 24,000 tonnes. [16] However, the associated project has now come to an end and the data is no longer being updated. For assessing potential and effective management of secondary raw materials, continuously updated estimates would be needed with the highest possible geographical resolution. This applies even more to the AI assessment methods presented below.

3 Possible contribution of AI

3.1 Technical potential

Data science and machine learning could significantly enhance the search for lucrative excavation sites in the future. Various research teams and exploratory start-ups are currently developing big data projections relying on geophysics and boreholes to reduce existing uncertainties about the resource

[12] S&P Global Market Intelligence (2022). World Exploration Trends. PDAC Special Edition April 2022, p. 5.
[13] S&P Global Market Intelligence (2022). World Exploration Trends. PDAC Special Edition April 2022, p. 12.
[14] Tercero, L., Rostek, L., Loibl, A. & Stijepic, D. (2020). The Promise and Limits of Urban Mining. Fraunhofer Institute for Systems and Innovation Research ISI.
[15] Federal Environment Agency (2022). Urban Mining.
[16] Urban Mine Platform (2018). Composition of Batteries.

potential in many areas of the world. When assessing geological resources, conflicting factors must be evaluated to create a functioning decision model. Using AI-driven software in this context could accelerate the discovery of new ores and, at the same time, reduce costs. The first practical cases relating to oil fields, geothermal systems, contaminated sites and recharging groundwater already exist and provide a glimpse into the future.[17] For example, data-driven estimation methods were recently used to assess the Sandstone greenstone belt in Western Australia; the projected undiscovered gold deposits can now be used to guide future exploration expenditure.[18] In December 2022, the technology magazine Wired promised a soon-to-be-launched "marriage of cutting-edge artificial intelligence with one of mankind's oldest industries".[19]

The basic building block for such a connection between AI and mining is the existence of machine-readable data. Many mining or exploration companies have large amounts of historical data hiding evidence of mineralised systems. Unfortunately, much of this data is in an analogue, often poorly preserved state, requiring significant investment to digitise and validate. Important information for an AI-driven assessment of resources is contained, most notably on geological maps and in field reports. Extracting valuable and accurate information from these maps is a time-consuming and laborious process requiring much human labour. American experience shows that a typical data-driven assessment of a critical mineral takes about two years to produce.[20] This is because only about 10% of geological maps are available as georeferenced images and, in turn, only about half of these are the fully digitalised vector files required for analysis (the rest are typically scanned images of paper maps).

Due to these problems, researchers and companies are increasingly turning to alternative data sources that are easier to obtain and still provide relevant exploration forecasts. Today's standard of exploration generally involves direct exposure through drilling as well as indirect exposure through probing. Crucial technological advances have been made recently, particularly in geophysical surveying and hyperspectral drill core analysis, which significantly improve the technological possibilities for storing and processing rich data.[21] Measuring instruments such as gravimeters, gravitational wave sensors and magnetometers are used to detect and record fluctuations in the gravitational and magnetic fields. The data thereby collected can then be examined to identify potentially valuable resource deposits, for example, by analysing the spectral density and time-frequency localisation of a signal.

Finally, in the last ten years, it has become possible to bring this one-dimensional or two-dimensional data into the 3D domain. Since 1999, **MiraGeoscience** has pioneered the application of advanced geological modelling, 3D GIS technology and 4D multidisciplinary data management in the mining

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[17] Scheidt, C., Li, L. &. Caers, J.K. (eds) (2018). Quantifying Uncertainty in Subsurface Systems. Hoboken, NJ, USA: Wiley. For a concise summary, see also: Caers, J.K. (2018). Quantifying uncertainty about Earth's resources. Eos (99). https://doi.org/10.1029/2018EO097471

[18] Davies, S. (2020). Assessment of Methodologies to Predict Potential Mineral Endowment on Entering an Immature Exploration Space, using the Western Australian Sandstone Orogenic Gold District as a Natural Laboratory. Doctoral Thesis, The University of Western Australia.

[19] Beiser, V. (2022). These Algorithms Are Hunting for an EV Battery Mother Lode. WIRED (12.12.2022). https://www.wired.com/story/these-mining-algorithms-are-hunting-for-an-ev-battery-mother-lode/.

[20] DARPA (2022). DARPA Announces Winners of AI for Critical Mineral Assessment Competition (Dec. 16, 2022). https://www.darpa.mil/news-events/2022-12-16

[21] Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243.

industry with the integrated Common Earth Model.[22] The company provides the mining industry with modelling and data management solutions for mineral exploration and geotechnical hazard assessment. This is important because, in order for AI systems to predict where the most promising targets are located, it needs data that can be stored in a 3D space representing the cubic area in which targets are to be evaluated.[23] Startups and mining companies are now increasingly using AI methods to effectively analyse these combined datasets and 3D models. The hope is that the algorithm can detect meaningful correlations that would not be apparent to a human. Below we give some interesting examples stemming from this new development.

3.2 Practical examples

The most promising player in the emerging field of AI and mining is **KoBold Metals,** a four-year-old start-up that, in collaboration with Stanford University and with support from Bill Gates and Jeff Bezos, has developed and now successfully deployed an AI-based system for finding potential mineral deposits. According to reports, KoBold's approach is based on a database that gathers information about the earth's crust from geological reports, soil samples, satellite imagery, academic research papers and handwritten field reports.[24] This information - which amounts to about 30 million pages - is being digitised and standardised with the help of "Optical Character Recognition" to enable AI to identify geological patterns and other features of places where metals have been found in the past. The algorithms trained in this way will be able to find promising locations with similar patterns that have not yet been explored, and produce virtual maps indicating where target metals are likely to be found. KoBold is using this technology primarily to search for copper, cobalt, nickel, lithium and rare earths. How the underlying supervised learning of the AI system works is considered and explained in more detail in section 3.3.

To give a concrete example: In remote parts of Quebec, KoBold Metals uses, among other things, a helicopter with a 35-metre-wide copper coil dangling from its belly,[25] which sends electromagnetic waves into the earth generating currents in the rock. Electrical conductors send signals back to the receiver coil, indicating whether the scanned rock could contain valuable nickel and cobalt deposits. The helicopter covers around 160 kilometres per day and transmits the data to the KoBold scientists via satellite. They enter the new survey data directly into their database, combine it with existing observations and update their AI models so that they can model the geology of the region under investigation more effectively. Thus, with the help of AI-driven software, airborne survey plans can be adjusted on a daily basis and speed up the identification of promising places to drill. KoBold claims that using such technologies can increase the usual discovery rate by a factor of 20.

As mentioned above, KoBold recently partnered with the **Stanford Center for Earth Resources Forecasting** (SCERF), whose methodological expertise was used to create an AI "decision agent" that can generate an exploration plan. This digital decision maker quantifies the uncertainty in KoBold's

[22] Mira Geoscience (2023). About us. https://mirageoscience.com/about-us/

[23] Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243, p. 4.

[24] Beiser, V. (2022). These Algorithms Are Hunting for an EV Battery Mother Lode. WIRED (12.12.2022). https://www.wired.com/story/these-mining-algorithms-are-hunting-for-an-ev-battery-mother-lode/.

[25] Stone, M. (2021). The big tech quest to find the metals needed for the energy overhaul. MIT Technology Review (11.08.2021). https://www.technologyreview.com/2021/08/11/1031539/the-big-tech-quest-to-find-the-metals-needed-for-the-energy-overhaul/

model results and, on this basis, designs a data collection plan to reduce this uncertainty sequentially. SCERF conducts research in the field of exploration, evaluation and development of earth resources, be it energy, water or minerals, and develops solutions ranging from data acquisition to decision analysis.[26] It focuses on integrating spatial data, quantifying the uncertainty of geological systems and the added value of data sources for decision making. A look at the research results from the Center shows where the potential and the problems of this technology currently lie.

The quantification of uncertainties is the unifying element in SCERF research, which is not surprising as it is the main issue in the predictive evaluation of deposits. When developing geological resources, decisions must be made on where and how to extract them, when to stop extraction and the environmental impacts of extraction.[27] This is true for all the rare metals mentioned in the introduction, so these issues are also of utmost interest for any European efforts in the field (see section 4). As SCERF researchers show in various application areas, computer-aided analysis helps with this type of decision-making because it can propose concrete measures under conditions of uncertainty, based on specific observational data and a basic global understanding of subsurface systems – without, however, being able to fully predict their outcome. If AI systems are thus able to help optimise the exploration, evaluation and extraction of mineral resources, it could benefit many European mining regions. Geothermal energy, such as that used extensively in Iceland to generate electricity and heat buildings, is one such subsurface resource where quantifying uncertainty could facilitate decision-making.

One example of recent progress in quantifying uncertainty in the mining sector is the research of David Zhen Yin, who is involved at SCERF as programme director of the Stanford Mineral X Initiative, where he leads research on the sustainable development of critical minerals for the energy transition.[28] Based on so-called Bayesian Evidential Learning (BEL),[29] which uses machine learning to find a direct relationship between predictor and target, his research aims to develop an automated framework for quantifying uncertainties in geological models for deposit evaluation. When new boreholes are "sunk" (i.e. vertical cavities are created for extraction), multiple components of the geological model must be updated jointly and automatically. Sinking is one of the riskiest mining operations and is a considerable challenge for the engineer employed.[30] During the updating, the AI-driven system developed by Yin extends the direct forecasting to perform an automatic model uncertainty reduction by evaluating new well observations. In other words, geological analysis immediately becomes less error-prone without the need for conventional model rebuilding, which significantly reduces the time required and, at the same time, minimises any risks relating to the environment.

The SCERF programme is funded by industrial members of the minerals and energy industries, as well as government agencies and the Stanford Doerr School of Sustainability in Groundwater and

26 The following analysis refers to an evaluation of all SCERF projects that can be found on this page: SCERF (2023). Research. https://scerf.stanford.edu/research

27 Caers, J.K. (2018). Quantifying uncertainty about Earth's resources. Eos (99). https://doi.org/10.1029/2018EO097471.

28 Yin (undated). Automated uncertainty quantification of geological model using Bayesian Evidential Learning. SCERF. https://scerf.stanford.edu/automated-uncertainty-quantification-geological-model-using-bayesian-evidential-learning

29 The approach cites Bayes and his notion of "prior uncertainty", which captures what we already know about the unknown before acquiring data. Thus, even before specific deposits are exploited, we already know a lot about the subsurface, since a geological depositional system has numerous analogies to other parts of the earth. The Bayesian approach requires a quantification of this geological ex-ante information.

30 Sinking is the construction of vertical cavities such as shafts or cavities for the extraction of deposits.

Geothermal Resources. Current SCERF corporate collaborations are looking at groundwater management in Denmark, production planning for a complex reservoir in Libya, appraisal of a West African deep-water turbidite reservoir using seismic data, remediation of uranium contamination in the US, predictive Big Data analytics for shale deposit optimisation, automated data prediction in mineral resource evaluation, and the use of BEL for gas reservoir management.[31] As this list indicates, previous modelling of the ground topography has mainly taken place in the non-European area, most notably Antarctica, Canada, China, and the USA, as well as in the Gulf of Mexico. From a European perspective, it is therefore worth highlighting that the SCERF programme has also looked at geophysical data in the Danish aquifer system, in a research paper by Lijing Wang on quantifying uncertainty on the flow and transport of nitrate.[32] In terms of content, this is essentially about the management of fertiliser residues rather than rare earths, but methodologically it is of interest that the analysis was also able to draw on high-quality data in this European context, including hydrological and geochemical information on nitrate distribution as well as so-called tTEM data. The tTEM system is an electromagnetic system designed for detailed, yet fast and cost-effective 3D geophysical and geological mapping of the shallow subsurface.[33]

In addition to the cooperation between KoBold and Stanford University, there are a handful of other startups working in this area. **EarthAI** is an Australian start-up that also uses AI methods to find potential raw material deposits.[34] The company describes itself as a "vertically integrated metals exploration company", specialising in those metal ore deposits needed to build renewable energy infrastructure. So far, it says it has tested 135 AI-generated targets in previously unexplored land and discovered 35 deposits. This amounts to a success rate of 26%; i.e. significantly higher than for the conventional process described above. After discovering relevant deposits, EarthAI enters into collaborations with developers to bring these deposits into production (unlike KoBold, which does the development itself, which increases the entrepreneurial risk). The projects are currently being run in Australia (Northern Territory and New South Wales) with a focus on battery metals (nickel, cobalt, vanadium, chromium), electronics metals (gold, silver, platinum, palladium), electricity metals (copper, zinc, lead, manganese) and generator metals (rare earths, tin, tungsten, molybdenum, tantalum, niobium).

In order to expand European sovereignty in the area of critical minerals, further complementary initiatives are necessary that concern other parts of the value chain besides the exploration of existing deposits, but which can also benefit from machine learning methods. For example, scientists have recently found a new AI-driven way to facilitate the search for new rare earth compounds. Here, too, the algorithm examines a database of information (in this case relating to rare earth compounds) and recognises correlations that make it possible to find new potential compounds. Since it is impossible to theoretically or experimentally test all possible compounds, scientists have built an AI model that can quickly test hundreds of permutations and then evaluate the phase stability of each compound. In other words, the AI can judge whether or not a rare earth compound will come apart. If Europe wants to achieve strategic sovereignty in the field of critical metals and, at the same time, its ambitious goals

[31] SCERF (2023). Research. https://scerf.stanford.edu/research.

[32] Wang, L. (undated). Quantifying uncertainty on flow and transport of nitrate using geophysical data in the Danish aquifer system. SCERF. https://scerf.stanford.edu/quantifying-uncertainty-flow-and-transport-nitrate-using-geophysical-data-danish-aquifer-system-0

[33] HydroGeophysics Group (undated). tTEM. https://hgg.au.dk/instruments/ttem

[34] See the company's profile at: https://earth-ai.com/

for an ecological transformation of the economy, such creative thinking and a comprehensive approach to promoting appropriate AI systems are urgently needed.

3.3 Problems and limits

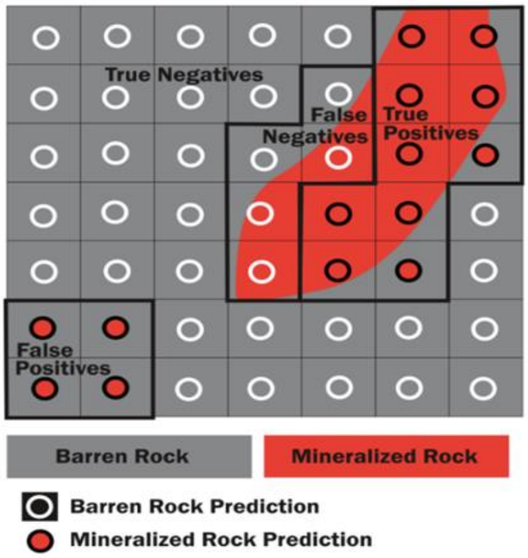
Although this **cepInput** argues that the use of AI systems in exploration and surveillance, such as those currently being developed by companies like KoBold and EarthAI or researchers like those at Stanford University, could make a significant contribution to improving Europe's information base, it is essential to consider the potential technical problems and regulatory uncertainties of this technology, before deploying and promoting it in Europe. Unlike many other areas of AI application, which can draw on a treasure trove of relevant observations gathered over many years, drilling data for the areas where completely new deposits are to be discovered does not yet exist. The clustered nature of the data around known deposits is probably the biggest challenge for the application of AI-driven software in this field, as geologists do not usually have many positive examples with which to train an algorithm to recognise similar areas or minerals. Currently, therefore, the greatest potential for AI-driven exploration is to rely more on indirect measurements from geophysics and geochemistry and to extrapolate them or subject them to more detailed interpretation. It is no accident that one of the key arguments for KoBold's initial focus on Canada was the simple fact that the country has vast amounts of publicly available survey data, including detailed field reports, geochemical data from borehole samples, aerial magnetic and electromagnetic survey data, lidar measurements and collections of satellite imagery going back decades.[35] The question is, therefore, whether there is similarly detailed data that is just as readily available for the European continent. To give an impression of the necessary granularity of the data: As mentioned above, AI systems for predicting critical minerals need data stored in a 3D space representing the cubic area in which targets are to be evaluated. The distance between the "blocks" in this 3D space should ideally correspond to the scale of a drilling target, i.e. 50 to 200 metres.[36]

The quality of existing data is relevant, not least in the context of emerging EU data regulation. Geological data is often very patchy in terms of both space and time. This patchiness, together with inconsistent data quality, can lead to AI systems detecting false signals or making incorrect predictions. For a clear understanding of the problem, it is necessary to briefly outline how supervised learning of AI systems works. At its core, supervised learning means that an AI system learns through examples. The model is given an input variable with a corresponding correct identifier or "label". During training, the model sees which label corresponds to the data and can thus find patterns between the data and these labels. Spam detection systems, whereby a model is trained to classify which emails are spam and which are not, are a typical example of such supervised learning. An analogous application of machine learning for targeted exploration in the mining sector would be the classification of ore and waste. Figure 1 illustrates the typical procedure whereby companies such as KoBold or EarthAI feed the relevant data into a machine learning algorithm to optimise the automatic classification of ore blocks and waste blocks in 3D space. The "true positives" identified in this process promise a high probability of success in the event of drilling.

[35] Stone, M. (2021). The big tech quest to find the metals needed for the energy overhaul. MIT Technology Review (11.08.2021). https://www.technologyreview.com/2021/08/11/1031539/the-big-tech-quest-to-find-the-metals-needed-for-the-energy-overhaul/

[36] Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243, p. 4.

Figure 1: Illustration explaining possible AI predictions in mineral exploration



Source: Desharnais et al. (2017).

The problem now is that any imbalance in the number of positive and negative examples in the data set is highly problematic for machine learning - and potentially makes it error-prone, which can lead to an increased number of so-called "false negatives" and "false positives" (see Figure 1). In practice, this would correspond to an increased error rate during drilling. Regrettably, a review of existing data sets in the mining sector suggests that they do indeed contain an uneven distribution of positive and negative examples.[37] The data is often heavily clustered around known deposits with few data points in areas that have yet to be explored. Drill data is the most reliable but very localised, while geophysical or geochemical surveys sometimes cover only a fraction of the terrain to be investigated. In some cases, there are no known deposits of certain minerals on the property in question, so no positive examples are available at all. In addition, there is a significant disparity within the different classes of data required for AI-driven exploration; in particular, the number and quality of geochemical data vary greatly. Using an AI system that has been trained on an apparently analogous project can therefore prove to be completely misleading: "Training an algorithm on data from Alaska and applying it to Nevada means it might have a lot of wrong assumptions," Sam Cantor, head of product at **Minerva Intelligence**, another AI-driven mining exploration startup, stated in an interview.[38]

The question, therefore, is whether, in the future, it will be necessary to carry out special quality control of the training data of AI mining start-ups in the EU. This would be the case, in particular if such systems were developed and used not only for the quantification of geological resources but also for extracting the reserves. In the latter case, they could be considered "high-risk" under the EU AI Act currently under negotiation, meaning they would have to meet specific requirements regarding the design and quality of training datasets (these should be relevant, representative, error-free and complete). The proposal for the AI Act was presented by the European Commission on 21 April 2022 and aims to regulate AI based on its potential for harm. The Commission is now waiting for the Council

37 Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243, p. 4.

38 Beiser, V. (2022). These Algorithms Are Hunting for an EV Battery Mother Lode. WIRED (12.12.2022). https://www.wired.com/story/these-mining-algorithms-are-hunting-for-an-ev-battery-mother-lode/

and the European Parliament to define their positions before the inter-institutional negotiations take place in 2023.

A crucial part of this AI legislation is the question of which AI applications should be classified as high-risk, as these will have to meet strict requirements. According to the current draft, a high-risk classification can be made in two ways.[39] Firstly, an AI system may be contained in a product that falls under EU harmonisation rules, such as an AI-driven machine for mining. In this case, the text specifies that an AI system must be classified as high-risk if its failure or dysfunction could endanger a person's health, safety or fundamental rights. The aforementioned dysfunction of AI classifications in the mining sector could result in damage to health or safety if, for example, unintended environmental damage results from a mining area identified by AI, which a human could have foreseen. Secondly, AI applications will be considered high-risk if they fall within the areas and types of use listed in Annex III of the draft. Although specific mining activities are not yet listed in Annex III, it does contain a category entitled Critical Infrastructure, which so far includes AI systems used as safety components in the management and operation of critical digital infrastructure, road transport and the supply of water, gas, heating and electricity. In addition, the Commission will presumably have the power to amend the list in Annex III by adding or deleting high-risk areas or specific types of use if the AI system "poses a serious risk of harm to health and safety or a risk of adverse impact on fundamental rights, the environment or democracy and the rule of law". For the same reasons as outlined above, mining companies that develop or use AI systems could be expressly included in the regulatory framework of the AI Act at a later stage, when they become more active on the European market.

In this discussion, it is essential to differentiate between exploration and the extraction of raw materials. The algorithms described in section 3.2 are initially aiming to quantify geological resources, not reserves (i.e. that part of the resources that can be economically extracted). The decision to mine - and thus the responsibility for most of the potential environmental damage - would thus remain with the mining companies. In addition, the EU's proposed AI Regulation does not apply to AI systems, or their results, that are specifically developed or put into operation for the sole purpose of scientific research and development. Nevertheless, the example of KoBold described above shows that in the future there will be vertically integrated companies that translate the findings of their AI systems directly into the purchase and physical analysis of certain areas. In addition, it should be emphasised that AI systems are generally developed and distributed via complex value chains, which makes it difficult to precisely determine the legal responsibility of AI software developers towards its users within the meaning of the AI Act. The Commission's proposal is essentially based on a linear view of the AI value chain, whereby a company brings a particular AI system onto the market and, if the system is deemed to be high-risk, is made responsible for compliance with the Regulation.[40] In this regard, reference should be made to the recent compromise text, which contains some amendments aimed at exploring the distribution of roles and responsibilities in the AI value chain.[41] Even if the EU legislation is not applicable to pure quantification efforts, in all cases where the number and/or quality

[39] Bertuzzi, L. (2022). Leading MEPs exclude general-purpose AI from high-risk categories - for now. EURACTIV (12.12.2022).

[40] On this issue, see: Engler, A. & Renda, A. (2022). Reconciling the AI Value Chain with the EU's Artificial Intelligence Act. CEPS In-Depth Analysis, September 2022 - 03. https://www.ceps.eu/ceps-publications/reconciling-the-ai-value-chain-with-the-eus-artificial-intelligence-act/

[41] Proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts - General approach. Brussels (25.11.2022) 25 November 2022 (OR. en), 14954/2.

of geological and physical data is not guaranteed, greater validation by experts should be secured in order to avoid erroneous conclusions which could have negative consequences.[42]

Even if a sufficiently granular and high-quality set of training data for Europe, that is possibly compliant with the AI Regulation, can be generated and shared, the current technical application problems of AI-driven systems still need to be taken into account. Exploration geologist Guy Desharnais, who has researched mining applications for machine learning and in principle advocates its usefulness, joins several colleagues in urging further basic research to ensure robust application of AI in the mining sector.[43] According to his findings, further research is needed to identify the most robust and productive algorithms capable of predicting ore bodies. The input data as well as the "output" must also be carefully checked to ensure that the model does not simply predict what is already known or provide incorrect results. This, says Desharnais, will require high-quality geoscientific data, solid interpretations, common sense and, in most cases, several iterations to understand what exactly the AI is predicting.[44]

This requirement is also in line with recent developments in the EU's digital legislation. Already the Ethics Guidelines of the Commission on Trustworthy AI, published in 2019, have identified human agency and oversight as one of the core principles of ethical AI.[45] This document introduces the concepts of "human in the loop" as the capability for human intervention and "human on the loop" for monitoring overall activity. As far as the AI Act is concerned, the current draft of Article 14 (1) requires that high-risk AI systems be designed and developed in such a way that they can be effectively overseen by natural persons during the period in which the AI system is in use, including with appropriate human-machine interface tools. Some critics argue that the AI Act so far fails to identify and regulate more precise mechanisms for effective human oversight.[46] They call for greater clarity about when and where humans will have the final word in decision-making, or when mere human monitoring of the system is enough. Due to the imponderables that have been identified, this would also be desirable for the technology's outlined areas of use in the mining sector.

Since the target metals, once located, still need to be physically mined, which is environmentally damaging, an important task for any AI-driven exploration tool is also to minimise the environmental impact. According to KoBold, the company itself decides where prospecting takes place, and states that it will only work in areas where the mining of certain minerals is ethical and supported by the affected community.[47] It is questionable whether interdependencies between the potential excavation

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42 This is also the demand of: Davies, S. (2020). Assessment of Methodologies to Predict Potential Mineral Endowment on Entering an Immature Exploration Space, using the Western Australian Sandstone Orogenic Gold District as a Natural Laboratory. Doctoral Thesis, The University of Western Australia.

43 Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243

44 These statements refer to the interview Guy Desharnais gave to MIT Technology Review. See: Stone, M. (2021). The big tech quest to find the metals needed for the energy overhaul. MIT Technology Review (11.08.2021). https://www.technologyreview.com/2021/08/11/1031539/the-big-tech-quest-to-find-the-metals-needed-for-the-energy-overhaul/

45 European Commission (2019). Ethics Guidelines for Trustworthy AI. https://ec.europa.eu/futurium/en/ai-alliance-consultation.1.html.

46 Domingo, S. (2022). Human intervention and human oversight in the GDPR and AI Act. Trilateral Research Ethical AI (31.05.2022). https://trilateralresearch.com/research-highlights/human-intervetion-in-gdpr-and-ai.

47 Stone, M. (2021). The big tech quest to find the metals needed for the energy overhaul. MIT Technology Review (11.08.2021). https://www.technologyreview.com/2021/08/11/1031539/the-big-tech-quest-to-find-the-metals-needed-for-the-energy-overhaul/

site and other nearby metals, ethical legitimacy and local popularity of the measures, can be taken into account by an AI system. This is not the case, at least, for the AI exploration systems whose functioning is described in publicly available documents, because these consider each 3D block as a single entity, and there are no feedbacks to external metadata.[48] In other words, each virtual block in the 3D system is analysed in isolation, without taking account of its spatial position within a larger image. Creating an AI system whereby potential trends in data could be correlated between neighbouring blocks would exponentially increase the mathematical problem to be solved and probably poses insurmountable problems for most start-ups in this field. Nevertheless, these considerations only apply to the consideration of spatial interdependencies. Social indicators regarding the ethical defensibility and acceptance, such as are already regularly collected in surveys across Europe, or could easily be collected, can presumably be integrated into the data set relatively easily as overarching external parameters; if only because they are necessarily more large-scale than the geological investigations. As explained lower down, when it comes to social and ecological sustainability, the algorithms promoted for the exploration of rare earths in Europe should not, therefore, be limited to just the primary deposits but should also evaluate information on the expected environmental effects of commercial exploitation.

This underlines the ultimate need for a so-called "human in the loop" system for the mining sector, in line with the aforementioned Ethical Guidelines of the Commission for Trustworthy AI and the demands of most experts. In recent years, the term has become widely used in the field of AI, where it essentially refers to AI systems in which the combined effort of humans and machines helps to improve overall results and accelerate machine learning.[49] In such systems, there is usually continuous interaction between the human supervisor and the AI to train a model and then continuously update it as soon as it is deployed. A good example is the AI system of the SGS Geostat team, which won the "Integra Gold Rush Challenge" in 2016. This innovation competition released historic data on the Sigma-Lamaque gold property in Val D'Or, Canada, and challenged the public to find innovative ways to identify relevant drill targets. The winning submission combined a traditional weight of evidence approach with machine learning and virtual reality target vetting.[50] Only through this combination of qualitative and quantitative analysis and human validation did a concrete added value emerge while reducing unforeseen risks. Kobold had the same experience: Once the AI predictions had been made by the company's in-house computer scientists, it was necessary for staff with geological expertise to apply their intuition to sift out unlikely proposals and figure out how to drill a single hole to narrow down the remaining possibilities as much as possible to be even more cost-effective.[51]

Finally, there are challenges in the area of education. Significantly, two-thirds of the KoBold team are data scientists or software engineers who have never worked in exploration; the other third are

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48 This relates to the model outlined in: Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243, p. 5.

49 Humans in the Loop (undated). What is a Human in the Loop? https://humansintheloop.org/what-is-a-human-in-the-loop/.

50 Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243, p. 3.

51 Beiser, V. (2022). These Algorithms Are Hunting for an EV Battery Mother Lode. WIRED (12.12.2022). https://www.wired.com/story/these-mining-algorithms-are-hunting-for-an-ev-battery-mother-lode/

experienced miners.[52] So if Europe wants to import this technology, technical expertise in AI, ideally coupled with some basic knowledge of earth sciences, is urgently needed. However, according to experts, there are very few courses, information platforms or vocational training programmes that comprehensively cover all aspects of decision-making under uncertainty in the mining industry.[53] The problem lies in the multidisciplinary aspect, which requires knowledge of geosciences, data science, computer science and decision science. Empirically, this problem manifests itself in inconsistencies between expert estimates and data-driven estimates, as well as in inconsistencies between different groups of experts charged with assessing the presence of certain minerals.[54] This can be explained by the use of different strategies as well as differences in background experience leading to varying uncertainty assessment skills. The authors of this comparison therefore suggest practical scenario-based training programmes and careful team selection to maximise skill diversity as a way to improve assessments.[55]

[52] Beiser, V. (2022). These Algorithms Are Hunting for an EV Battery Mother Lode. WIRED (12.12.2022). https://www.wired.com/story/these-mining-algorithms-are-hunting-for-an-ev-battery-mother-lode/

[53] Caers, J.K. (2018). Quantifying uncertainty about Earth's resources. Eos (99). https://doi.org/10.1029/2018EO097471

[54] Davies, S. (2020). Assessment of Methodologies to Predict Potential Mineral Endowment on Entering an Immature Exploration Space, using the Western Australian Sandstone Orogenic Gold District as a Natural Laboratory. Doctoral Thesis, The University of Western Australia.

[55] Davies, S. (2020). Assessment of Methodologies to Predict Potential Mineral Endowment on Entering an Immature Exploration Space, using the Western Australian Sandstone Orogenic Gold District as a Natural Laboratory. Doctoral Thesis, The University of Western Australia.

4 Promoting AI in the context of EU raw materials policy

4.1 Consideration in the EU raw materials strategy

The strategic importance of critical raw materials was first highlighted by the European Commission in 2008 by way of a "Raw Materials Initiative".[56] Even then, the Commission saw that expanding the knowledge base concerning deposits located in the EU was an essential step on the way to reducing supply uncertainties. To this end, a better exchange of information between the national geological institutes was called for. At that time, there was no talk of using artificial intelligence in exploration. The subsequent Communication "Commodity Markets and Raw Materials" in 2011 then presented the first list of critical raw materials.[57] The existence of such critical raw materials led to the call for a harmonised European database on raw material deposits to be set up. The Commission's Report on *Critical Raw Materials and the Circular Economy*, published in 2018, recommends the same thing for recording secondary resources from waste along the supply chain.[58] The 2020 *Action Plan on Critical Raw Materials* points to the significant potential of remote sensing offered by the European Earth Observation Programme *Copernicus*. These will be used to a greater extent in future, as part of the action plan, both for locating deposits and for the environmental monitoring of existing extraction regions.[59] Even if the use of AI is not explicitly mentioned here, it is clear, according to experts, that the large volume and diversity of the data provided by *Copernicus* suggest an increasingly AI-based evaluation.[60] In this context, it should be noted that new and improved ways to access *Copernicus data* have been available since the end of January 2023, making it easier for interested companies to obtain relevant geodata for training AI systems.[61]

The Commission has announced the drafting of comprehensive legislation, for the end of March 2023, to improve the handling of critical raw materials. Initial details of the content emerged in autumn 2022 as part of the associated consultation process. Thus, "improving the EU's monitoring, risk management and governance in the field of critical raw materials" will be one of four main pillars of the legislative proposal.[62] In addition to mapping tools, early warning systems and stress tests for supply chains are mentioned as possible monitoring tools, i.e. domains whose complexity will most likely require the use of AI. The Commission's concept indicates that the contribution of AI to securing the supply of raw materials could therefore be of a more comprehensive nature and go beyond the mere exploration of deposits. The extent to which this will also be linked, under the legislative proposal, to rules or recommendations on the use of state funding instruments is unclear from the consultation documents.

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56 European Commission (2008). The raw materials initiative - meeting our critical needs for growth and jobs in Europe Communication from the Commission to the European Parliament and the Council. COM(2008) 699.

57 European Commission (2011). Tackling the Challenges in Commodity Markets and on Raw Materials Communication from the Commission to the European Parliament and the Council. COM(2011) 25.

58 European Commission (2018). Report on Critical Raw Materials and the Circular Economy.

59 European Commission (2020). Critical Raw Materials Resilience: Charting a path towards greater security and sustainability. Communication from the Commissions to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. COM(2020) 474.

60 German Federal Government (2021). Copernicus: Neue Dimensionen. Nationales Forum für Fernerkundung und Copernicus 2021 - 23. bis 24. März 2021. Ergebnisbericht.

61 EARSC (2023). EOcafe: The New Copernicus Data Access Service (06.01.2023). https://earsc.org/2023/01/06/eocafe-the-new-copernicus-data-access-service/.

62 European Commission (2022). European Critical Raw Materials Act - Call for evidence for an impact assessment. Ref. Ares(2022)7155798.

4.2 Justifying eligibility for funding

From an investor's perspective, the decision to explore new resource deposits - just like the mining of existing deposits - must be subject to a dynamic optimisation calculus. Exploration activities give rise to costs in the present; the return on these costs can only be expected in the future in the form of a larger reserve of mineable resources. This return is subject to uncertainty at the time of the decision and must therefore be significantly marked down. The uncertainty relates not only to the question of finding resources but also to their economic viability. In addition, there are also regulatory risks in many cases, i.e. uncertainty as to whether commercial mining of new deposits will be permitted in the long term and, if so, under what conditions. Compared to alternative investments, therefore, the expected return from exploration projects will typically have to factor in high risk premiums. Taking AI-generated indicators into account in decision-making can help to reduce uncertainties or at least make existing risks more transparent. From an investor's perspective, AI can thus help to reduce capital costs and make exploration projects more attractive.

Nevertheless, a political push is needed to set up suitable service markets in Europe. This is due to two peculiarities: the existence of information externalities in the exploration sector[63], and economies of scale in the market for AI service providers. Exploratory activities always give rise to new knowledge, even if unsuccessful. Obligations to disclose data collected during exploration (as in Australia, for example[64]), give rise to an immediate information gain for the public domain, and thus also for potential competitors. And even without mandatory disclosure, conclusions can be drawn from observing whether or not projects are continued. Investors themselves see no benefit in this **positive information externality**, which, in the worst case, may even result in reluctance to invest. From society's point of view, this means that even if the existing risks are correctly assessed, there is a tendency to invest too little in exploration activities. In principle, this speaks in favour of publicly funded financial support for exploration projects.

In the case of AI-based exploration, the economic characteristics of algorithms provide an additional justification. **Economies of scale** exist here in both static and dynamic forms. On the one hand, the fixed costs of algorithm development and verification dominate the cost structure compared to the variable costs of selling algorithm-based products. The costs to be covered per customer are thus likely to be relatively high when entering the market and to fall continuously as the customer base grows. This effect is reinforced by the dynamic economies of scale: A growing customer base means there is more data to optimise the algorithms, further improving the quality of the AI service.[65] Not only could State support accelerate this process, but in the case of Europe, it could also help prevent the long-term emergence of non-European monopolies in this segment, thus contributing to the overarching geopolitical goal of reduced dependence and increased European sovereignty, including in the raw materials sector.

Both effects also reinforce one another. In addition to data provided by the customer, information externalities from external projects may also contribute to the optimisation of the algorithms.

[63] Fogarty, J.J., & Sagerer, S. (2016). Exploration externalities and government subsidies: The return to government. Resources Policy (47), pp. 78-86.

[64] Australia Minerals (2022). Legislation, regulations and guidelines. https://www.australiaminerals.gov.au/legislation-regulations-and-guidelines#exp.

[65] Varian, H. (2018). Artificial intelligence, economics, and industrial organisation. In: The economics of artificial intelligence: an agenda. Chicago, US: University of Chicago Press, pp. 399-419.

Conversely, the widespread use of specialised AI will enable more efficient use of publicly available information. These potentials can be used for both entrepreneurial and regulatory purposes. In the future, for example, AI could potentially be used in public approval procedures for the award of exploration and mining licences. AI could thus help to reduce administrative costs and the length of approval procedures, one of the most significant bottleneck factors in project development.

5 Recommendations for EU action

Following pandemic-related uncertainty at the start of 2020, which stalled field activity in the mining sector, drilling picked up again as of September 2020, leading to full-year results of 41,026 wells drilled on 1,098 projects. Both figures increased considerably in 2021: 68,982 wells were registered with 1,611 projects, representing an increase on the previous year of 68% and 47%, respectively.[66] This trend has not yet reached Europe, however. Based on our research into examples of current applications in the field of AI-driven discovery and extraction of critical minerals; and based on the preceding discussion of eligibility for funding and the potential technical and regulatory uncertainties, we recommend the following supporting measures at the European level.

1. **Requirements for better access to reliable geodata**

There is a need for better, simpler and cheaper ways to access high-quality public geodata. It is worth using sufficient resources to quickly push ahead with the necessary digitalisation process because the data that is generated, and the AI systems that are developed based on that data, will have implications far beyond the extraction of rare metals and may also galvanise other areas of application that use geological or ecological map data. The experience of the US defence agency DARPA, and the companies MITRE and NASA Jet Propulsion Laboratory, show that the most significant potential for a short-term solution to acute data needs is to improve geo-referencing and the extraction of individual geological features on existing digitised or scanned maps.[67] Targeted financial support, innovation challenges (see below) and regulatory frameworks for the acquisition, exchange and use of relevant data should therefore be aimed primarily at this point in the AI “workflow”.

On the latter point, necessary regulatory steps have already been taken or are currently in the process of becoming law: At the European level, the INSPIRE Directive 2007/2/EC already stipulates that Member States must provide certain geodata sets. The Data Governance Act, applicable from 24 September 2023, will regulate access to protected public sector data and facilitate the sharing of data within the EU, for example, through data brokering services, data cooperatives and "data altruism" organisations.[68] However, as the EU Regulation only encourages (rather than obliges) public authorities to provide data, success depends mainly on their willingness to do so voluntarily.[69] Last but not least, there is the Data Act, which aims to ensure that the value creation derived from data is distributed more fairly among the actors in the data economy, and to that end formulates data sharing obligations for data owners (usually manufacturers of Internet of Things products and providers of connected services).[70] However, in view of the very varied challenges regarding the exchange of data, illustrated

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66 S&P Global Market Intelligence (2022). World Exploration Trends. PDAC Special Edition April 2022, p. 17.

67 See the report at: DARPA (2022). DARPA Announces Winners of AI for Critical Mineral Assessment Competition (16.12.2022). https://www.darpa.mil/news-events/2022-12-16

68 Regulation (EU) 2022/868 of the European Parliament and of the Council of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724 (Data Governance Act), OJ L 152, 3.6.2022, p. 1-44.

69 Eckhardt, P. & Anzini, M. (2021). cepPolicyBrief on COM2020_767. cep**PolicyBrief** 6/2021.

70 Proposal for a Regulation of the European Parliament and of the Council on harmonised rules on fair access to and use of data (Data Act). COM/2022/68 final.

here by the example of mining, specific data-sharing obligations adapted to the particular features of the respective sector would be more effective, which tends to argue in favour of a more nuanced, sector-specific regulatory approach.[71] The scope of the Data Act also needs to be clarified. Finally, the EU is currently planning twelve common European data rooms in strategic sectors and areas of public interest. They are intended to enable more intensive sharing and reuse of data.

The Commission also published a list of so-called "high-value datasets" on 20 January 2023, which public bodies must make available for re-use free of charge within 16 months.[72] The data sets must be made available in machine-readable format via a programming interface, which is why they can be used easily and quickly as training data for machine learning applications - such as those already being developed by the start-ups described above. The Regulation is based on the Open Data Directive, which defines six categories of high-value data sets: geospatial, earth observation and environment, meteorological, statistics, companies and mobility. Of particular relevance for mining start-ups will be the earth observation and environment category, which includes space-based, remote sensing, ground-based and in-situ data, as well as environmental and climate datasets that fall within the INSPIRE data themes under Directive 2007/2/EC.[73] The latter heading includes data themes such as hydrography, geology, biogeographical regions, land use, mineral resources and soils – precisely the kind of data that start-ups like KoBold are already successfully analysing outside Europe. In addition, it should be noted that the Regulation allows this range of themes to be expanded at a later date. This should allow even greater account to be taken of technological and economic developments in the mining start-up sector in the future. In addition, there should be insistence on rapid implementation of the Regulation: If possible, the data needed for rare metal exploration should be made available sooner than the 16 months specified in order to support the Commission's current *cleantech initiative*, even if this may only be possible for certain regions of Europe. Finally, domain experts should check whether the data provided is actually granular enough to enable AI activities by mining start-ups.

2. Promotion of AI-supported raw material exploration

More financial support is needed for European start-ups in this niche sector because previous investments and support programmes have focused mainly on non-European regions and companies. Prices for most commodities continued their upward trend in 2021, which was rewarded accordingly by the capital markets: Financing by junior and intermediate companies increased to $21.55 billion in 2021, almost double the amount disbursed in 2020.[74] However, almost two-thirds of the increase came from companies in Australia and Canada, whose total budget increased by $556 million compared to 2020.[75] Europe urgently needs to catch up here. The argument in favour of supporting exploration activities does not yet include a call to embark on mining in Europe because, due to the resulting (positive) information externalities, exploration can still offer added social value, even if one concludes that starting to mine would have predominantly (negative) environmental effects. Accordingly, it must be emphasised that our argument for funding eligibility refers to the use of AI in exploration, which is not to say that AI in mining is not useful, but the funding eligibility of a European metal mining industry is a more fundamental question that is beyond the scope and scale of this cep**Input**.

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[71] Eckhardt, P. & Hoffmann, A. (2022). cepPolicyBrief on COM(2022) 68. cep**PolicyBrief** 11/2022.

[72] Commission defines high-value datasets to be made available for re-use. https://digital-strategy.ec.europa.eu/en/news/commission-defines-high-value-datasets-be-made-available-re-use.

[73] Commission Implementing Regulation (EU) 2023/138 of 21 December 2022 laying down specific high-value data sets and the arrangements for their publication and re-use, OJ L 19, 20.1.2023, p. 43-75.

[74] S&P Global Market Intelligence (2022). World Exploration Trends. PDAC Special Edition April 2022, p. 5.

[75] S&P Global Market Intelligence (2022). World Exploration Trends. PDAC Special Edition April 2022, p. 12.

3. Organising innovation competitions for deploying AI in the mining sector

The interaction between research and the application of AI in the mining sector can be improved enormously by way of targeted innovation competitions, even with small financial incentives. Given the current urgency to increase and further secure the supply of critical minerals, the US defence agency, DARPA, together with the US Geological Survey (USGS), launched the AI for Critical Mineral Assessment Competition in August 2022.[76] The partnership will help the USGS to conduct assessments for more than 50 critical mineral resources to improve economic planning and land-use decision-making. The competition aimed to gather ideas to drastically speed up at least parts of the assessment process by using AI to automate critical processes. A total of 18 teams from industry, academia and even a high school student competed for cash prizes in the low five-figure range. Holding a similar competition in Europe could help the Commission and specialised mining companies to automate key steps in the evaluation of geological maps of mineral deposits crucial to the European economy and security.

4. Establishing technical standards and transparency rules for the use of AI in the mining sector

Avoiding errors or inconsistencies in the underlying data is crucial in preventing false results or undesirable side effects. Experts in the mining sector point out that even simple inconsistencies such as differences in the units – for example, g/tonne versus ounce/tonne – occur and have a detrimental effect on AI forecasts.[77] This can be counteracted by uniform standards and minimum quality requirements for the data sets to be used. A good example is the guidelines and standards for collecting, processing and inversion of tTEM data recently developed by the Danish Environmental Protection Agency and the Institute of Geosciences at Aarhus University.[78] In addition, it is necessary to ensure that interdependency effects - especially the critical environmental aspects - are always taken into account, even in AI-driven processes ("human in the loop"). In order to meet the high-quality standards set by the future European data legislation, existing AI solutions need to be further evaluated and developed to become operational in the European context. In particular, neural networks, which have already proven extremely promising in many other industries, are usually entirely opaque and offer no way to understand the logic behind the conclusions reached. This could be problematic, for example, in the context of the EU's AI Act, mentioned above, which aims to make AI systems more transparent. Article 13 of the current draft states: "High-risk AI systems shall be designed and developed in such a way to ensure that their operation is sufficiently transparent to enable users to interpret the system's output and use it appropriately." However, as critics have pointed out, it does not sufficiently specify what it means for users of an AI system to interpret its results, nor does it indicate the technical measures that a provider must take to demonstrate the compliance of its system.[79] To counteract this legal uncertainty and to increase the confidence of the population and decision-makers in AI-driven exploration, the use of other more transparent methods,

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[76] DARPA (2022). DARPA Announces Winners of AI for Critical Mineral Assessment Competition (16.12.2022). https://www.darpa.mil/news-events/2022-12-16

[77] Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243, p. 4.

[78] HydroGeophysics Group (2020). Guideline and standards for tTEM data collection, processing, and inversion. Version 1.1 - November 2020. https://hgg.au.dk/fileadmin/HGGfiles/Reports/Guide_tTEM.pdf.

[79] Grady, P. (2022). The EU Should Clarify the Distinction Between Explainability and Interpretability in the AI Act. Centre for Data Innovation (31.08.2022). https://datainnovation.org/2022/08/the-eu-should-clarify-the-distinction-between-explainability-and-interpretability-in-the-ai-act/.

alongside a pure AI approach, is recommended, which would provide qualitative information on the relative weighting of different factors, referred to as "grey-box methods".[80]

Finally, standards will also be crucial if AI-driven process optimisation in existing mining areas takes place at a later date. As the aforementioned research by David Zhen Yin at SCERF shows, there have been significant automation gains in the field of well drilling that could generate economic efficiencies as well as reduce risks to the environment. Unlike the funding of exploration activities, the aim here is not to create positive externalities but to avoid already quantifiable negative externalities. This supports the use of binding standards as a control instrument.

5. **Creation of coordinated training and further education options**

Targeted training and further education options in the geosciences should be created and promoted. A review of the literature from experts in the sector showed that, in particular, information opportunities and training opportunities that comprehensively cover aspects of decision-making under uncertainty in the extractive industries, as well as practical scenario-based training programmes and careful team building, will facilitate direct and rapid improvements. Targeted funding and further training is therefore also necessary in the human capital sector in Europe. This is especially true since a recently published analysis of around 900 AI doctoral students in Germany showed that the EU only plays a subordinate role in this regard: The main countries of origin of these researchers are China, India and Iran; in addition, once doctorates have been completed, Europe loses a considerable proportion of its AI expertise to the USA, where talent is hired primarily by the well-known big tech companies.[81]

6 Conclusion

As the world shifts from fossil fuels to greener alternatives, it is becoming increasingly difficult to find the vast quantities of cobalt, lithium and other rare metals needed to build mobile phones, laptops and electric cars. Recently, the first start-ups have emerged that are capable of automating the search for potential mineral deposits with the help of AI, and thus make it more cost-efficient and faster. At the same time, this is a promising approach to identifying deposits eligible for funding, inside and outside the EU, if it is ensured that the underlying systems are trained on high quality data and that environmental aspects and interdependencies of the potential extraction sites are taken into account by "humans in the loop". However, the importance of information externalities in raw material discovery, the existence of economies of scale in algorithm development and the lack of technical standards make intensive regulatory support necessary for market development. The forthcoming EU legislation on critical raw materials should address this issue.

This cep**Input** argues in favour of a targeted EU funding policy in the field of AI-based exploration methods for rare commodities. It began by asserting that the technical possibilities for using modern AI in this area have also increased significantly in recent years. It uses several examples of non-European companies to demonstrate that these techniques are also viable for the raw material sector. At the same time, the analysis shows that the necessary regulatory conditions must first be created for successful take-up of AI in mining. On a practical level, this firstly involves ensuring that there is

[80] Desharnais, G., Paiement, J.P., Hatfield, D. & Poupart, N. (2017). Mining BIG Data: the Future of Exploration Targeting Using Machine Learning. Conference Paper October 2017. https://www.researchgate.net/publication/323243243, p. 3.

[81] Maham, P., Heumann, S., Denkena, W., Hemmen, L. & Semenova, A. (2022). Germany as an AI location: Destination or hub? Empirical investigation of the career paths of AI doctoral students at German universities. SNV Policy Brief (14.12.2022).

adequate human decision-making capacity within such automated systems. The evaluation of raw material deposits should never be limited to purely geological or economic parameters but should always include the social and ecological dimension. This makes algorithm development and the evaluation of algorithmic results particularly complex. Ensuring that there are "humans in the loop" increases the reliability of the analyses and at the same time guarantees that ethical standards are maintained. Secondly, state support will be necessary in the initial phase of market development in order to realise the economies of scale more quickly and to prevent the emergence of new monopolies in this sector from outside Europe.

Against this background, the cep**Input** makes five concrete recommendations to the EU for action. It should use provisions under data law to ensure that reliable and granular geodata are sufficiently accessible to the public. It should financially support promising AI start-ups in this field, during the initial phase, in addition to driving European innovation in this field such as using innovation competitions. Furthermore, the EU should set technical standards and transparency rules for using AI in the mining sector to reduce legal uncertainty and build trust in these technologies. Finally, it should launch targeted education and training programmes at the interface between AI and geosciences.

This article has focused on identifying existing resources by using new AI methods. Of course, this technology can also be used in many other ecological contexts. For example, a group of environmental scientists recently used AI to create a plan to end the dispute between Egypt, Ethiopia and Sudan over Africa's largest hydropower dam.[82] The countries had been trying unsuccessfully, since the start of construction in 2011, to agree on parameters such as the speed of project completion and the amount of water to be released. Using AI and climate models, the researchers were able to identify a scenario that balances transboundary economic and biophysical interests, maximises economic benefits and allows for the impact of climate change. This research illustrates how AI can map geological and socio-economic uncertainties more effectively, not least those arising from climate change, and create much-needed win-win solutions in sustainability management.

At the same time, AI-based exploration is only a first step towards strengthening Europe's security of supply in the area of critical raw materials. The resources identified must also be harnessed without jeopardising sustainability goals and Europe's economic performance. This will require various other measures with a view to the circular economy, administrative processes and resource diplomacy. AI can also be helpful in this regard, such as in identifying and categorising the raw material resources lying dormant in consumer products. Some of the necessary regulatory instruments will also be the subject of forthcoming EU legislation concerning critical raw materials, which cep will continue to follow closely. In this respect, it is essential that we take a first important step towards a future-proof supply of raw materials in Europe – which includes recognising and promoting the potential of AI as a digital divining rod.

[82] Basheer, M., Nechifor, V., Calzadilla, A. et al. (2023). Cooperative adaptive management of the Nile River with climate and socio-economic uncertainties. Nat. Clim. Chang. (13), S. 48–57.

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