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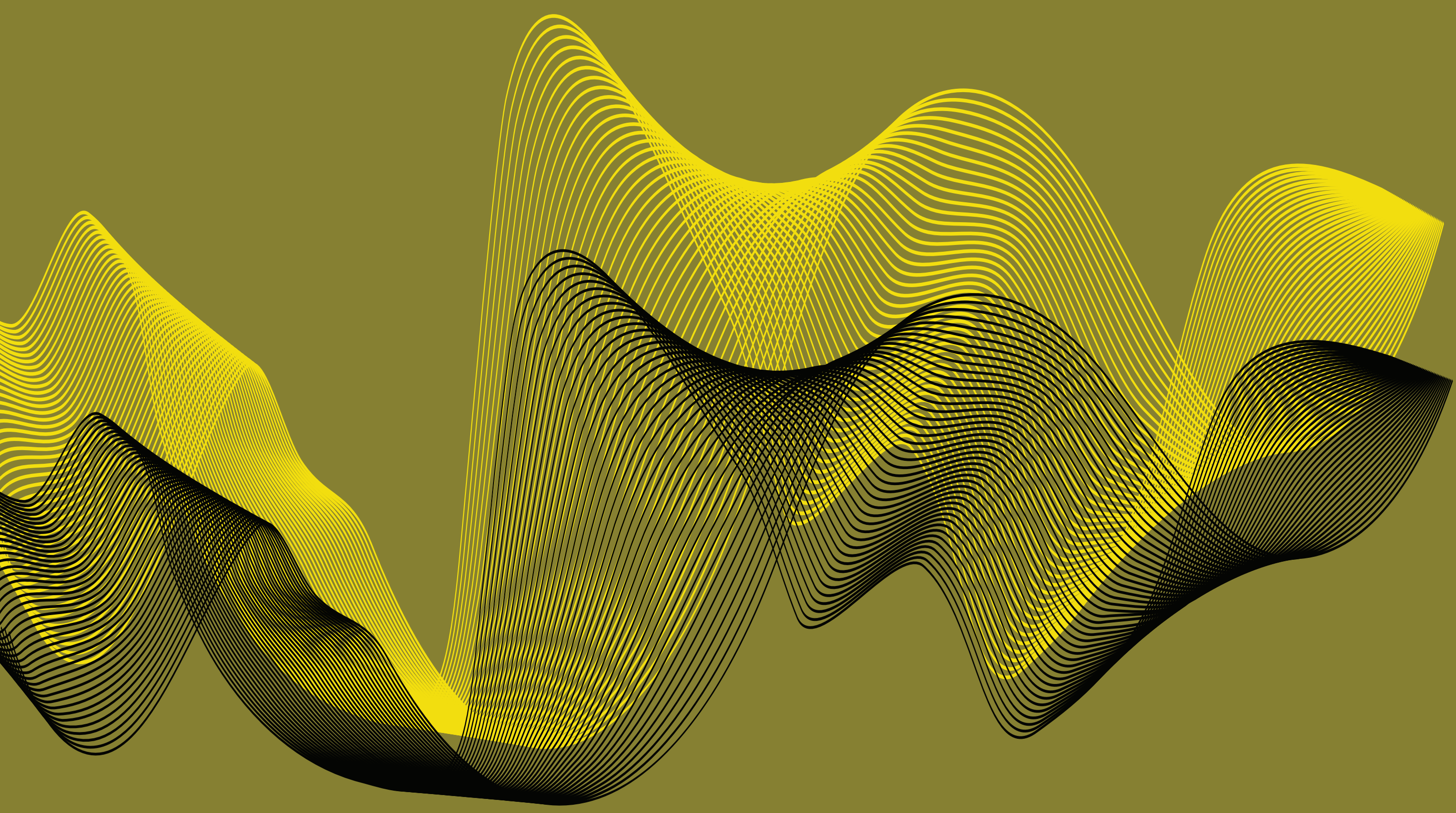
POLICY GUIDELINE

Recommendations on the Use of Synthetic Data to Train AI Models



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1. Scope

Using synthetic or artificially generated data in training Artificial Intelligence (AI) algorithms is a burgeoning practice with significant potential to affect society directly. It can address data scarcity, privacy, and bias issues but does raise concerns about data quality, security, and ethical implications. While some systems use only synthetic data, most times synthetic data is used together with real-world data to train AI models. Our recommendations in this document are for any system where *some* synthetic data are used. The use of synthetic data has the potential to enhance existing data to allow for more efficient and inclusive practices and policies. However, we cannot assume synthetic data to be automatically better or even equivalent to data from the physical world. There are many risks to using synthetic data, including cybersecurity risks, bias propagation, and increasing model error. This document sets out recommendations for the responsible use of synthetic data in AI training.

Definition: Synthetic Data are information created by computer simulations or algorithms that reproduce some structural and statistical properties of real-world data. Data produced by this "synthesis" process can be images, videos, text, or tabular data. Synthetic data are generally produced by a generative model, based on ground truth (domain knowledge, scientific theories, or collected data), which will produce new samples of synthetic data. More rarely, synthetic data can consist of logical rules.

It is important to note here that Large Language Models (LLM) also produce synthetic data. The output of LLMs is representative of the data they have been trained on, and data that were scarce in the training set will also be scarce in the output.

Synthetic data are increasingly being used to train AI algorithms, especially when real data is sensitive, scarce, or biased. The three main categories of synthetic data are fully synthetic — not based on real data, partially synthetic — only replacing (sensitive) elements of the real data with synthetic data, and hybrid synthetic – merging both real and synthetic data.

There are various ways of creating synthetic data. The earliest forms of synthetic data generators use statistical techniques to add missing data. Synthetic data can also be noisy versions of real-world data. With artificial intelligence advancements, Deep Generative Models based on neural networks have become the most preferred technique for generating synthetic data. Unlike AI models that classify inputs, Deep Generative Models are specialized in generating new outputs. They learn to generate new examples that mimic existing collected data. Such models can produce high-fidelity images, musical compositions, sensory data for autonomous cars or robots, patient electronic health records, or human mobility patterns in cities. LLMs are an example of Deep Generative Models.

There is a link between synthetic data and fake data, which is explored in Section 6. Note that fake data are synthetic data that are the *output* of an AI model, whereas our scope is synthetic data used to *train* an AI model. However, synthetic data can be derived from fake data.

2. Aims and objectives

The UN Secretary-General's AI Advisory Body has issued a report on Governing AI for Humanity,[1] and this needs to be complemented with recommended policy actions in specific areas such as synthetic data. Our recommendations aim to assist the work of all institutions who want to ensure that AI benefits humanity, and who need to consider synthetic data. The use of synthetic data is increasing globally, for two reasons. First, the increase in the adoption of AI systems requiring training data is leading to more pressure to create synthetic data, either to protect privacy or due to data scarcity. Secondly, generative AI systems have recently become much more accessible, lowering the technical requirements for those who wish to create synthetic data. In the coming years, therefore, appropriate governance of synthetic data systems will become central to AI and data governance conversations globally.

Furthermore, synthetic data, as they address data scarcity issues, have been seen as opportunities for fostering equitable AI development at the service of the SDGs (Sustainable Development Goals). Our aim is therefore that these recommendations support the attainment of the SDGs through AI in the Global South.

Our objective is to make recommendations useful to practitioners as well as lawmakers and even policymakers. The practitioners are Information Technology professionals, but also quality control inspectors, data curators, data governance officers, and others. As with so much of the IT sector, companies and governments have complementary roles and our recommendations are aimed at both.

3. Values

In constructing synthetic data, the source and nature of values driving the generation process significantly impact its relevance and ethical implications. The distinction between public and private sector values introduces considerations of transparency, accountability, and the potential influence of profit motives. Moreover, a rights-based approach emphasizes the importance of respecting individual privacy and ensuring that the synthetic data align with legal and ethical standards. Cultural values further contribute to shaping the context in which the data are generated, influencing decisions about what aspects of a society or community should be represented and how. Recognizing and navigating these diverse values is crucial for developing synthetic datasets that not only accurately reflect real-world scenarios but also uphold ethical principles, safeguard privacy, and avoid perpetuating biases or inequalities.

Synthetic data have a social impact on the global population. National and regional recommendations are important, but there is also a need for a global perspective. This report recommends ways to adhere to universal values recognizing the global data flows while simultaneously attending to the cross-cultural values that shape decision-making around synthetic data for training AI in varied local contexts. In making our recommendations, we bear in mind a variety of values that are foundational to the UN such as respect for fundamental human rights, social justice, equality, human dignity, and the right to development.

These recommendations also echo the values governing AI development expressed in the interim report 'Governing AI for Humanity' by the UN Secretary-General's AI Advisory Body, which include peace and security, human rights, sustainable development, governing in public interests, inclusiveness, promoting public data commons, universal, networked and multi-stakeholder collaboration, interoperability, etc.[2]

These values are linked to synthetic data in Sections 4 and 5.

4. Advantages of synthetic data

Synthetic data offer solutions to numerous challenges, such as rebalancing biased datasets, protecting privacy, and reducing the cost of data collection. These are summarized in Table 1, below.

Synthetic data use	Description
Data availability	Synthetic data can address data deficits and representation concerns by "completing" training datasets for AI systems.
Privacy protection	Synthetic data should not represent actual people, and so should not contain any personally identifiable information that might harm them in the case of a breach.
Bias reduction	Synthetic data can address imbalanced training datasets that lead to AI bias, as in the case of gender, or racial bias.
Compliance	Synthetic data can be used to train AI models when the use of real data is restricted by data protection policies or legislation, such as in the medical field.
Cost	There can be cost benefits of using synthetic data instead of real data collection, although computational and environmental costs can still be important.

Table 1: Use of synthetic data

In several of these cases, synthetic data will be used alongside original data. For example, an AI model might be trained on real-world data, with gaps in the data filled by synthetic data. However, they come with specific challenges and risks that need to be addressed when deciding to use synthetic data – these are highlighted later in this report.

Data availability: Synthetic data can overcome limitations associated with data scarcity, enabling more robust AI training and development. Synthetic data generated using Large Language Models have been used to train AI models for tasks such as disease diagnosis and developing new treatments (SDG 3). In the financial services industry (SDG 8), synthetic data have been used to train AI models for economic forecasting, fraud detection, and risk assessment, among other tasks. In the climate science industry (SDG 13), synthetic data are used to train AI models for weather forecasting and climate modelling, among other uses. Synthetic data have been shown to be essential for developing new mitigation and adaptation strategies for climate change.

Privacy protection: Synthetic data do not contain Personally Identifiable Information (PII), making it a valuable tool for complying with data protection regulations and protecting user privacy. In the health-care industry, PII is removed or de-identified before using real-world health-care data to generate synthetic data, allowing AI models to be trained on realistic data while protecting patients' privacy (SDG 3).

Bias reduction: Synthetic data can be designed to be balanced and representative, helping to reduce bias in AI models. For example, synthetic data has been proposed to ensure that gender discrimination is minimized in artificial intelligence models, thereby advancing SDG 5.

Compliance: Synthetic data can be used to comply with regulations that restrict the use of real-world data. For instance, synthetic data can be utilized to train machine learning models without accessing sensitive data. Synthetic data have been used to generate sensitive medical images for training medical students, thereby advancing SDG 4.

Cost: The generation of synthetic data can be more cost-effective than the collection of real-world data. This can be significant for applications requiring costly data collection, such as clinical trials and market research. However, the computational and environmental costs of generating synthetic data are sometimes substantial. Therefore, it is essential to consider this when choosing a generative model to synthesize data to advance SDG 13.

5. Synthetic data and the divide between the Global South and Global North procedure for handling algorithmic bias

As the multilateral system begins to turn towards the global governance of artificial intelligence, an important challenge will be addressing the growing digital divide. Today, in an era of accelerating digital transformation, the digital divide manifests itself not only in terms of lack of Internet access but also in digital exclusion in datasets and lack of voice and representation.

The scope of our recommendations is the use of synthetic data to train AI models, but we can only make these recommendations if we consider the social and economic context on a global scale. Access to data used to train AI models is uneven across the world. Synthetic data make it possible to scale up smaller datasets and generate robust AI models from them. This helps to reduce the global inequality in access to locally relevant AI and improve regional AI systems. Synthetic data can also give greater visibility to marginalized groups within society. By the mechanisms of scaling up, increasing visibility, and de-biasing, synthetic data can help reduce the digital divide.

Data used to train AI systems sometimes underrepresent women, people of colour, and people of other minority groups. This has led to discrimination, for example in human resources, financial decision-making systems, and facial recognition systems. However, the problem of homogeneity in AI data is even more critical in the Global South. Local subtleties and minority traditions, from the use of local languages to clothing to many other social, cultural, and economic dimensions are still poorly represented in datasets. This is increasingly leading to effects on sustainable development, from poorer performance of AI systems in health, education, and government services to longer-term effects on peace and governance.

Synthetic data can complement traditional data sources and address some of the chronic challenges associated with data-driven innovation, planning and governance, environmental sustainability, and security in the Global South:

1. Data deficits and innovation: synthetic data can serve as a substitute for scarce or unavailable data and enable researchers to innovate more targeted and efficient solutions to health, education, and agricultural challenges.

2. Infrastructure planning and governance: with limited financial and human resources, governments can use synthetic data to experiment via simulations and boost data-driven strategies to address disaster responses, rapid urban development, etc.

3. Environmental sustainability: socio-ecological modelling helps with water allocation planning, crop yield predictions, biodiversity preservation, wildlife conservation, etc.

4. Security and safety: by improving the accuracy of AI models that have few original data, synthetic data can improve the security and safety of AI applications.

5. Diversity and inclusion: by widening the distribution of the training data, synthetic data can improve the diversity and inclusion of AI models.

It is important to remember that the use of synthetic data in certain sectors is more controversial than in others. For instance, banking, health-care, insurance, and telecommunications are the most enthusiastic adopters in the Global North. AI is widely adopted in the private sector in the Global North and much less in the public sector due to governance and ethical considerations, as well as resource constraints. Yet, there is potential for the use of synthetic data to enhance policymaking and governance. On the contrary, in the Global South there is more incentive to bridge the data divide and create “integrated national data systems” for higher efficiency in interoperability, welfare dissemination, national assessment, and planning.

Finally, cultural values influence the approach to synthetic data development and shape decisions about data generation, privacy considerations, and the ethical use of technology. Different cultures may have distinct perspectives on 1) privacy norms, ethics, and regulations, 2) data localization policies on data ownership and governance, 3) enforcement and compliance measures, 4) cultural sensitivities and discriminations, 5) participatory practices with civic actors, for democratic decision-making, 6) media discourses and public engagement, and 7) languages and dialects use.

6. Main risks of synthetic data

Data are critical at all stages of artificial intelligence development, especially during the training and testing phases. AI models trained on datasets representing only a segment of the population risk much higher rates of error for those not represented. Many of the risks of artificial intelligence articulated in recent years have been due to the homogeneity of datasets within and between countries. It is noteworthy that sometimes the problems to be tackled lay in the very imbalance of data.

There are many risks to using synthetic data, such as data quality, cybersecurity, misuse, bias propagation, IP infringement, data pollution, and data contamination.

Data quality: The quality and realism of synthetic data are crucial for effective AI training. Poorly generated synthetic data can lead to inaccurate and unreliable AI models. Statistical models can generate more evenly distributed data but do not work well for high-dimensional data such as text, images, or video.

Several variables can impact the integrity of synthetic data. Firstly, the method used to generate synthetic data can substantially affect its quality. Data created by generative models are often more realistic than data generated by statistical models, but their distribution can be more challenging to control. Second, when more data is used to train the model, the quality of the synthetic data can be enhanced. This is because the model will have more data from which to learn and generate more realistic synthetic data. Third, if the quality of the real-world data used to train the model is high, the quality of the synthetic data will also be high because the model can learn from real-world data and generate similar synthetic data. Good quality data have to be FAIR: findable, accessible, interoperable, and reusable.

Security risks: Synthetic data, if reverse-engineered, have sometimes been shown to reveal information about the underlying real data or the process used to generate it, posing security risks. This has happened in Large Language Models. Re-identification is, therefore, a real risk for synthetic data, especially if the source data used is published with the synthetic data, or if the model used to create the synthetic data “overfits” the training data, meaning that it too closely resembles the original dataset.

Misuse: The use of synthetic data in AI training raises ethical questions, such as the potential for misuse in creating deepfakes and false information, or other deceptive AI technologies. Synthetic data have also been increasingly found to have intellectual property risks, especially when generating images from artistic source materials, or from other sources where human beings would have intellectual property.

Synthetic data containing false information can be used to train LLMs that can easily and quickly generate a high volume of false information. This can significantly amplify misleading views by creating an illusion of a majority perspective.
False information that includes both disinformation and misinformation has become a profound governance issue because of its serious impact on political elections and public information flows. Synthetic data based on disinformation and misinformation are an important risk to global peace and stability and have begun to affect elections, peacekeeping operations, humanitarian interventions, and local conflicts.

Bias propagation, data pollution, or data contamination: If the synthetic data are not balanced, misrepresent a population group, or are otherwise biased, their biases could propagate throughout trained models and even to other synthetic datasets. Synthetic data are generated from a dataset, and if that dataset is not representative, then that narrowness is projected into the synthetic dataset.

As the use of synthetic data is democratized and becomes cheaper, more and more data available on the Internet will be generated by Deep Generative Models, and these inputs will be used again to train AI systems. In the end, this will make it more and more difficult to separate what is synthetic data from what is real data and point out where bias has come from.
Debiasing data is a critical process to enhance the quality

of synthetic data, a crucial component in training machine learning models. However, biases present in the original data can inadvertently be propagated into the synthetic counterpart, compromising the model's fairness and generalization capabilities. To address this challenge, debiasing techniques may involve reweighting samples, adjusting features, or applying algorithms that minimize specific biases. By systematically identifying and mitigating biases during the synthetic data generation process, the resulting dataset becomes more representative and less prone to perpetuating discriminatory patterns. Debiasing not only contributes to the ethical use of AI but also ensures that machine learning models built upon synthetic data exhibit improved performance across diverse and real-world scenarios.

Exclusion: If data about marginalized population groups can be generated without the engagement and participation of those groups, there is a risk of continued marginalization and exclusion. This represents a deeper and more fundamental risk to democratic participation and self-determination; especially if the resultant models are used in the governance contexts.

The Global South often faces a "data deficit," limited data availability due to factors like resource constraints, uneven resource distribution and representation, and underdeveloped data infrastructures. Synthetic data can help bridge these gaps by providing additional and diverse data for analysis and model training. This is especially critical for digital inclusion by building robust and fair AI-enabled systems to serve their populations in today's data-driven governance and economy, where a substantive number of their vulnerable populations remain invisible or misrepresented in such models.

However, if the parameters and guardrails around synthetic data generation are not clearly and ethically defined, they may inadvertently perpetuate or even amplify existing biases present in the original data. This could lead to real-world harms as essential institutions for welfare, health-care, and education are becoming increasingly automated. Moreover, in low-rights environments, these tools can be weaponized against specific groups of people who have been historically targeted.

Operationalizing debiasing datasets requires faithfully representing the characteristics, values, and criteria of real-world data, much of which is a value-driven and subjective process requiring democratic decision-making. Without a governance system in place to ensure the validity, authenticity, and transparency of these models, it could lead to skewed generalizations in practice.

Risk of lawmakers ignoring synthetic data: Policies based on synthetic data may not adapt well to dynamic and evolving real-world conditions. Governments need to ensure that their governance systems are designed in a manner that ensures that they generate synthetic data regularly to capture the complexity of changing circumstances, or else these policies may become outdated or ineffective over time. This requires democratic and global coalition building to safeguard the debiasing process and independent auditing of these trained AI systems to align with democratic values and build public trust.

7. Recommendations

Recommended technical actions:

1. Mitigate bias.

Document any remaining quantitative and qualitative bias and reduce both types of bias. Use rich and diverse data sources to construct synthetic data.

Use statistical analysis and procedures to minimize quantitative bias in the synthetic data. Report on what data sources have been used, and what statistical techniques have been used to avoid bias. If data sources are not open access, give statistical descriptions. Characterize any remaining quantitative bias in the synthetic data.

Use techniques from social sciences and humanities to describe the qualitative bias that may be present in the data. Special attention should be paid to proxies of discrimination that can be identified by studying the context within which the synthetic data are to be applied. Practitioners in many areas of social science and the humanities should be involved proportionally in characterizing what can introduce qualitative bias. There needs to be sufficient domain knowledge when generating synthetic data.

Reduction of quantitative and qualitative bias in synthetic data requires a significant effort. It is not a one-off process. There need to be regular checkpoints to assess the status of bias in this data and watch for emerging and potentially new forms of bias that may surface when in deployment.

2. Use a range of generating mechanisms for synthetic data.

Addressing the invisibility and misrepresentation of marginalized communities in existing datasets demands creative and intentional measures in generating synthetic data. Traditional data collection often overlooks certain communities, perpetuating biases. Creative approaches involve participatory data collection, community partnerships, and innovative technologies. Incorporating storytelling, cultural sensitivity, and co-creation with community members can yield richer representations. Diverse teams in data collection and analysis enhance perspectives on how synthetic data is generated and deployed to ensure equitable debiasing of existing data for training algorithms.

Generative AI models are still evolving and there is no single standard algorithm to generate synthetic data. Using a range of generating mechanisms may not only produce data that is fit for purpose but may also show new routes for avoiding bias. That could include finding efficient data synthesis methods, comparison between synthetic data generation methods and other privacy-enhancing technologies, and finding the best data generation settings or paths.

3. Ensure transparency.

Document the methods and parameter settings used for generating synthetic data, providing detailed documentation about the synthetic data set. This enables other developers to understand the source and characteristics of the data.

4. Calculate and disclose quality metrics for synthetic data, and validate the data.

The quality targets for synthetic data can be vague, and it is important to have clear metrics to show how effective the synthetic data are in training AI models. By defining and adhering to these benchmarks, the development and adoption of synthetic data can be guided by a commitment to accuracy, privacy, fairness, and transparency, fostering trust and responsible use across various domains.

5. Synthetic data should preferably be open access and always watermarked to disclose their origin.

High-quality synthetic data can be indistinguishable from real-world data to a human observer. An AI model could be trained on synthetic data without the knowledge of the designer. For this reason, it is important that synthetic data can be recognized as such. Watermarks should be embedded in the data and be readable by machines as well as humans. Watermarks should not just flag synthetic data but also disclose their origin.

6. Develop and maintain cybersecurity measures to protect synthetic data.

Synthetic data, like all data, can be subject to so-called ‘poisoning’ attacks, and have to be protected using cybersecurity measures. Protecting synthetic datasets from unauthorized access, manipulation, or malicious use is essential to maintain data integrity and user privacy. Robust encryption measures, secure storage solutions, and stringent access controls must be implemented to mitigate the risk of data breaches. Additionally, thorough validation of synthetic data sources and continuous monitoring for anomalies can help detect and address potential security threats. As synthetic data become increasingly integral to AI applications, a proactive and comprehensive cybersecurity strategy is imperative to instill confidence in the responsible and secure use of synthetic datasets.

7. Model validation and evaluation.

In addition to training on synthetic data, models should be validated on real data to ensure their performance and robustness. Regularly updating synthetic data sets to adapt to new scenarios and changes in data distribution is also a vital means of maintaining model performance.

Recommended policy actions:

8. Establish global quality standards and security measures.

AI is a global good, and only global governance can ensure it benefits everybody. Synthetic data should be linked to global AI governance efforts. They are a critical and unique issue in global data governance.

Global quality standards will ensure trust and interoperability among the global user base of AI models trained with synthetic data and add AI models trained with synthetic data to the digital public infrastructure. Global security measures are needed to ensure that what has been developed in one part of the world is not compromised by malicious actors in another part.

Security measures are also needed to avoid the misuse of AI models trained on synthetic data.

9. Locally enforce quality standards and security measures.

Enforcement of the globally established standards and security measures has to happen locally to be effective. Local authorities need to regulate where necessary and have the means to enforce standards and measures. It is important to be able to assign responsibility, as AI models may run on computers outside the country where they are used.

10. Create ethical guidelines that take synthetic data into account.

Some of the technical actions recommended above are also ethical imperatives. Transparency, safe use, diversity, and avoiding bias need to be part of an ethical framework, and not just technical challenges.

11. Balance the relationships between experts, curators, and generators of synthetic data.

Ownership of synthetic data may not be clear and may be vested to different degrees in actors involved in the creation of the data. The designers of AI models should not be monopolistic providers of AI services but have open relationships with all those involved in the creation of synthetic data.

12. Promote global research networks on the safe and ethical use of synthetic data.

Policies have to be evidence-based on a global scale. AI is multi-faceted, and reaching a global consensus on the safe and ethical use of synthetic data requires global interdisciplinary research networks.

13. Create policies to make sure synthetic data reduce the divide between the Global South and Global North.

We have argued in Section 5 that synthetic data can reduce the divide between the Global South and the Global North. This will only happen if there are global policies that ensure that this divide is addressed.

8. Conclusion

These 13 recommendations are about a technical subject that underlies many AI models and is growing in importance. Existing AI policies are very broad, and now is the moment to look at detailed recommendations for the techniques underlying AI models. Our recommendations are at the technical and policy level. There is a need to go beyond current security concerns, and earnestly address issues of bias and the North/South divide.

ENDNOTES

1 UN AI Advisory Body (2023) Interim Report: Governing AI for Humanity. https://www.un.org/en/ai-advisory-body. Accessed 7 Feb 2024.
2 UN AI Advisory Body (2023) Interim Report: Governing AI for Humanity. https://www.un.org/en/ai-advisory-body. Accessed 7 Feb 2024.
3 Acknowledges European Union Horizon Europe research and innovation grant 101070212.
4 With thanks to Jingbo Huang. Based on initial research and recommendations published as UNU Technology Brief No 1, 2023: "The Use of Synthetic Data to Train AI Models: Opportunities and Risks for Sustainable Development. Understanding the broad impact of synthetic data used to train AI systems." Tshilidzi Marwala, Eleonore Fournier-Tombs, Serge Stinckwich, United Nations University.

EDITORIAL INFORMATION

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Prof. Tshilidzi Marwala is the Rector of United Nations University, headquartered in Tokyo, and Under-Secretary-General of the United Nations. He was previously the Vice-Chancellor and Principal of the University of Johannesburg. Prof. Marwala has published over 300 research papers and articles, over 250 articles in newspapers and magazines, 27 books on AI and related topics, and holds five patents. He is a member of the American Academy of Arts and Sciences, the Chinese Academy of Sciences, the World Academy of Sciences (TWAS) and the African Academy of Science.

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