

Perspective

Can we share models if sharing data is not an option?

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THE BIGGER PICTURE Data are the fuel for data-driven scientific discovery in the modern world. However, not all data are suitable or easily shared because of privacy, ownership, trust, and incentive issues. This significant amount of “closed data” is a hidden gold mine in the big data era. In this perspective article, we propose the notion of the model-sharing strategy to conceptualize the recent practical attempts and technological advances in distributed modeling and data collaboration. The model-sharing strategy leverages emerging technologies, especially artificial intelligence, to safely use closed data by sharing models instead of data between data owners and model users. Future applications of this strategy will make it possible to create more added value from the conventionally unusable data and trigger a transformation for better data collaboration and governance.



Concept: Basic principles of a new data science output observed and reported

SUMMARY

In the big data era, vast volumes of data are generated daily as the foundation of data-driven scientific discovery. Thanks to the recent open data movement, much of these data are being made available to the public, significantly advancing scientific research and accelerating socio-technical development. However, not all data are suitable for opening or sharing because of concerns over privacy, ownership, trust, and incentive. Therefore, data sharing remains a challenge for specific data types and holders, making a bottleneck for further unleashing the potential of these “closed data.” To address this challenge, in this perspective, we conceptualize the current practices and technologies in data collaboration in a data-sharing-free manner and propose a concept of the model-sharing strategy for using closed data without sharing them. Supported by emerging advances in artificial intelligence, this strategy will unleash the large potential in closed data. Moreover, we show the advantages of the model-sharing strategy and explain how it will lead to a new paradigm of big data governance and collaboration.

INTRODUCTION

The rapid development of information and communication technologies has brought us into the big data era, in which all parties of our society have benefited from large volumes of diverse data generated every day. Scientific discovery has shifted into “the fourth paradigm,” which is data intensive and requires collaboration on data synthesis.^{1,2} In this paradigm, data have become one of the essential resources in research that supports scientists in generating new knowledge and developing innovations.

However, data in the big data era are distributed or even isolated across organizations and sectors (e.g., research institutes, governments, companies),^{3–5} and making them accessible is vi-

tal to creating and delivering the data’s value.^{4,6} Over the past decade, advocates of open science around the world have brought about new initiatives and projects to encourage data sharing for research.^{5,7} Data sharing has significantly promoted research and innovations by increasing researchers’ capacities, creating research collaborations, reproducing and verifying experimental results, and making extant data available for analysis with better techniques that were not developed yet at the time of data generation.⁸ For example, studies show that the open data movement has triggered more publications and citations, especially when the data in publications are provided in archives.^{9,10} In addition, current practices in confronting coronavirus disease 2019 (COVID-19) show that data sharing across



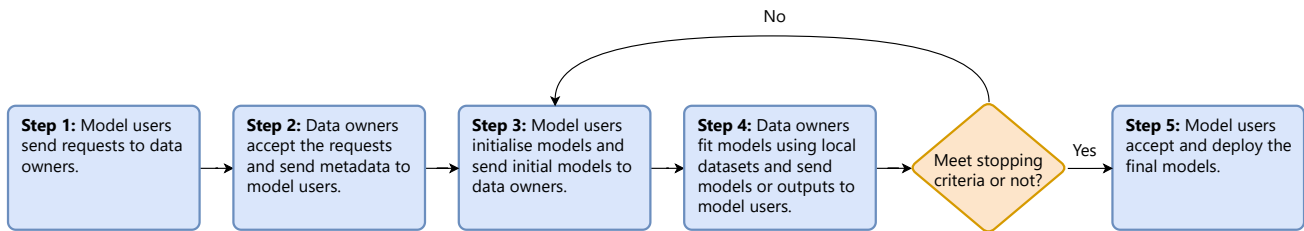


Figure 1. Workflow of the model-sharing strategy

The blue blocks refer to the five stages, and the yellow diamond refers to the judgement statements.

countries is essential to inform the research response to global health emergencies.¹¹

Opening and sharing data are critical ways of supporting data-driven scientific discovery and problem solving. However, not all research data are suitable for opening or sharing because of issues such as data privacy, loss of ownership, lack of trust, and insufficient incentives. The majority of scientifically valuable data are closed from being used, and they are a hidden gold mine in the big data era.^{8,12,13} However, according to a recent survey, most researchers from across nations and disciplines considered that lack of access to research data significantly impedes scientific discoveries.¹² We believe that finding ways to use these closed data will greatly benefit research communities in knowledge generation.

In recent years, a growing number of technologies have been developed to explore data collaboration in a data-sharing-free manner.^{8,14–17} However, these technical advances and practical attempts have not been theorized into a general concept, which hinders the evaluation of their shared features, discussion of their societal implications for data governance, and exploration of their future development.

In this perspective, we aim to address the aforementioned challenge of using closed data and propose a concept of the model-sharing strategy (MSS). Although we contend that this strategy applies to a wide range of fields, we choose research data or data for research purposes as the scope of discussion to make the paper more focused. In the next section, we introduce the MSS concept and explain how it is rooted in recent technological advances and practical innovations. We then evaluate how the MSS facilitates data collaboration by allaying four major concerns over privacy, ownership, trust, and incentives and discuss its application conditions. Thereafter we explore how the MSS can be used to shape future research data governance and guide future development in data technologies and infrastructure. Finally, we summarize our conclusions.

THE MODEL-SHARING STRATEGY EMERGES FROM TECHNOLOGICAL ADVANCES

The MSS is proposed as a general concept to summarize and describe the current practical innovations and technical advances that attempt to achieve data collaboration among stakeholders without sharing the raw data. We define the MSS as a series of actions to create data value via data collaboration by keeping raw data locally and transferring models between data owners and users. The MSS has at least two features. First, data are invisible but interoperable by models. A model-to-

data manner is adopted for model updating, and the data-fitted models are shared. Second, the models that have been fitting the data are abstract representations of the knowledge of data, and it is infeasible to infer the raw data from the models, making the risk for data leakage extremely low compared with conventional data sharing.

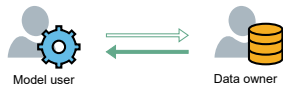
In the MSS, two main roles are involved in implementing the strategy: data owner and model user. Data owners hold the raw data, and model users use the data via models. The term “model” in the MSS follows a broad definition, ranging from basic regression models to more sophisticated artificial intelligence (AI) and deep learning models. The whole modeling process, including pre-processing of data, is all conducted in the data owners’ local repositories. To demonstrate how stakeholders interact with one another, we summarize a general workflow of the MSS in five steps (Figure 1). Model users first send modeling requests to data owners (step 1). Once the data owners accept the requests, the data owners send metadata to the model users for model initialization (step 2); the metadata include the attributes and features of the data. For example, the metadata of CIFAR10, a widely used image classification dataset for AI research,¹⁸ include the following information: it is a 10-class image classification dataset, the training set size is 50,000, the test set size is 10,000, the size of one image is 32 × 32 pixels, etc. In step 3, on the basis of the received metadata, the model users set up their models and send the initial models to the data owners. In step 4, the data owners let the models fit local datasets and update the models and then send the models or the outputs back to the model users. The MSS can be iterative (i.e., multiple rounds of local updating) or one shot (i.e., one-round updating). If it is iterative and does not meet stopping criteria, the model users send another round’s initial models to the data owners, jumping back to step 3; otherwise, the model users deploy the final models for use in step 5.

The concept of the MSS emerges from and is supported by recent technological advances, such as cloud computing, distributed artificial intelligence, and blockchain. Here we summarize four of these technologies that have demonstrated their applicability in practice. These examples adopt different technologies to realize model sharing and emerge from various motivations. Still, they all satisfy the MSS definition and principles and can achieve data rights-protecting collaborations beyond data sharing.

First, an early form of MSS is “model-to-data remote access,” emerging with secure remote and virtual data enclave technologies.^{8,14} Suppose researchers want to use the private and sensitive data held by data owners, but the data owners refuse to

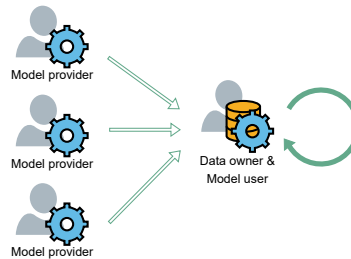
A Model-to-data remote access

Key technologies: Remote execution system & Virtual data enclave



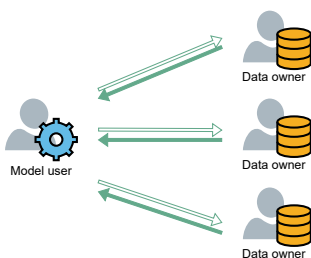
B Model-to-data crowd-sourced modelling

Key technologies: Container software & Cloud computing



C Federated learning

Key technologies: Distributed artificial intelligence



D Swarm learning

Key technologies: Distributed artificial intelligence & Blockchain

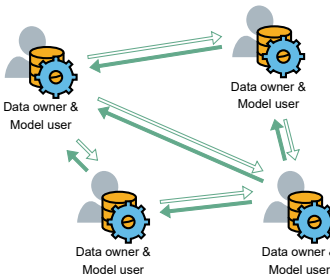


Figure 2. Schematic diagrams of four current MSS methods

- (A) Model-to-data remote access.
- (B) Model-to-data crowd-sourced modeling.
- (C) Federated learning.
- (D) Swarm learning.

disclose and share the data. In that case, they can use the model-to-data remote access approach to use the data in the virtual data enclave without having access to the raw data. In this method, remote execution systems allow researchers to submit the program codes of initial models; virtual data enclaves enable them to work on a data owner’s computer from a secure remote access technology.¹⁴ The data owners review the models and the outputs before they are sent to the users, and the data are never moved from the repository. In model-to-data remote access, two-party stakeholders are usually engaged in the process, the data owner and the model user, as shown in Figure 2A. Model-to-data remote access was adopted early in a few data repositories (e.g., the National Opinion Research Center, Statistics Netherlands), and it was reported to adopt virtual data enclave technology for secure and private data collaboration in 2011.¹⁹ Because of the rising advocations of open data and concerns about data sharing, more institutions have chosen to adopt model-to-data remote access to allow researchers to use their sensitive data locally. For example, the Inter-University Consortium for Political and Social Research, the world’s largest social science data repository, has enabled model-to-data remote access by adopting virtual data enclave technology since 2017.^{8,20} The model-to-data remote access is shown to be effective in opening the utility window of closed data to researchers while keeping the data rights and privacy.

Second, “model-to-data crowd-sourced modeling” has successfully demonstrated its applicability in medical diagnosis.¹⁵ The first large-scale crowd-sourced modeling competition using

model sharing was the Digital Mammography DREAM Challenge in 2016.^{15,21,22} This challenge aimed to reduce the high false-positive rate in cancer detection on mammographic screening. Advanced AI algorithms can be applied to improve accuracy, but training them requires extensive patient data, most of which are sensitive and private. The organizers wanted to use crowd-sourced competitions to encourage researchers to design effective and powerful models for the mammary cancer detection task but without sharing the sensitive patient data. Therefore, the organizers designed the challenge using model-sharing thinking. Participated researchers were requested to submit containerized programs to train models on unseen training data, which were then validated on new testing data. In the whole process, data were all kept locally by the organizers, and the participants had only the metadata to set up the initial models

before sending the models and receiving prediction feedback. In this case, the organizers are both the data owner and the model user, and the participating teams are model providers (Figure 2B). This model-sharing collaboration is extensive in this example, with more than 12 TB of images open to the participating researchers.¹⁵ Because of its success, afterward, other competitions have also used the MSS design to accelerate innovations in precision medicine, including the Multiple Myeloma DREAM Challenge and the NCI-DREAM Proteogenomic Challenge.¹⁵ This model-to-data crowd-sourced modeling is supported by two technologies: container software, used for containing the models and transferring the models in a platform-agnostic way, and cloud computing, used for secure data storage and local modeling. Although most competitions are about AI models,^{15,21,22} this method can also be applied to other model structures. It can help data owners to solve modeling problems in a crowd-sourced manner without sharing the raw data.

The third example is federated learning (FL), which is an emerging distributed AI framework initially proposed by Google in 2016.¹⁷ FL’s main idea is to build AI models on the basis of distributed and local datasets across multiple parties without data collection to prevent data leakage and privacy violation. FL assumes multiple data owners adopt an iterative model training process. Illustrated in Figure 2C, FL requires a central server as the coordinator for model averaging and model communication, and the central server usually plays the role of model user;¹⁷ sometimes, the data owners are also model users

who benefit from data collaboration.^{23–26} In the first round of FL, the central server sends the initial model to data owners, and the data owners train the model using local data for some epochs. Then the central server collects models from the data owners, merges the model parameters and starts the next round of training. Current FL algorithms are communication efficient and privacy preserving, and promising applications have been made, especially in medical AI. For example, electronic health records (EHRs) use a standard data format to collect information from patients and store the data using a standardized model, including personal demographic information, symptoms, diagnoses, etc. Researchers use FL and distributed EHR data in cross-hospital cooperation to predict medical indicators (e.g., cardiovascular disease, mortality within seven days among hospitalized COVID-19 patients, and adverse drug reaction) in a privacy-preserving manner.^{23–26} The results showed that the FL-based models had comparable performance to the centralized learning models and outperformed the localized learning models,^{23–26} which shows the efficacy of the FL MSS in that it achieves model performance gains among multiple data owners.

The last example is swarm learning (SL), a distributed AI framework.¹⁶ SL takes the peer-to-peer protocol in model sharing rather than a centralized framework using a coordinator, as FL does (Figure 2D). To enable reliable model sharing, SL implements blockchain technology in the system. On the basis of SL, multiple medical institutions with heterogeneous patient data can form a peer-to-peer network conducting model-sharing AI training for disease diagnosis without sharing their data. SL has been shown to be effective in multi-party modeling of COVID-19 diagnosis, improving accuracy compared with solely trained models,^{16,27–29} and it even can facilitate data collaborations across countries.¹⁶ This framework brings promising potential to global collaboration in medicine under the consideration of data privacy and ownership.

THE MODEL-SHARING STRATEGY FACILITATES DATA COLLABORATION

Introducing the concept of the MSS enables us to analyze and discuss the shared features and advantages of data-sharing-free technologies and practices. The most significant benefit the MSS brings is that it helps facilitate data collaboration by reducing concerns over data sharing in at least four aspects: privacy, ownership, trust, and incentive.

First, data privacy is a major issue in research data sharing,³⁰ especially when the data are associated with human behaviors and information, such as the biological, psychological, or medical data generated by human individuals, including X-ray radiography or health record data.³¹ Sharing these data will cause privacy risks because the identity of each data sample can be easily identified using other public information data.^{19,32} Furthermore, sharing sensitive and private data is confronted with ethical issues. For some of these data, it is strictly permitted only if the participants agree with the informed consent and are aware of the downstream usage of their sensitive data. For data owners, sharing or opening these sensitive data takes tedious procedures to complete the legal agreements and after that, once sharing out, they will bear potential risks for privacy leakage. Although anonymization can reduce sensitivity, privacy leakage

accidents still happen when sharing anonymized data.¹⁹ Thus, researchers often assume that the rights of the research participants are better preserved without data opening and sharing.⁸

MSS approaches can relieve the privacy issue while facilitating data collaboration because private and sensitive data are not transferred from local repositories, and the microdata are not accessible to model users. The shared models can be used for predicting classifications, indicating correlation relationships, or other uses, but they cannot be used to infer the detailed information of individual data samples; thus, data privacy is protected. Although reverse attacks on models will cause potential risks for privacy leakage,³³ it is acknowledged that the MSS has largely reduced privacy risks compared with data-sharing approaches and advanced privacy-preserving technologies, such as differential privacy,³⁴ homomorphic encryption,³⁵ and secure aggregation,³⁶ can be used in the models of the MSS, further reducing the risk for privacy leakage.

Second, the MSS preserves data ownership because it does not incur data dissemination and distribution. Data have a unique feature of ownership; once the data are shared, the ownership of the data is duplicated.^{37,38} Researchers' ownership concern about data sharing results mainly from the worry about intellectual property rights. The intellectual property rights are two-fold: the first concerns the intellectual efforts researchers invest in producing or collecting the data, and the second concerns the authorship of research generated from the shared data. Because of the intellectual efforts in generating the data, many researchers choose to withhold their data without sharing them because of the desire to retain ownership of data that had taken many years to produce.^{39,40} They are afraid that their intellectual efforts are not being rewarded or credited after sharing or opening the data, and free riders will use the data without crediting the data owners.^{8,14} Another aspect is the authorship of research. Some researchers refuse to share their data before their papers are published and fear that the research findings may be scooped.⁴¹ Even if the first-hand research finding is published, data owners want to withhold the data for future study;⁴² if they open the data, other researchers will use the data for publication without giving authorship or even citation to the data owners.

The MSS solves the data ownership issue by keeping the data locally "closed" in the data owners' repositories. The data owner can decide whether to collaborate with other researchers by model sharing. In MSS methods, every model sharing history is verifiable and traceable, and data owners can retain their credits by directly communicating and negotiating with model users. The ownership and property rights of data are preserved.

Third, the MSS can promote data collaboration by establishing a more trustworthy relationship among stakeholders. Trust involves tackling uncertainty and risk.⁴³ Thus, trust in data collaboration is easier to establish and maintain if data use is more traceable, secure, and at lower risk. Although restrictions can be announced at the beginning of data sharing, data downloaders may still disseminate or manipulate data in any way without the supervision of the origins. As a result, the ownership of data is duplicated when sharing, and it will cause uncertainty of data use and risk for data abuse.⁴⁴ Without sufficient trust, it is a challenge to share data among individuals and organizations.⁴⁵ In addition, low- and middle-income countries (LMICs) fear the

free riding of their data, which will likely increase inequalities and result in the pitfalls of colonial science.⁴⁶ Therefore, the trust barrier will impede the process of data collaboration with LMICs.

Data-sharing methods meet the trust barrier mainly because of their nature in uncertainty and untraceability. In contrast, the MSS can relieve the concern by maintaining the locality of the data and increasing communication among stakeholders. Communication is vital in constructing trust between data owners and model users.^{41,47} The MSS can provide a platform where both data owners and model users are in an equal relationship to communicate, where the data owners have the right to decide whether and how the users can use their data for modeling. After receiving the initial models provided by the model users, data owners can be aware of the properties (e.g., types and architecture) of models for local updating and final use. Data use is no longer a black-box problem for data owners. In this way, data owners will be more prone to trust the users, and the model users can also know the information of data from the metadata and description provided by data owners.

Last, the MSS can better facilitate data collaborations from the perspective of incentives. Incentives are a critical driver for data collaboration,⁴⁸ coupled with the ownership issue discussed above. However, data sharing is not always well supported by incentive mechanisms,⁴⁹ and the incentive problem is a critical barrier in current data-sharing practices. Without direct benefits, data owners have limited incentives to participate in open data initiatives.⁴⁶

Incentive problems can be better settled under the MSS. For example, data owners and model users can agree on credits on the basis of model use. In this context, the rewards can be of various forms, including monetary and honorary. Monetary rewards are suitable when the models are used for prediction tasks, especially AI models,^{50,51} and the “paying by models” incentive mechanism can be adopted. Data owners can be paid by the performance gains of the models after being trained on the local data, and methods such as Shapley value in cooperative game theory can be used to clarify individuals’ contributions.^{50–52} However, “paying by models” may cause an inequality issue, which is the opposite of open science: some people needing the data cannot afford the price. Therefore, beyond monetary reward, the honorary reward is also important in the MSS, especially when the model use is not just the prediction task but for research or other purposes. Authorship or citation is especially important here. According to Bethlehem and Seidlitz,⁴⁹ citing data sources in publications and addressing the contribution of data are strong incentives to data owners, and these agreements can also be achieved in collaborations via the MSS. The MSS can provide a platform where the data owners and model users can reach a consensus on rewards and credits before going into the modeling process. The relationship is much more equal in the MSS, and the data owners can argue for their rewards. In contrast, in the data sharing paradigm, data owners are more passive and vulnerable to contributing their data to the community.

However, applying the MSS has its conditions and limitations. First, not all data uses are based on models, so not all data collaborations can be transformed into the MSS. For many types of applications for which researchers do not use models, the MSS is less relevant. Although the concept of “model” in the MSS can

be broad, it does not include all data operations. Therefore, in some cases, data sharing is the only option for data collaboration between researchers.

Second, the MSS has a high demand for interoperability, which takes more resources and time for both data owners and model users. It relies on interoperable platforms on which the stakeholders upload metadata and initial models, fit models with the data, and download models and outputs. In addition, the platform needs to meet security and reliability requirements to safeguard the process. The MSS also requires stakeholders to have standard metadata schemas, and data owners must have the skills and expertise to fit a model on their data.

Another concern about the MSS is the transparency of model sharing. On one hand, sharing models instead of data is seen to protect the privacy and ownership of researchers or participants represented in the data. On the other hand, making data “unseen” also does not allow questioning of biases present in the data, but the biases will be passed on and embedded within models as they fit the data. It is hard for model users to know more about the data if biases exist. It may meet a “black box” problem that loses the context of the data, but model users sometimes need to know the details of the data for interpretation and understanding.

THE MODEL-SHARING STRATEGY SUPPORTS FUTURE DATA GOVERNANCE AND TECHNOLOGICAL DEVELOPMENT

The MSS has shown a new way of data collaboration, as discussed above. We believe it can be used to shape future research data governance and guide future development in data technologies and infrastructure.

Current open data initiatives advocate for researchers to open and share their data while publishing research findings, but the MSS provides a new way of “opening.” The MSS transforms “open data” into “open modeling,” which encourages researchers to collaborate with data owners via local modeling. This innovative data collaboration mode poses new opportunities for all stakeholders in research data governance. Among these, the collaboration between publishers and researchers under the MSS should receive further attention. For example, the publishers can transform their perception of data collaboration from “open data” to “open modeling” and offer MSS options in publication. Publishers provide platforms, such as journals and conferences, where researchers publish their new scientific findings. Some publishers have the option of data sharing and encourage the researchers to upload their research data onto a public archive once their paper is accepted. However, most researchers refuse raw data sharing because of a range of aforementioned concerns.^{8,14,41} In this case, to further encourage open science, “open modeling” can be adopted as a journal’s publishing option to motivate researchers to update their metadata and provide the application program interface (API) for model sharing request access. The API is for model sharing-based data collaborations, where MSS methods such as model-to-data remote access and federated learning can be applied to use the closed data stored in the data owners’ repositories. For example, publishers can add “open modeling” badges to papers that claim model sharing accesses are

available. It is evidenced that this incentive mechanism can result in a higher opening rate⁴¹ and promote data collaboration within and beyond research communities.

In addition to the new insights into research data governance, the MSS also suggests future technological development and infrastructure construction directions to meet its high demand for interoperability and reliability. Interoperability is important in data sharing. It is reported that the preparation for the data to be interoperable in the data sharing process causes extra burdens to data owners.⁸ However, the MSS has an even higher requirement on interoperability than data sharing, which poses more significant challenges. It is because the MSS needs both data owners and model users to have the same metadata schema for model initiation and updating. All stakeholders must actively interoperate with one another to guarantee the modeling procedure goes well. To promote the MSS in more research scenarios, advanced data infrastructure and platforms with higher interoperability and usability are needed. Besides, the MSS relies on a more secure, reliable, and trustworthy platform than data sharing because it needs to be ensured that the raw data are safe from privacy leakage and right violation. Apart from differential privacy,³⁴ homomorphic encryption,³⁵ and secure aggregation,³⁶ improved technologies to enhance privacy, security and reliability need to be developed, verified, and adopted in the MSS ecosystem.

As recent MSS methods are driven by AI technologies, such as FL and SL, more interoperable and reliable MSS AI systems and platforms are also vital to go one step forward. Recently, FL-based platforms, such as galaxy learning³⁷ and FedML,⁵³ are emerging. Galaxy learning is a decentralized FL platform based on blockchain and smart contract technologies, on which data owners can implement collaborative modeling while preserving data rights and receiving incentives.³⁷ FedML is an edge AI platform that covers popular federated learning algorithms. It aims to build an end-to-end machine learning ecosystem for individuals or organizations to transform their data into intelligence with minimum effort.⁵³ However, these platforms are not enough for the MSS ecosystem because they are tool-oriented and only provide MSS-based tools for the researchers and the commercials. Instead, a data-oriented MSS platform is more useful in integrating closed data resources for establishing a better data ecosystem.

Analogous to open data platforms, for future development, we provide an outlook on a future “open modeling” platform, which opens access to local modeling instead of data itself. The open modeling platform is a data-oriented MSS platform that aims to integrate the resources of closed data for model-based data collaboration and is established to enable data access with minimal sharing concerns. It will open a new door for such closed data, aiming to break data collaboration barriers. In such a platform, data owners can openly access modeling using their local data. Each data owner can share the metadata of the data repository and demos of models that show the data use. They are encouraged to tag their desired credits from modeling, both monetary and honorary. Researchers or potential model users can browse the platform and send modeling requests to the data owners of favorable datasets. Once the consensus is reached, the model-sharing process starts, and the collaboration begins. In the platform, it can also be helpful to support

model-to-data crowd-sourced modeling that solves modeling problems for data owners. As used in medical competitions mentioned under “the model-sharing strategy emerges from technological advances,” data owners can start a competition to encourage crowd-sourced researchers to solve their modeling problems without disclosing the data. The participants will receive the rewards according to the rules laid down in advance.

It is exciting to see an increasing number of AI-driven, MSS-based applications in medical research. However, there is significant potential to move from these narrowly focused applications to more general ones by applying the MSS and further developing MSS-relevant technologies in broader fields. For example, in the trend of AI for science,⁵⁴ the availability of multiple-source data is critical for using AI technologies to facilitate scientific discovery, where MSS can play a crucial role in establishing a more reliable and trustworthy data ecosystem. Furthermore, in fields such as life science, environmental science, energy infrastructure science, and national security, the sensitive and scattered “closed data” must be well protected, but also need to be used collectively to maximize their added value at the same time.^{54–56} In these scenarios, the MSS will take advantage of trustworthy and privacy-preserving data collaboration.

CONCLUSION

In this perspective, we focus on using the conventionally closed data to collectively generate positive impacts for research and society. We argue that if opening or sharing the closed data is not an option, we should share the models built upon these data. This new concept of the model-sharing strategy will allow us to benefit from multiple-source data, strengthen the incentives and trust in data collaboration, and avoid the risk of violating privacy or ownership principles. We believe that the strategy will lead to a new paradigm of big data governance that better facilitates data collaboration and data value creation, which in return will generate new opportunities for innovations in technological development and data infrastructure construction.

The outlook of MSS offers new forms of data collaboration that will lead to a paradigm shift in data governance. Efforts from all sectors are needed to build up a harmonious model-sharing ecosystem. In this ecosystem, all stakeholders (e.g., governments, private sectors, non-government organizations [NGOs], researchers, citizen scientists) are motivated and encouraged to be engaged. Easy-to-use model-sharing platforms need to be set up. We encourage more researchers from across disciplines to be involved in this discussion and development of this model sharing-based data governance and build a more trustworthy, reliable, privacy-preserving, and right-protecting data ecosystem.

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AUTHOR CONTRIBUTIONS

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DECLARATION OF INTERESTS

The authors declare no competing interests.

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