

# SoK: Decentralized AI (DeAI)

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**Abstract**—Centralization enhances the efficiency of Artificial Intelligence (AI), but it also brings critical challenges, such as single points of failure, inherent biases, data privacy concerns, and scalability issues, for AI systems. These problems are especially common in closed-source large language models (LLMs), where user data is collected and used with full transparency. To address these issues, blockchain-based decentralized AI (DeAI) has been introduced. DeAI leverages the strengths of blockchain technologies to enhance the transparency, security, decentralization, as well as trustworthiness of AI systems. Although DeAI has been widely developed in industry, a comprehensive understanding of state-of-the-art practical DeAI solutions is still lacking.

In this work, we present a Systematization of Knowledge (SoK) for blockchain-based DeAI solutions. We propose a taxonomy to classify existing DeAI protocols based on the model lifecycle. Based on this taxonomy, we provide a structured way to clarify the landscape of DeAI protocols and identify their similarities and differences. Specifically, we analyze the functionalities of blockchain in DeAI, investigate how blockchain features contribute to enhancing the security, transparency, and trustworthiness of AI processes, and also ensure fair incentives for AI data and model contributors. In addition, we provide key insights and research gaps in developing DeAI protocols for future research. The full list of papers and industry solutions covered in this SoK is available at <https://github.com/Flock-io/awesome-decentralized-ai>.

## I. INTRODUCTION

Centralized Artificial Intelligence (AI) systems, due to their efficiency, have been widely adopted in various domains today. However, centralization typically means that a single entity controls the training process, computing resources, as well as data storage, which leads to several challenges. For instance, for AI systems, centralization can cause a single point of failure, making AI systems more vulnerable to disruptions or attacks [1]. It can also limit the perspective diversity reflected in AI outputs, because controlling entities may impose their biases and constrain the representation of viewpoints [2], [3]. Furthermore, centralized control can cause data privacy concerns, such as in closed-source Large Language Models (LLMs), users' data may be monitored and recorded [4]–[6]. Moreover, as data volumes and task complexities [7] increase, the limited processing power of centralized systems might become a bottleneck in scalability. In addition, the concentration of resources for model training among a limited number of entities might constrain AI innovation advanced by a broader community [8]–[10].

To address the challenges mentioned above, decentralized AI (DeAI) has recently emerged as a promising solution. DeAI

leverages blockchain strengths [11] such as transparency and decentralization to improve the trustworthiness and security of AI systems [12]. DeAI can provide robust and decentralized AI ecosystems that address key challenges such as data privacy, model integrity, and equitable access to AI resources [13]. Although DeAI has been widely adopted in industry [14]–[20], the academic community still lacks a systematic analysis of its technical architecture, strengths, and limitations.

Integrating blockchain and AI systems present opportunities along with challenges. Indeed, blockchain can provide immutable audit trails for AI models, ensuring improved trust among participants [21]. DeAI platforms can also leverage distributed computing resources to lessen dependence on centralized servers and diminish single points of failure [22]. However, the scalability of DeAI remains an important challenge [23]. For instance, the intensive computational requirements for AI models might overwhelm blockchain networks, causing latency as well as performance degradation [24]. Additionally, balancing data privacy with transparency is also a challenge within DeAI systems [25].

This work presents a Systematization of Knowledge (SoK) for DeAI to answer the following research questions:

- ☞ **RQ1:** What is the general taxonomy for DeAI?
- ☞ **RQ2:** How can blockchain be used to decentralize and secure AI systems?
- ☞ **RQ3:** What insights and research gaps can be drawn from existing DeAI solutions?

By systematically reviewing existing DeAI solutions in practice, we provide the following contributions.

**Contributions.** Our contributions are summarized as follows:

- ★ We provide a taxonomy to summarize the existing DeAI solutions and categorize them based on the lifecycle of an AI model. We analyze DeAI solutions and identify their similarities and differences structurally (see Table I).
- ★ We investigate the functionalities of blockchain in DeAI solutions. We analyze how blockchain features such as immutability and decentralization contribute to improving the security, transparency, and trustworthiness of AI systems. We also analyze how blockchain enables fair incentives for data and model contributors to build collaborative AI in a decentralized ecosystem.
- ★ We highlight the insights and research gaps to build blockchain-based DeAI solutions for future work.

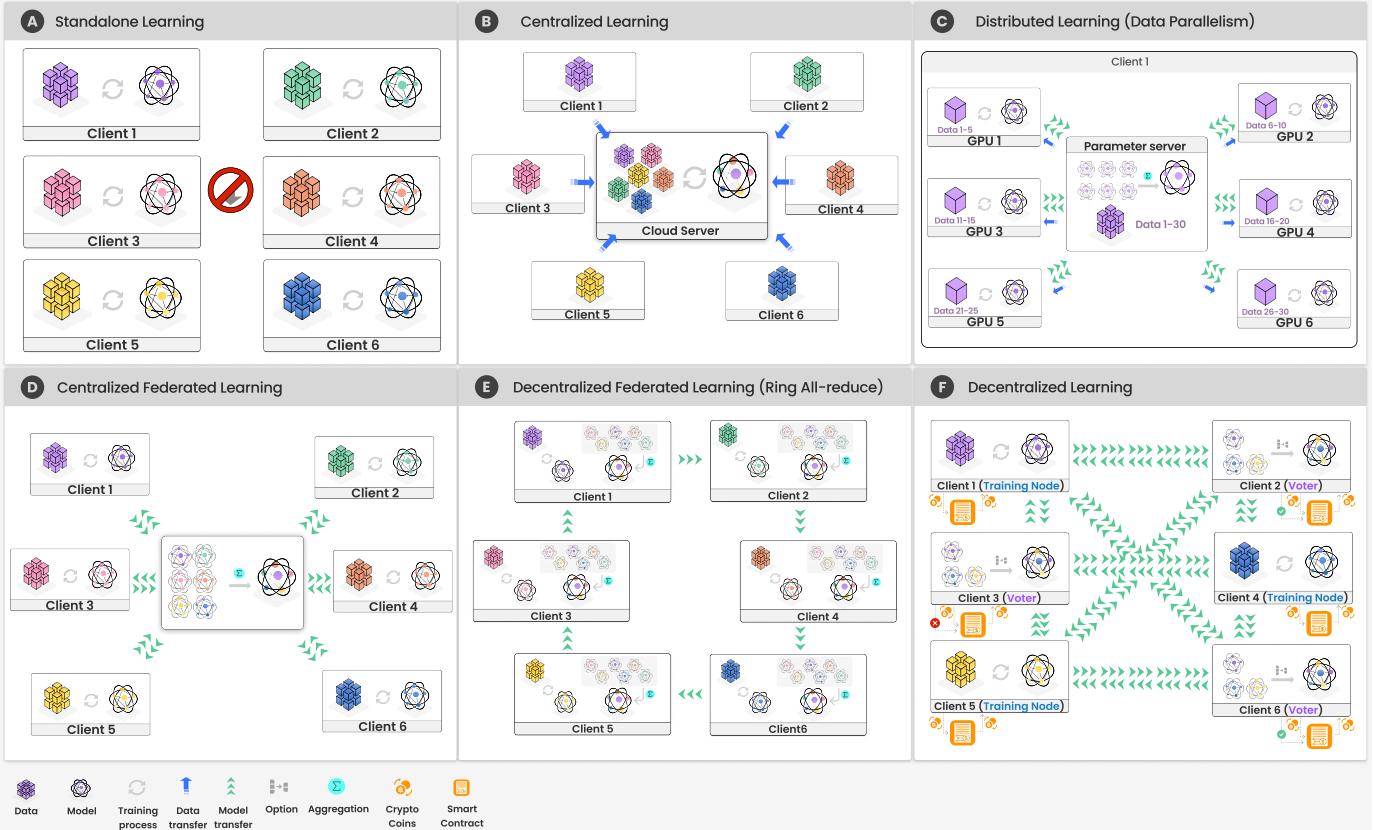


Fig. 1: Comparison of different machine learning paradigms: (A) Standalone Learning, (B) Centralized Learning, (C) Distributed Learning (Data Parallelism), (D) Centralized Federated Learning, (E) Decentralized Federated Learning (Ring All-reduce), and (F) Decentralized Learning.

## II. BACKGROUND

### A. Artificial Intelligence

AI systems can perform tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and language understanding [26], [27]. Modern AI development is mainly driven by machine learning (ML), which enables computers to learn and make decisions by using complicated algorithms [28], [29] with the computational power and the availability of large datasets. AI also leads to significant progress in many fields such as computer vision [30], natural language processing [31], and game playing [32].

However, most existing AI systems are centralized, where the creation, training, and deployment of AI models are controlled by a single or a few entities. A typical centralized AI system is shown in Figure 1(B): centralized entities (e.g., companies) collect personal data from multiple sources (e.g., clients, mobile app users) and aggregate it into a central repository. This allows their pre-designed ML models to learn from this unified dataset. Although this approach can be effective for building powerful algorithms and applications, centralized AI faces several challenges, such as computing resource bottlenecks, data availability, privacy concerns [33], value bias [34], governance issues [35], and ethical concerns [36].

**Distributed Machine Learning (DML)** is a training approach that can overcome the computational limitations of single-machine learning systems with large models and datasets. As the size and complexity of AI models increase, a single computational unit may lack the memory or processing power to manage the workload efficiently. DML solves this challenge by distributing the computational tasks across multiple computational units (e.g., CPUs, GPUs, TPUs) and enabling parallel execution [37]. DML can be broadly grouped into two main categories: *data parallelism* and *model parallelism*. In data parallelism (see Figure 1(C)), the entire model is replicated across multiple units, and each unit processes a subset of the data in parallel. After local computations, the results are aggregated to update the global model. In model parallelism, the model is split across multiple machines, and each machine is responsible for computing different parts of the model. This method is useful for extremely large models that cannot fit on a single device, but it requires all machines to access the entire dataset, which may increase data privacy risks.

**Federated Learning (FL)** is a distributed and collaborative machine learning approach designed to address the privacy concerns and limitations of traditional centralized AI systems by utilizing decentralized computational resources. In conventional AI, one straightforward solution to protect user privacy

is to allow each client to perform standalone (on-device) learning without transmitting any information externally, as shown in Figure 1(A). However, this might lead to the data silo problem, where isolated data across devices severely limits model performance.

To address the data silo issue while protecting data privacy, FL enables model training locally on individual devices (e.g., smartphones or edge devices) or within organizations (e.g., companies or institutions) without sharing raw data. Each FL client computes model updates based on its local data, and only the model parameters (gradients) are shared with a central server for aggregation [38] (Figure 1(D)). This approach allows collaborative model training across distributed clients while guaranteeing data privacy on local devices.

However, centralized FL still has limitations such as fault tolerance, privacy issues, as well as communication costs. Decentralized FL adopts a ring-allreduce [39] paradigm (see Figure 1(E)) to mitigate these limitations. Specifically, participating devices are organized in a logical ring topology and collaborate to train a global model without relying on a central server. Each device trains a local model on its private data and then shares its model updates with its adjacent device in the ring. The updates are passed around the ring in multiple iterations, with each device receiving, forwarding, and aggregating updates from other devices along the ring. While decentralized FL improves centralized FL without relying on a centralized server. It is still challenging to simultaneously protect data privacy and ensure robust collaboration between untrusted parties in decentralized environments.

### B. Blockchain and Smart Contracts

**Blockchain** is a distributed ledger technology that enables transactions among participants over a decentralized network. It does not rely on a centralized server and can provide transparency and decentralization [40]. In a blockchain system, transactions are grouped into blocks. Blocks are linked together in a chain through cryptographic hash functions. Blockchain participants achieve agreement on the ledger status through the underlying consensus mechanism.

**Smart Contracts** are self-executing programs stored on a blockchain. They can automatically execute the terms of an agreement upon predefined conditions. Smart contracts are typically written in code to support transparent deployment and execution. Smart contracts are widely used in various applications, such as Decentralized Finance (DeFi) [41], [42] and supply chain management [43].

### C. Blockchain-based AI

Blockchain technology offers innovative solutions to address the limitations of centralized AI [44] and provide many advantages. For instance, blockchain enables secure and privacy-preserving data sharing for AI model training. As shown in Figure 1(F), blockchain can support decentralized AI models that reduce centralized control and distribute computational resources more efficiently. Blockchain's immutable and auditable ledger can also enhance trust in AI systems [22],

[45], [46]. However, challenges such as scalability issues, performance bottlenecks, the balance between privacy and transparency, and the complexity of implementation persist [25], [47], [48]. Numerous ongoing academic and industry works [14], [15], [49], [50] aim to leverage the strengths of blockchain to build more robust and DeAI systems.

## III. DEAI FRAMEWORK

To enable practical DeAI applications in real-world scenarios, we propose a framework to ensure that AI processes are traceable and decentralized throughout their lifecycle.

### A. DeAI Model Lifecycle

As shown in Figure 2, the lifecycle of a DeAI application consists of five phases: task proposing, pre-training, on-training, post-training, and a feedback loop that may return to task proposal for model refining or fine-tuning.

**① Task proposing** involves *algorithm preparation*, where algorithms are designed to ensure privacy, scalability, and communication efficiency within decentralized environments. Additionally, *code verification* is conducted to verify that the submitted code complies with DeAI standards.

**② Pre-training** is the stage where data and compute resources necessary for the training process are set up. This step includes *data preparation* and *compute power preparation*. During *data preparation*, the data is collected, cleaned, preprocessed, and partitioned to ensure compatibility with the training process while maintaining privacy and security. For *compute power preparation*, the required computational resources, such as GPUs, CPUs, or distributed systems, are allocated and configured to enable efficient and reliable training.

**③ On-training** focuses on how information and updates are managed safely and efficiently during the training process, ensuring proper communication and parameter sharing among the participating nodes. This step contains *model training* and *model validation*. During *model training*, participating nodes collaboratively update model parameters by processing local or public datasets and maintaining synchronization. During *model validation*, the trained models are evaluated on a shared validation dataset or through cross-validation to ensure their accuracy and generalization capability across participants.

**④ Post-training** is the phase where the focus shifts from model development to deployment and utilization. In this stage, the trained model is shared and integrated into applications. It ensures the model is ready for real-world use and continuous improvement. This step includes *model inference*, *AI agents* and *model marketplaces*. During *model inference*, the trained model is employed to generate predictions or perform tasks on new data, ensuring accuracy and efficiency in diverse applications. For *AI agents*, the model is embedded into autonomous systems that interact with users or environments to execute tasks intelligently. In *model marketplaces*, the trained model can be shared, traded, or monetized, fostering collaboration and accessibility for broader use cases.

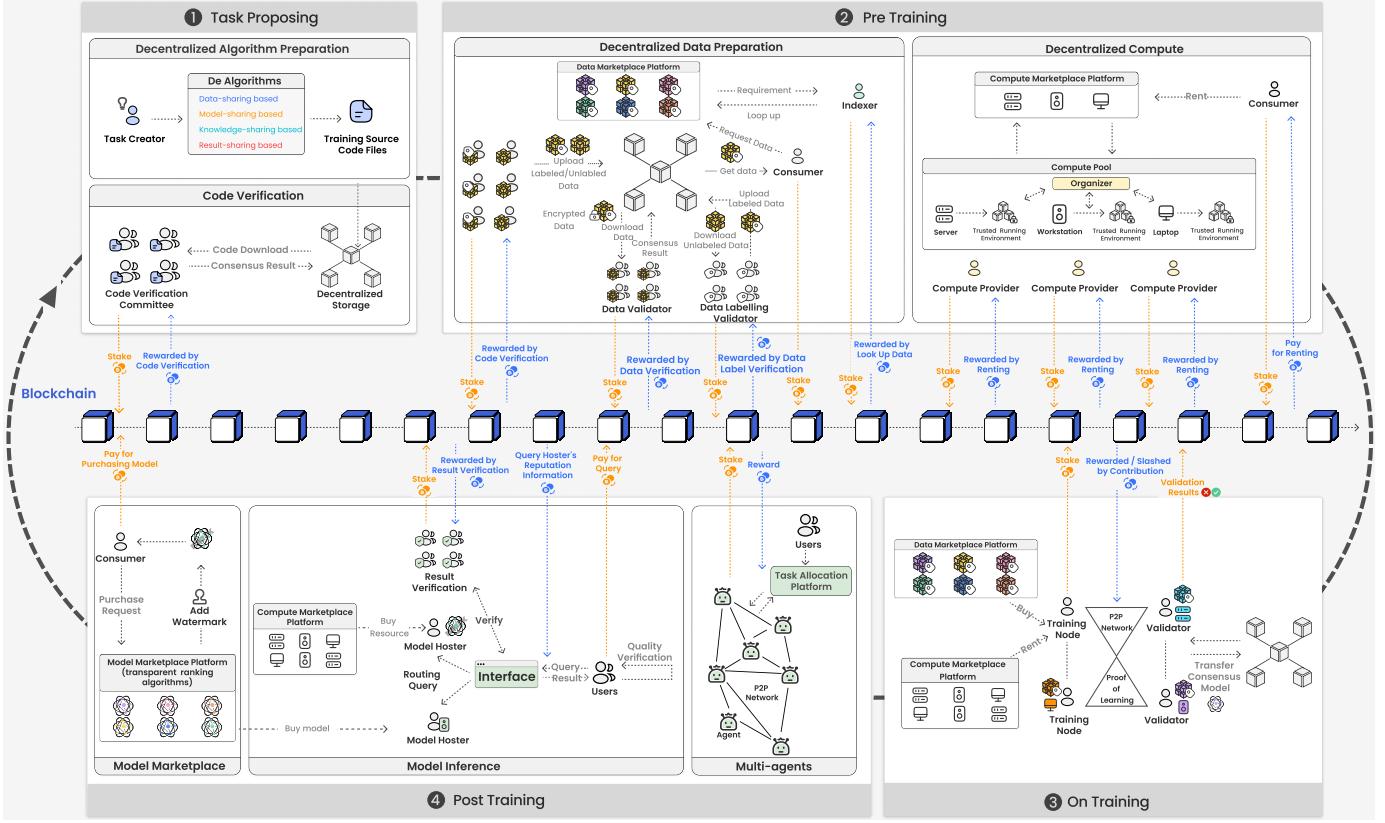


Fig. 2: A DeAI model lifecycle consists of four phases: ① task proposing, ② pre-training, ③ on-training, and ④ post-training.

### B. Blockchain Functionalities in DeAI

The functionalities of blockchain in each category within DeAI are diverse and offer significant advantages in enhancing the security, transparency, and efficiency of DeAI processes. These functionalities can include:

- ⇒ **Incentive Mechanism:** A blockchain-based incentive mechanism can incentivize participants to contribute to the DeAI ecosystem. For example, data providers, model trainers, and validators can be rewarded with tokens or cryptocurrency for their contributions. This mechanism encourages active participation and ensures that contributors are fairly compensated, fostering a collaborative and sustainable DeAI community.
- ⇒ **Decentralized Permission Control:** Blockchain enables a decentralized and trustless environment where permission control is managed through smart contracts or consensus mechanisms. This ensures that access to data, models, and computational resources is securely controlled without relying on a central authority. In a collaborative AI environment, decentralized permission control can prevent unauthorized access and maintain the integrity of shared resources.
- ⇒ **Data Storage:** Blockchain can provide a secure, immutable, and decentralized data storage solution for AI. By storing datasets or model parameters on a blockchain or an associated decentralized storage network, the in-

tegrity and availability of the data are ensured. This is particularly important for maintaining transparency and trust in AI applications, as all data modifications and access can be traced and audited.

- ⇒ **Public Reference:** Blockchain can serve as a public reference for AI models and datasets, ensuring that they are accessible and verifiable by anyone. This public ledger can store cryptographic hashes or metadata of models and datasets, providing proof of their existence and authenticity at a specific point in time. This transparency is crucial for building trust in ML systems, as stakeholders can independently verify the provenance and integrity of the data and models being used.
- ⇒ **Auditability and Traceability:** Blockchain's immutable ledger provides a complete and transparent history of all transactions and actions within the AI lifecycle. This auditability is essential for tracking the origin and evolution of datasets, models, and decisions made by AI systems. Stakeholders can trace back every step of the AI model lifecycle, ensuring compliance with regulatory requirements and ethical standards.
- ⇒ **Enhanced Security:** The decentralized nature of blockchain enhances the security of AI systems by reducing the risk of single points of failure and making it more challenging for malicious actors to manipulate data or models. Blockchain's cryptographic techniques also

TABLE I: Overview of DeAI Projects.

Projects	DeAI Framework							Blockchain Functionalities							Decentralization <sup>†</sup>	Staking	Security Guarantee
	Task Creation	Data Preparation	Compute	Training	Model Inference	Model Marketplace	Agents	Incentive Mechanism	Enhanced Security	Permission Control	Data Storage	Public Reference	Auditability	AI Assets Tokenization			
Vana [16]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	ZKP
Fraction AI [51]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	Reputation
Ocean [52]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	On-chain Consensus
Numbers [53]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Stake
The Graph [54]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	On-chain Consensus
Synternet [55]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Delivery/Consumption
OriginTrail [56]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Knowledge
ZeroGravity [57]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Random Access
Grass [58]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	ZKP + Reputation
OORT Storage [59]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Honesty
KIP [60]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	○	●	On-chain Consensus
Filecoin [61]	○	●	○	○	○	○	○	●	●	●	●	●	●	●	●	○	Proof-of-Replication/Spacetime
IO.NET [62]	○	○	●	○	○	○	○	●	●	●	●	●	●	●	○	●	Reward + Slash
NetMind [63]	○	○	○	●	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Authority
Render Network [64]	○	○	○	●	○	○	○	●	●	●	●	●	●	●	○	●	Reputation + Proof of Render
Akash [19]	○	○	○	●	○	○	○	●	●	●	○	●	●	●	○	●	Tendermint Consensus
Nosana [65]	○	○	○	●	○	○	○	●	●	●	●	●	●	●	○	●	On-chain Consensus
Inferix [66]	○	○	○	●	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Rendering
OctaSpace [67]	○	○	○	●	○	○	○	●	●	●	●	●	●	●	○	●	On-chain Consensus
DeepBrain Chain [68]	○	○	●	○	○	○	○	●	●	●	●	●	●	●	○	●	Delegated Proof of Stake
OpSec [69]	○	○	●	○	○	○	○	●	●	●	●	●	●	●	○	●	Delegated Proof of Stake
Gensyn [70]	○	○	●	○	○	○	○	●	●	●	●	●	●	●	○	●	Proof of Learning
Lilypad [71]	○	○	●	○	○	○	○	●	●	●	●	●	●	●	○	●	Mediators + On-chain consensus
Bittensor [72]	●	○	○	●	○	○	○	●	●	●	○	●	●	●	○	●	Yuma Consensus
FLock.io [15]	●	○	○	●	●	●	○	●	●	●	○	●	●	●	○	●	FLock Consensus
Numerai [73]	○	○	○	●	●	●	○	●	●	●	○	●	●	●	○	●	On-chain Consensus
Commune AI [74]	●	○	○	●	○	○	○	●	●	●	○	●	●	●	○	●	Yuma Consensus
Modulus [75]	○	○	○	○	●	○	○	●	●	●	○	●	●	●	○	○	zkML
Hyperspace [76]	○	○	○	○	●	○	○	●	●	●	○	●	●	●	○	○	Fraud Proof
Sertn [77]	○	○	○	○	●	●	○	○	●	●	●	●	●	●	○	●	ZKP+FHE <sup>‡</sup> +MPC
ORA [78]	○	○	○	○	●	●	○	●	●	●	○	●	●	●	○	●	opML
Ritual [79]	○	○	○	○	●	●	○	●	●	●	○	●	●	●	○	●	On-chain Consensus
Allora [80]	○	○	○	○	●	●	○	●	●	●	○	●	●	●	○	●	CometBFT
Fetch.AI [18]	○	○	○	○	○	○	○	●	●	●	○	●	●	●	○	●	Proof of Stake
Arbiter [81]	○	○	○	○	○	○	○	●	●	●	○	●	●	●	○	●	Proof of Useful Work
Theoriq [82]	○	○	○	○	○	○	○	●	●	●	○	●	●	●	○	●	Proof of Contribution/Collaboration
Delysium [83]	○	○	○	○	○	○	○	●	●	●	○	●	●	●	○	●	On-chain Consensus
OpenServ [84]	○	○	○	○	○	○	○	●	●	●	○	●	●	●	○	●	On-chain Consensus
Autonolas [85]	○	○	○	○	○	○	○	●	●	●	○	●	●	●	○	●	Tendermint Consensus
ELNA [86]	○	○	○	○	○	○	○	●	●	●	○	●	●	●	○	●	On-chain Consensus
OpenAgents [87]	○	○	○	○	○	●	●	●	●	●	○	●	●	●	○	●	On-chain Consensus
SingularityNET [88]	○	○	○	○	○	●	○	●	●	●	○	●	●	●	○	○	Multi-Party Escrow
SaharaAI [89]	○	○	○	○	○	●	●	●	●	●	○	●	●	●	○	●	Proof-of-Stake
Shinkai [90]	○	○	○	○	○	●	●	●	●	●	○	●	●	●	○	●	ZKP+MPC
Balance DAO [91]	○	○	○	○	○	●	●	●	●	●	○	●	●	●	○	●	Proof-of-Stake
Immutable Labs [92]	○	○	○	○	○	●	●	●	●	●	○	●	●	●	○	●	Green Proof of Work
Prime Intellect <sup>§</sup> [93]	○	○	●	●	●	○	○	○	○	○	○	○	○	○	○	○	Centralized Server

<sup>†</sup>Decentralization: We mark most existing DeAI solutions as “partially” decentralized as they have centralized or off-chain components.

<sup>‡</sup>FHE: Fully Homomorphic Encryption.

<sup>§</sup>Prime Intellect: We also present the project which aims to build DeAI but does not explicitly mention blockchain in its design.

ensure that data is securely encrypted and only accessible to authorized parties.

⇒ **Trustless Collaboration:** Blockchain facilitates trustless collaboration in AI, where participants can interact and share resources without needing to trust each other. Smart contracts automatically enforce agreements and execute transactions, reducing the need for intermediaries and minimizing the risk of fraud.

⇒ **Tokenization of AI Assets:** Blockchain enables the

tokenization of AI assets such as datasets, models, and computational power. These tokens can be traded on decentralized marketplaces, providing a liquid market for AI resources. Tokenization also allows for fractional ownership of AI assets, enabling more flexible and accessible investment opportunities.

⇒ **Interoperability and Integration:** Blockchain can facilitate interoperability between different AI platforms and systems by providing a standardized and secure

framework for data exchange. This interoperability is essential for integrating diverse AI tools, libraries, and datasets into a cohesive and efficient workflow.

#### IV. PRE-TRAINING

##### A. Data Preparation

**Data preparation** involves processes such as data collection, cleaning, normalization, transformation, and feature selection. These steps are crucial for effective AI model training and can directly affect model performance, especially accuracy [94]. Well-cleaned data can also reduce dimensionality, mitigate the overfitting problem, and enhance model interpretability [95].

1) *Weaknesses of Centralized Data Preparation:* The effectiveness of LLMs substantially depends on access to vast amounts of high-quality, diverse, and well-labeled data. While computational power and model architectures have seen significant advancements, the availability of such data has not kept pace [96], [97]. Recent advancements in LLMs have significantly increased the demand for large volumes of high-quality public data for training purposes. OpenAI's GPT-2 was trained on approximately 40GB of text data [98], while its successor, GPT-3, utilized an estimated 1.2TB of data [99]. Similarly, Google's T5 required about 750GB of cleaned text [100], and their PaLM model consumed an estimated 3.1TB of data [101]. Meta's LLaMA pushed these boundaries further by training on 1.4 trillion tokens, amounting to an estimated 5.6TB of data [102]. Moreover, recent analyses estimate that the total amount of high-quality, publicly available text data suitable for training LLMs is approximately 6TB [103], indicating that we are nearing the limit of available data for future models. The escalating data requirements underscore a critical challenge for centralized AI: the finite pool of publicly available high-quality data is nearing exhaustion [104], which hampers the potential for further scaling of LLMs and restricts model performance enhancements. Thus, being reliant solely on publicly available, centralized data presents limitations in several key areas. First, the pool of openly accessible data is finite, leading to potential saturation where new insights from existing data sources diminish, thus restricting model performance. Second, centralized data collection often lacks representation across domains, languages, and regions, which can result in biased and less effective models for diverse applications. Furthermore, the increasing concerns around data privacy and security hinder access to private, domain-specific datasets, which are crucial for developing specialized and high-performance models.

2) *Decentralized Solutions for Data Preparation:* Decentralized data preparation offers a compelling solution by enabling access to diverse and geographically distributed data sources without requiring centralized storage. For instance, through blockchain or federated learning frameworks [105], data providers can contribute data securely, preserving privacy and ensuring data ownership. However, different from centralized systems, where a single entity oversees data quality, a decentralized approach lacks a central authority to manage

data submissions. This raises the following challenges: ① Malicious participants may contribute harmful or low-quality data; ② Free-riding actors may exploit the system for rewards without actual contributions; ③ The private data of honest participants might be leaked in a decentralized system.

In the following, we investigate existing methods for overcoming these challenges in decentralized data preparation, as well as the relevant protocols [16], [51]–[61].

a) *Incentive Mechanisms for Data Contributions:* To incentivize participants to contribute high-quality data, existing decentralized data preparation platforms typically leverage blockchain to build reward mechanisms.

**Dataset Tokenization.** Existing data preparation platforms, such as Ocean Protocol [52] and Vana [16], support decentralization by providing a marketplace where data assets are tokenized. Such a solution allows data providers to publish datasets as datatokens, which are tokens that represent access to the underlying data. Data consumers can purchase these datatokens to access or use the data, creating a market-driven approach to data sharing. Ocean Protocol also uses staking and curation to promote high-quality data contributions. Users can stake tokens on data assets they believe are valuable, and in return, they earn a portion of the transaction fees when others access that data. This mechanism incentivizes users to identify and promote high-quality data, as their earnings depend on the data's utilization within the network.

**Proof-of-Data Contribution and Scoring-based Rewards.** To verify that a participant has provided valuable data, a proof-of-contribution mechanism can be implemented, which utilizes a model influence function to assess the impact of new data points on improving the AI model. For instance, in Vana [16], validators are responsible for evaluating data quality. They apply a predefined function to quantify each data point's contribution and assign scores based on its calculated influence. These scores directly connect data quality to contributor rewards, encouraging participants to submit high-quality, meaningful data rather than arbitrary entries.

**Stake and Reputation-based Rewards.** Another solution is to use stake and reputation-based mechanisms to reward data contributors. In this solution, data contributors and verifiers stake tokens to participate in the system. Contributors earn rewards based on their reputation, which reflects the quality of their work. For instance, in Fraction AI [51], contributors with higher reputations are more likely to be selected for tasks and earn greater rewards, while poor-quality contributions can lead to a loss of reputation and staking penalties.

b) *Data Privacy Protection:* Privacy-enhancing technologies, such as public encryption and zero-knowledge proofs (ZKPs), are typically used to protect the privacy of data contributors in decentralized data preparation platforms. For instance, Vana [16], [106] incorporates ZKPs, such as Groth16 [107], with blockchain to verify the authenticity and integrity of data without revealing its full content. Specifically, when data contributors or custodians submit data, a zero-knowledge proof is generated and recorded on the blockchain. This on-chain verification allows validators to confirm that

the data meets certain criteria without accessing the actual data, ensuring that data privacy is maintained. Ocean Protocol [52] employs encryption and blockchain-based access control mechanisms to protect data privacy. When a user wishes to access a dataset, they must acquire the corresponding datatoken, effectively buying a token that serves as a key to unlock the data. Blockchain's smart contracts enforce these access controls, ensuring that only authorized users can retrieve and work with the data.

*c) Data Verification and Authentication:* As AI systems increasingly depend on large datasets, ensuring that this data is authentic and unaltered is critical for maintaining the reliability of AI models. Blockchain's cryptographic mechanisms enable the detection of any data tampering, making it a valuable tool for safeguarding data integrity. By leveraging blockchain's inherent characteristics, such as immutability, transparency, and decentralization, data can be securely traced and verified without reliance on a central authority. For example, Numbers Protocol [53] establishes a transparent, immutable ledger that records the history and metadata of each data piece or digital asset. Storing this information on the blockchain ensures that all transactions and modifications are permanently recorded and cannot be altered retroactively. Additionally, ownership and licensing information can be embedded directly into the content's digital footprint through smart contracts. These on-chain smart contracts can automatically manage data rights and permissions, ensuring that creators receive proper credit and compensation for their work.

❖ **Insight 1.** *Decentralized data preparation requires:* ① *ensuring the authenticity and integrity of data and digital content;* ② *establishing well-defined, robust, and sustainable incentive mechanisms to encourage broader data contributions;* and ③ *implementing systems that protect data privacy to foster trust among data contributors.*

*3) Discussion:* Despite the existing attempts [16], [51]–[53] to build decentralized data preparation systems, addressing the trade-offs between rewards, privacy, and authenticity in these solutions highlights several pressing research gaps. First, optimizing incentive structures that offer fair rewards without risking inflation or reward dilution remains a challenge, as current mechanisms such as Liquidity Pools [16] and Revenue Rights Certificates [51] may vary widely in effectiveness and scalability. Second, safeguarding privacy in a decentralized setting requires advanced cryptographic techniques, such as ZKPs and Trusted Execution Environmentss, but these methods may face limitations in terms of computational load and compatibility across diverse data types and platforms. Additionally, ensuring data authenticity through decentralized consensus mechanisms, such as Proof of Contribution in Vana [16], may present scalability issues, particularly as data volumes increase and the need for real-time validation grows. Additionally, once data consumers have paid the fees and gained access to the data, they may forward the data to other consumers without sharing any rewards with the original data providers. Further research is needed to address these gaps by developing

more efficient reward models, scalable privacy solutions, and lightweight yet robust consensus algorithms that together balance data contributor incentives, privacy preservation, and data authenticity in decentralized ecosystems.

○ **Gap 1.** *How to develop efficient and scalable privacy solutions, and lightweight yet robust consensus mechanisms that collectively balance data contributor incentives, privacy, and authenticity in decentralized ecosystems?*

## B. Decentralized Compute

**Compute resource** plays a pivotal role in the development of AI systems and directly impacts model training and inference performance. Large AI models rely on vast datasets and intricate architectures, especially in deep neural networks (DNNs) that can contain millions or even billions of parameters. During the training phase, models learn patterns from data by optimizing these parameters through iterative processes, which involve substantial matrix operations and gradient descent algorithms [97]. For instance, in the case of backpropagation training algorithm [108], each iteration requires the adjustment of a large number of weights. The computational cost scales exponentially with the number of parameters, making traditional CPUs inefficient for such tasks. This has led to the widespread adoption of specialized hardware accelerators such as GPUs and Tensor Processing Units (TPUs) that are designed for parallel processing and high-throughput computations [109].

Studies have shown that the computational requirements for training AI models have been doubling every 3.4 months since 2012 [110], [111], particularly as models have grown more complex and larger in scale. This growth far exceeds Moore's Law, which traditionally predicts a doubling of computational power every two years. This sharp increase is attributed to advancements in deep learning and the ever-growing complexity of models, which demand more extensive compute resources to achieve state-of-the-art performance.

1) *Challenges of Accessing Compute for AI Training:* Access to sufficient compute resources has become a significant barrier in the field of AI, especially for LLMs [93], [99], [112]. For instance, GPT-3 is trained on approximately 570B tokens, equivalent to about 450B words sourced from publicly accessible Internet data, aiming to cover a broad spectrum of visible knowledge. This training effort requires around 175B model parameters [99]. Such an extensive computational task is infeasible for individuals to undertake, even when it comes to fine-tuning pre-trained models. Instead, it demands the resources of data centers or distributed computing clusters.

GPUs, optimized for parallel processing and critical to efficient model training, are prohibitively expensive and often inaccessible to smaller organizations and independent researchers. The high costs of acquiring, maintaining, and scaling GPU infrastructure create a growing gap between entities with ample compute resources and those without. Although cloud service providers such as AWS and Google Cloud offer

GPU rental services to meet the needs of smaller players, the fees remain substantial. This makes large-scale model training financially unsustainable for many, particularly as the demand for compute continues to grow. Moreover, issues of scalability and availability are compounded by resource inefficiency, with many GPUs remaining underutilized in data centers and organizations.

Furthermore, most current large-scale models are pre-trained on publicly available data scraped from the Internet. This widespread use of similar public data narrows the performance gap between various large models, as they draw knowledge from the same data distribution. Consequently, improving these models in the near future will likely depend on incorporating more diverse, private datasets. Traditional machine learning methods typically collect both shared and private data for centralized training, but with the growing emphasis on data protection regulations (e.g., GDPR [113]), this centralized approach is becoming increasingly impractical. As a result, decentralized training methods, which leverage local computing power and process data at its source, are becoming necessary. While such decentralized approaches address privacy concerns, reduce data transmission, and lower computation costs for model vendors, they introduce several challenges in terms of orchestrating and managing distributed computation effectively.

2) *Blockchain-Enabled Decentralization of Compute Access:* Given the significant barriers in accessing affordable and scalable compute resources for large-scale AI training, blockchain technology offers a transformative solution. The properties of blockchains, including transparency, tokenized incentives, and decentralization, provide innovative ways to address the challenges associated with compute in AI training [19], [62]–[71], [74].

**Permissionless Access to Compute.** Blockchain's trustless nature allows compute users and providers to interact without the need for intermediaries, such as cloud service providers. This enables a permissionless environment where anyone with underutilized compute power can contribute, and AI developers can access those resources directly. For instance, Lilypad [71] leverages blockchain to create a distributed network where users can run containerized workloads on idle compute nodes without relying on centralized providers. This opens up access to high-performance compute for AI training, as anyone with idle hardware can participate, contributing to the overall decentralization of compute access.

**Incentive Mechanisms for Efficient Resource Utilization.** Blockchain-based compute networks [19], [62] introduce tokenized economies, where compute contributors are rewarded with tokens for their participation in a fair way. This design allows compute providers to monetize their idle resources and makes high-performance compute more affordable. For example, IO.NET [62] implements a decentralized marketplace where GPU users can pay for compute resources with tokens. GPU owners are incentivized to offer their idle GPUs, while users benefit from a competitive, market-driven pricing system that balances supply and demand. Similarly, Akash [19] also

implements a tokenized system where compute providers are rewarded based on a Proof-of-Stake consensus mechanism. In Akash, providers stake tokens to contribute compute resources, and rewards are distributed based on network usage and demand. Akash also implements a reverse auction model, which enables AI developers to access compute at market-driven prices, ensuring a cost-efficient resource allocation.

**Decentralized Compute Resource Scalability.** Blockchain enables scalable networks that aggregate compute resources from a global pool of contributors. This allows decentralized compute networks to handle large-scale AI workloads while maintaining flexibility and performance. Lilypad's [71] distributed architecture allows it to scale horizontally by adding more compute nodes as demand increases. This enables AI developers to access compute resources on demand, with tasks dynamically allocated to available nodes, ensuring scalability for compute-intensive workloads such as large language models. Similarly, Render Network [64] leverages its P2P architecture to dynamically allocate GPU resources for AI computation tasks. As more nodes join the network, Render can scale its compute capacity, ensuring that workloads are distributed efficiently across the network.

**Compute Task Verification.** Blockchain's immutability and transparency ensure that every task and transaction is recorded on a decentralized ledger, enabling verifiable compute processes. This helps create an open system where users can trust that their workloads will be executed honestly, and providers can verify that they are compensated fairly. Render Network [64] utilizes this property by recording every transaction and task on-chain, ensuring that node operators are incentivized to provide compute services while AI developers can trust that their tasks will be executed without manipulation. The on-chain reputation system further ensures that compute resources are allocated to reliable nodes, reducing risks and increasing accountability. Gensyn [70] also leverages blockchain's transparency for task verification. Using graph-based pinpoint protocols and staking mechanisms, Gensyn ensures that computational tasks are verified without requiring centralized oversight. This decentralized verification system guarantees that work is performed accurately, and rewards are only distributed when tasks are completed correctly.

**Security and Integrity of Compute Resources.** Blockchain's properties of immutability and cryptographic security can ensure the integrity of compute resources. NetMind [63], for example, uses blockchain and multi-party computation (MPC) to protect AI training and inference tasks across its network. The decentralized nature of the network reduces the risk of attacks or data breaches, ensuring that compute tasks are performed in a secure environment. Gensyn [70] enhances security through a staking and slashing mechanism that ensures compute providers perform tasks honestly. This system secures the network from malicious actors, while the decentralized task verification process ensures that AI developers can trust the integrity of the compute resources they access. Akash [19] secures its decentralized cloud compute resources through the Tendermint consensus mechanism [114], which ensures the

integrity of transactions on the network. This decentralized security model helps protect AI workloads from tampering, fraud, or service disruptions.

❖ **Insight 2.** *Decentralized computing systems require: ① permissionless access to computing resources; ② incentive mechanisms to promote efficient utilization of these resources; ③ scalable solutions for managing decentralized computing resources; and ④ mechanisms to ensure the security, privacy, and integrity of computing resources.*

3) *Discussion:* Staking mechanisms contribute significantly to the security and reliability of decentralized compute by aligning participants' incentives with network stability. Beyond its role in securing the network, staking also serves as a signal of demand in decentralized systems, acting as a proxy for market value and influencing rewards distribution.

**Alternatives for Staking.** It is important to note that staking is not the only way to achieve these goals. For instance, Lilypad [71], instead of using PoS, opts for a Proof of Work (PoW) consensus mechanism. Specifically, nodes must be online for a minimum of four hours a day continuously in order to be eligible for rewards. To verify the online time of individual nodes, Lilypad uses PoW to ensure compliance. This approach provides an alternative means of ensuring network reliability and incentivizing participation without relying on staking.

**Tokenomics Inflation and Deflationary in Decentralized Compute.** Different models are employed in tokenomics for decentralized computing. For example, Akash [19] uses an inflationary model, while IO.NET [62] adopts a disinflationary approach. Specifically, IO.NET reduces emitted rewards each month after the first year, whereas Akash's inflationary model starts at an inflation rate of 100% that halves every two years. In theory, an inflationary model can effectively incentivize compute providers during the early stages of network development, whereas a disinflationary model may help sustain the network's long-term economic health. An open question is to analyze the empirical impacts of these tokenomic models on decentralized compute networks, particularly given the fluctuating costs of compute resources such as GPUs.

○ **Gap 2.** *What are the empirical impacts of inflationary versus deflationary tokenomics models on decentralized compute networks?*

## V. ON-TRAINING

### A. Model Training in Traditional AI

In traditional centralized AI platforms, the process of training an AI model is typically managed by a single entity that controls both the data and the computational resources. Once a task for a target model is defined and the necessary training data is prepared, the following steps are undertaken:

- **Model Training:** The AI model is trained using computational resources provided by centralized data centers. These resources, such as GPUs or TPUs, are controlled

and managed by a central authority. The central authority oversees the entire training process, which includes adjusting hyperparameters, monitoring model performance, handling data preprocessing, and ensuring the computational infrastructure is functioning optimally. For instance, Google and Facebook train their AI models on proprietary datasets using their own data centers [7].

- **Model Evaluation:** After the initial training phase, the model is evaluated using a validation dataset to assess its performance, to determine whether the model generalizes well to unseen data. The evaluation process often involves calculating metrics such as accuracy, precision, recall, or F1-score, depending on the task. If the performance is not satisfactory, the model may be retrained with adjusted hyperparameters or with additional data augmentation techniques. All these activities occur within the centralized infrastructure, with data, model updates, and results stored and managed centrally. For example, in the development of image recognition models using ImageNet [115], organizations download the dataset, train their models on local or cloud-based centralized servers, and evaluate performance internally before deploying the models.

### B. Challenges in Traditional Centralized AI Training

Despite the widespread adoption of centralized AI training platforms, several challenges raise concerns:

- **Data Privacy and Control:** Centralized platforms require all training data to be uploaded to a central server, raising concerns about data privacy and security, especially when dealing with sensitive or proprietary information. For instance, hospitals may be reluctant to share patient data with external entities due to privacy laws such as the Health Insurance Portability and Accountability Act (HIPAA) [116], hindering collaborative AI development in healthcare.
- **Resource Centralization:** The reliance on centralized computational infrastructure means that only entities with significant resources can afford to train large-scale models. Training state-of-the-art models often requires extensive computational power and storage capacity, creating barriers for smaller companies or research institutions. For example, training models such as GPT-3 requires vast resources that are typically beyond the reach of most organizations [117].
- **Single Point of Failure:** Centralized systems might be vulnerable to outages and attacks. If the central server experiences downtime or is compromised, the entire training process can be disrupted. Moreover, central servers can become bottlenecks, limiting scalability when more users or data are added to the system.
- **Trust and Transparency:** Users must trust the central authority to handle data responsibly and to train models without introducing bias or errors. However, without transparency into the training process, it is difficult to verify that the models are being developed ethically and effectively. Instances of data misuse or lack of transparency can erode trust in AI systems [1].

### C. How Blockchain Makes AI Training Decentralized

Decentralized training platforms, such as Bittensor [72], FLock.io [15], Numerai [73], and Commune AI [74], leverage blockchain to distribute AI training tasks across a P2P network of participants, addressing key challenges in traditional centralized AI platforms in the following ways:

- **Trustless and Transparent Training:** Blockchain enables a trustless environment where participants do not need to rely on a central authority. All interactions, such as task assignments, model updates, and reward distributions, are recorded on an immutable ledger, ensuring transparency. For instance, in Bittensor, the rules governing the training process are encoded and the contributions of participants are recorded on the blockchain. This transparency builds trust among participants and allows for the verification of the training process. Similarly, Numerai provides a decentralized data science competition where participants worldwide can download training data, develop models locally, and submit predictions to the network.
- **Decentralized Model Validation:** After nodes complete their training tasks, the model updates are validated in a decentralized manner. Validators within the blockchain network are responsible for verifying the correctness of these updates. In Numerai, models are trained independently by participants, and their predictions are aggregated to form a meta-model that the platform uses for trading in financial markets. The performance of individual models is evaluated based on their contribution to the overall performance, ensuring that malicious or low-quality models do not negatively impact the system.
- **Consensus and Incentive Mechanisms:** Participants are rewarded based on their performance on the platforms, with the reward amounts determined by predefined consensus mechanisms. For instance, the Bittensor Yuma Consensus [14] allocates rewards to miners and validators according to their contributions. Similarly, in Flock.io [15], participants stake tokens to join as training nodes or validators, receiving rewards proportional to their performance and adherence to expected outcomes. Such incentive mechanisms encourage participants to develop high-quality models.

### D. Key Functionalities Blockchain in DeAI Training

Blockchain technology introduces several key functionalities that enhance decentralized AI training:

- **Public Task Coordination and Distribution:** Blockchain enables the coordinated and fair distribution of AI training tasks across the network. For example, in both Bittensor [14] and Flock.io [15], tasks are automatically assigned to training nodes based on decentralized protocols. The blockchain ensures that tasks are fairly allocated and that all nodes can view task assignments and completions, providing transparency that prevents any single node from monopolizing tasks or manipulating the process.
- **Fair Incentivization Mechanisms:** Blockchain provides fair incentivization mechanisms by using decentralized,

transparent protocols that allocate rewards based on objective contributions. Consensus mechanisms on blockchain platforms ensure that rewards are distributed equitably among participants, preventing any single entity from manipulating the reward process or monopolizing tasks. This transparency and decentralization motivate participants to contribute high-quality work, as they are rewarded fairly for measurable performance.

- **Immutable Audit Trails:** Every interaction in the blockchain is recorded immutably, creating a transparent audit trail. This is crucial for accountability and trust among participants. All transactions, including data sharing, model updates, and reward distributions, are recorded on the blockchain, allowing anyone to verify the history and integrity of the system.
- **Decentralized Governance:** Blockchain enables decentralized governance for DeAI through token-based voting mechanisms. DeAI stakeholders participate in governance decisions, influencing the system's direction and development [14], [74]. This decentralized control ensures that the system evolves according to the collective interests of its participants, rather than being directed by a central authority.

✧ **Insight 3.** Decentralized training systems require: ① verified task creation; ② trustless and transparent Training; ③ decentralized model validation; ④ fair incentive mechanisms; and ⑤ decentralized governance.

### E. Discussion

In implementing DeAI training, several challenges still remain, particularly regarding the trust and security of DeAI. **Ensuring Authentic Decentralized Training:** One core challenge in DeAI training is verifying that participants genuinely contribute to model training, rather than using pre-trained or stolen models [118]. Without a centralized authority to monitor activities, there is a risk of model stealing, where a participant may submit outputs from a pre-trained model rather than conducting legitimate training. To address this, a “proof-of-learning” mechanism [119]–[121] could be implemented. Proof-of-learning would require participants to demonstrate that their model has been genuinely trained on the provided dataset within the decentralized network. Techniques such as periodic accuracy or loss validation and comparison with expected learning curves could help in verifying that a model has been authentically trained [122], [123]. Additionally, cryptographic methods such as ZKPs [124], [125] could provide an additional layer of verification without exposing the model details, ensuring that participants have genuinely completed training tasks as specified by the protocol.

**Balancing Incentives with Security:** Finally, designing a fair and secure incentive mechanism is essential to maintaining participant motivation while safeguarding the network from misuse. As participants are rewarded for their contributions, care must be taken to ensure that rewards align with genuine training effort and model quality. Combining reputation scores

with token-based rewards may create a balanced incentivization model, encouraging long-term, honest contributions to the network. Reputation scores can reflect a participant's history of contributions, such as their model's performance, adherence to training protocols, and consistency over time. High-reputation participants could receive additional benefits or higher reward rates, motivating them to maintain trustworthy behaviors and discouraging short-term or exploitative actions.

**○ Gap 3.** How to combine proof-of-learning consensus, ZKPs, or reputation scoring schemes with staking mechanisms to enhance the existing DeAI training platforms?

## VI. POST-TRAINING

### A. Decentralized AI Model Inferences

In traditional AI systems, *model inference* refers to the process of using a trained machine learning model to make predictions or decisions based on new input data. This process typically involves deploying the model on centralized servers or cloud platforms, where it can receive input data, perform computations, and return results. The inference process is crucial for AI practical applications, enabling tasks such as image recognition, natural language processing, and predictive analytics in real-world scenarios [29].

The efficiency and accuracy of model inference directly impact the user experience and the overall effectiveness of AI applications. As models become more complex and data-intensive, the computational requirements for inference have grown significantly, leading to increased focus on optimizing inference processes and infrastructure [126].

1) *Challenges in Centralized Model Inference:* Two primary challenges face the current centralized model inference landscape: information inefficiency and inference integrity.

- *Information Inefficiency:* The performance of model inference is affected by the information inefficiency. Efficient exchange of information is crucial for actors to make informed decisions across domains, ranging from logistics and planning to governance and financial markets. However, when information is accessible only to a select group of ecosystem participants, those actors gain a distinct advantage over their competition.
- *Inference Integrity:* Model users typically require assurance that model developers have genuinely executed the requested model to generate the provided response. This is particularly important in high-stakes environments, such as the medical field, where predictions regarding diseases can be matters of life and death. Moreover, as companies introduce paid tiers or subscriptions, users naturally seek confidence that their inquiries are being processed using the promised advanced models, such as a premium version like o1-preview, rather than a basic model like the free GPT-3 version.

2) *Blockchain-Based Decentralized Model Inference:* Blockchain technology offers a framework for addressing the challenges associated with centralized model inference. Below,

we discuss various protocols [73], [75]–[80] which leverage blockchains to build decentralized model inferences.

**Incentives to Improve Information Inefficiency:** The decentralized nature of blockchain allows for the creation of incentive mechanisms to encourage the network participation. For instance, in Allora [80], two types of nodes, workers and reputers, are incentivized to collaborate to optimize outcomes of model inference based on the CometBFT consensus mechanism [127]. Workers produce inferences and forecast losses, while reputers stake and validate the work produced by workers, thus ensuring network reliability. Rewards for workers are based on the quality of their contributions and stakes, which helps incentivize high-quality inferences.

**Blockchain-Based Inference Verification:** There are two approaches to guarantee the integrity of DeAI model inference results: ① ZKP-based model inference [128]–[130] and ② Optimistic proof-based model inference. ZKP-based model inference, such as Sertn [77], enables participants to prove that a model's inference was conducted correctly without revealing the underlying data or model details. This method ensures privacy while maintaining the trustworthiness of the results. In contrast, optimistic proof-based model inference, such as ORA [78], inspired by Arbitrum [131], utilizes on-chain Optimistic Machine Learning (opML) for AI model inference. opML operates under the assumption that every submitted result is correct by default, but incorporates an interactive fraud-proof protocol to address potential malicious behavior. If a dispute arises, a challenge period allows participants to contest the inference result. During this period, an interactive pinpoint protocol generates a fraud proof, demonstrating that the submitted result is incorrect. This approach combines efficiency with robust mechanisms to detect and prevent fraudulent inferences.

**△ Insight 4.** Decentralized model inferences require: ① fair incentive mechanisms to encourage participants to optimize outcomes of model inference; and ② verification schemes to guarantee the integrity of inference results.

3) *Discussion:* The trade-off between ZKP- and optimistic proof-based model inference hinges on security versus performance. The ZKP-based approach ensures robust cryptographic protection for ML models but suffers from slower proof times as model size increases. In contrast, the optimistic proof-based approach leverages a fraud-proof system for model integrity, delivering better performance under specific trust assumptions. The choice between the two approaches should be determined by the specific requirements of the application scenario.

**○ Gap 4.** How to balance the trade-off between security and efficiency in AI model inference?

### B. Decentralized AI Agents

An *AI agent* is an autonomous system that can perceive its environment, make decisions, and take actions based on its objectives and goals [132], [133]. It often uses one or more AI models to guide its behavior and decision-making.

However, traditional AI agents often operate in centralized systems for data processing, storage, and decision-making, which restricts their scalability and autonomy. This section explores how blockchains can enhance the current agent-based systems.

**1) Challenges Facing Agents in Traditional AI:** Several challenges limit the development of traditional AI agents: ① *Scalability*. Traditional agents typically operate within centralized frameworks, which can become bottlenecks as the number of agents or the complexity of tasks increases. This centralization restricts the system's ability to handle a large volume of agents interacting simultaneously, leading to inefficiencies in communication and resource allocation [9]. ② *Interoperability*. In traditional systems, agents often operate in isolated environments with limited ability to interact with agents from other platforms or infrastructures. This lack of communication reduces the overall effectiveness of multi-agent systems. ③ *Trust and Security* issues arise when agents rely on centralized servers for decision-making and data storage, leaving them vulnerable to tampering or failures.

**2) Blockchain-Based Decentralized Agents:** Blockchain can address the challenges faced by traditional AI agents through many perspectives, as shown in various industry protocols [18], [81]–[87], [90], [91].

**Decentralizing Operating Environment.** Blockchain-based agents can operate in a decentralized environment, eliminating reliance on centralized infrastructure. For instance, Fetch.AI [18] enables the creation of autonomous economic agents, which operate in a decentralized manner and interact within an Open Economic Framework (OEF). The OEF is running on a directed acyclic graph-based blockchain to facilitate low-cost and scalable transactions, allowing agents to operate efficiently without central control. Similarly, Delysium [83] is another protocol dedicated to the decentralized agent network. In a nutshell, the Delysium protocol is comprised of three layers. The Communication Layer ensures fast, scalable, and secure data exchange between AI agents through unified communication protocols. Meanwhile, the Blockchain Layer governs the network, ensuring ethical behavior and accountability through Agent-ID and blockchain-enforced Intelligent Contracts. The Chronicle, on the other hand, records all agent actions in an immutable ledger for auditability, and security mechanisms such as homomorphic encryption and Secure Multi-Party Computation (SMPC) protect data integrity. Another example of decentralized agents protocol is Theoriq [82], which serves as a modular and composable AI Agent Base Layer. It provides critical interoperability, composability mechanisms, and governance for AI agents. Theoriq enables users and agents to dynamically discover, compose, and optimize Agent Collectives, which are teams of specialized AI agents collaborating on complex tasks. This approach fosters collaboration and flexibility, allowing agents to leverage each other's strengths and achieve more complex objectives in a decentralized manner.

**Enhancing Trust and Transparency.** Blockchain also enhances trust and transparency in agent interactions. In de-

centralized systems, agents can trust that their actions will be executed correctly, as actions are recorded in on-chain transactions. This transparency reduces the need for third-party intermediaries and ensures that agents can verify the actions of others. For example, Morpheus [20] offers a decentralized cloud infrastructure for agents, where smart contracts enforce agreements and ensure that interactions occur as predefined.

**Incentivizing Model Agents.** Blockchain-based tokenized incentive models can motivate agents to contribute resources, data, or computational power. This incentivization encourages agents to share their data and collaborate on tasks, fostering innovation and improving system efficiency. For instance, Fetch.AI leverages the Useful Proof-of-Work (uPoW) mechanisms, which allow agents to earn rewards by solving computational problems, further decentralizing the computational efforts [18]. Morpheus [20] also rewards participants based on their contributions to the network through a token-based incentive model to encourage collaboration among agents.

◊ **Insight 5.** *Blockchain can improve AI agents by: ① decentralizing operating environment; ② enhancing trust and transparency among participants; and ③ incentivizing model agents.*

**3) Discussion:** Existing decentralized AI agent protocols adopt various strategies to incentivize participation and maintain network integrity. For instance, Fetch.AI [18] uses Useful Proof-of-Work (uPoW), where participants perform valuable computational tasks instead of traditional mining, encouraging broader participation and efficient resource use. In contrast, Theoriq [82] employs a dual-proof system – Proof of Contribution and Proof of Collaboration – that focuses on reputation-based evaluation and collaborative optimization, with verifiable contributions strengthening trust. However, balancing computational contributions with reputation-based rewards remains challenging, potentially introducing biases. Furthermore, scalable and robust reputation mechanisms are crucial to prevent manipulation and ensure network integrity as these systems grow.

◊ **Gap 5.** *How can we design scalable, robust and unbiased incentive mechanisms for decentralized AI agents that reward them fairly based on their contributions and collaborative efforts?*

### C. Decentralized AI Model Marketplaces

*AI model marketplaces* [134] are platforms that enable developers to share and distribute machine learning models. These marketplaces allow model creators to upload their models, while users can easily access, fine-tune, and deploy them for a wide range of applications.

**1) Challenges in Centralized AI Model Marketplaces:** Current centralized AI marketplaces have several limitations: ① *Unfair Compensation*: They often fail to fairly compensate open-source model creators, who invest substantial time and expertise but face limited revenue opportunities, especially in

centralized systems that primarily reward a narrow set of contributions [135]. ② *Lack Transparency*: Marketplace rankings and recommendations are frequently driven by undisclosed algorithms [136]. Such algorithms leave users and creators without clarity on how models are prioritized, which can lead to concerns over bias and reduced trust.

2) *Blockchain-Based Decentralized AI Model Marketplaces*: Blockchain offers transformative solutions to traditional AI marketplace challenges by enabling decentralization, transparency, and fair incentivization.

**Fair Incentive Mechanisms.** Blockchain tokenization allows for AI assets, including models and datasets, to be represented as digital tokens, which are traded or licensed with transparent provenance and secure ownership. These blockchain transactions address the challenge of fair compensation by creating a system where contributors, from small developers to larger AI companies, can earn rewards directly proportional to the value they bring to the marketplace. For example, BalanceDAO [91] empowers model contributors by providing fair compensation through token-based rewards while ensuring security and integrity with ZKPs. SingularityNET [88] follows a similar approach, enabling developers to publish and monetize their models directly on the blockchain, which builds trust and transparency in the AI model exchange. Sahara AI Marketplace [89] leverages blockchain to build a decentralized hub for publishing, monetizing, and trading AI assets with a comprehensive portfolio of models and datasets. Sahara AI tracks participant contributions throughout the model lifecycle, ensuring that rewards are fairly distributed among contributors.

**Transparent Model Ranking Algorithms.** Blockchain-based AI model agent platforms offer transparent ranking and recommendation algorithms, leveraging public on-chain data. For example, Immutable Labs [92], which is based on the Green Proof of Work consensus mechanism [137], provides a blockchain-based multiple mode to choose the proper models: (i) in the Manual Mode, users manually select pre-approved models based on their criteria; (ii) As it progresses to Marketplace Mode, users can choose models via both manual and algorithmic methods, rewarding creators based on performance; (iii) In the final Distributed Mode, on-chain governance enables stakeholders to manage resource allocation and ensure fair and transparent ranking systems. Similarly, Sahara AI [89] uses blockchain protocols to enhance transparency, with non-fungible receipts serving as on-chain proof of AI model ownership. This decentralized system for ranking and visibility counters traditional biases, allowing all model contributors to be fairly presented in the marketplace based on reputation and contribution quality.

❖ **Insight 6.** *Blockchain can improve AI Model Marketplaces by providing:* ① *fair incentive mechanisms for model contributors; and* ② *transparent model ranking and recommendation algorithms.*

3) *Discussion*: The design of validation and provenance mechanisms is key to construct trust, transparency, and fair incentivization in decentralized AI model marketplaces. Im-

mutable Labs [92] and Sahara AI [89] offer distinct yet complementary solutions to these challenges using blockchain technology. Immutable Labs focuses on comprehensive validation through a combination of trust scores, machine learning models, and validation controls to ensure high-quality contributions and deter malicious activity. In contrast, Sahara AI Marketplace emphasizes asset provenance, employing blockchain protocols and a unique identifier system to verify participant identities, manage reputation, and secure AI ownership. Together, these approaches highlight the importance of both rigorous validation and secure provenance in establishing a reliable, decentralized AI ecosystem. While these approaches are effective individually, a comprehensive framework that integrates both robust validation and asset provenance remains underexplored, especially in addressing scalability and maintaining transparency without compromising model privacy.

○ **Gap 6.** *How to design a scalable incentive mechanism that ensures robust validation, secure asset provenance, model privacy, and fair model exchange?*

## VII. OPEN RESEARCH QUESTIONS FOR DEAI

In the following, we explore additional open research questions (besides the previously identified gaps) that span multiple stages of our proposed DeAI framework.

○ **Gap 7.** *Decentralized Solutions for Task Proposing*

Although task proposing marks the beginning of an AI model's lifecycle, a decentralized solution for this stage remains absent. As discussed in Appendix IX, a decentralized task-proposing platform typically requires solutions for both distributed learning algorithm preparation and decentralized code verification. The latter can offer a robust approach for DeAI by enabling objective, transparent, and efficient evaluations through consensus mechanisms, distributed validation, and reputation-based incentives. These features help address traditional verification challenges such as subjectivity, risks of collusion, and inefficiency. However, there is still a need for blockchain-enabled frameworks for decentralized code verification that can ensure both code security and operational efficiency in DeAI.

○ **Gap 8.** *Security Issues Caused by Centralized Components in DeAI*

Although DeAI protocols aim for decentralization, AI model training often relies on centralized third-party services. For example, on July 2, 2024, Bittensor faced a major security breach through its Python package on PyPi [138]. A malicious actor uploaded a compromised package disguised as a Bittensor update, containing code that stole unencrypted private keys (coldkeys) during key decryption operations. This allowed unauthorized access to users' wallets for fund transfers. The incident (see Appendix XI for the details) highlights a critical issue: in DeAI platforms, while the underlying blockchain

itself is secure, the vulnerabilities in centralized third-party tools can undermine the overall system security [139].

#### ○ Gap 9. Lightweight Privacy-Preserving DeAI Solutions

Our analysis of DeAI protocols shows a growing use of ZKPs for privacy, security, and integrity in decentralized ML. Examples include Vana's proof of data contribution [16], OpSec's task verification [69], and Sertn's proof of service [77], illustrating ZKPs' importance. However, on-chain ZKP generation and verification still remain computationally expensive, posing scalability challenges and necessitating optimizations. While the OML project [50] offers a promising concept of "AI-native cryptography", which is tailored for continuous AI data representations rather than discrete data, realizing such lightweight solutions for DeAI requires further research and innovation.

#### ○ Gap 10. Efficiency Evaluation and Scalability of DeAI

DeAI currently lacks standardized benchmarking frameworks tailored to its unique architecture, making it difficult to access and compare decentralized model's performance with advanced centralized models such as GPT and Llama. Developing robust evaluation criteria for DeAI models is an important research challenge. Moreover, the blockchain components in DeAI may introduce performance bottlenecks, especially when computations are performed on-chain. Moving heavy computations off-chain could reintroduce centralized control over critical elements of the AI pipeline, defeating blockchain's purpose. Effective scaling DeAI requires adaptive techniques for distributed model training, efficient communication, and convergence guarantees, yet real-world implementation and validation remain challenging. Addressing these issues is essential for DeAI to achieve both high performance and true decentralization.

#### ○ Gap 11. Combining DeAI with other Decentralized Applications

The integration of DeAI with other decentralized platforms offers promising new applications, particularly in areas such as IoT, and DeFi. A notable example is PINAI [140], which aims to create a decentralized platform for Personal AI, prioritizing user privacy, data ownership, and crypto-economic security. PINAI builds on open-source AI, leveraging blockchain to facilitate a secure and transparent environment where AI models can access rich contextual data without compromising privacy. Additionally, DeAI's integration with DeFi platforms, such as Giza ARMA agents [141], Compass Labs DeFi agents [142], and NOYA [143], can enhance algorithmic trading models, while its use in decentralized data marketplaces enables data sharing and monetization. Such combinations create new opportunities for building resilient, transparent, and efficient AI-driven applications across various domains.

## VIII. CONCLUSION

In this SoK, we provide a taxonomy to analyze current DeAI solutions. We analyze how blockchain can be used to address the challenges in AI systems. We highlight the insights and research gaps to leverage blockchain to build DeAI systems. We hope our work will guide future research and innovation for more secure and practical DeAI solutions.

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## IX. TASK PROPOSING

### A. Distributed Learning Algorithm Preparation

In DeAI systems, selecting and designing appropriate learning algorithms is essential for ensuring data privacy and communication efficiency. In zero-trust environments, where participants lack inherent trust in one another, the algorithms must satisfy key requirements: ① enable efficient learning with minimal information exchange, ② maximize data privacy by avoiding direct transfers of sensitive or any raw data, and ③ reduce communication overhead through limited and efficient message exchanges. Existing distributed learning approaches can be generally classified into data-sharing, model-sharing, knowledge-sharing, and result-sharing methodologies [144], [145].

**Data-sharing.** In this approach, DeAI systems centralize private or anonymized data for aggregation and training, enabling robust learning outcomes. However, techniques such as multi-agent reinforcement learning (MARL) [146] raise concerns about information leakage (e.g., states, actions, rewards), computational overheads, and latency in large-scale applications. Solutions like QPLEX [147] and UPDeT [148] enhance scalability but face bottlenecks in dynamic and resource-constrained environments.

**Model-sharing.** This method emphasizes decentralized model updates, preserving privacy by transmitting model parameters instead of raw data. Synchronous techniques, such as Distributed SGD [149], mitigate computational delays but impose high communication costs. Federated Learning (FL) [150] alleviates this by allowing multiple updates before aggregation, yet issues like gradient staleness in asynchronous approaches, such as Asynchronous Federated Learning (AFL) [151] warrant further optimization to balance efficiency and security.

**Knowledge-sharing.** Leveraging knowledge distillation (KD) [152] and split learning techniques (e.g., Splitfed [153]), this approach extracts insights from local datasets to inform global models. While privacy is maintained by keeping raw data local, challenges such as data heterogeneity and training complexity hinder scalability and generalization.

**Result-sharing.** This strategy shares only the final outcomes, ensuring maximum privacy for sensitive domains such as

healthcare. Methods like PATE-GAN [154] generate synthetic data to approximate true distributions, though inconsistencies in heterogeneous data environments remain problematic.

### 1) Challenges in DeAI Learning Algorithm Preparation:

**Privacy and Security Challenges** Privacy and security are primary concerns in decentralized learning. For example, in MARL, sensitive information shared among agents (e.g., states, actions, rewards) may lead to data leakage. Complex encryption techniques and differential privacy mechanisms protect privacy but are computationally expensive [149]. In decentralized settings with low trust, asynchronous updates or delayed synchronization could allow attackers to compromise data integrity and model accuracy [155].

**Scalability and Communication Efficiency** As the number of participating nodes increases, communication efficiency becomes a major issue [150]. Frequent data sharing, model updates, and knowledge transfer across nodes can create high communication costs, and real-time coordination in dynamic environments can lead to latency. Techniques such as model partitioning and asynchronous updates improve communication efficiency but still face constraints in bandwidth and computational resources. Balancing efficient learning with minimal information exchange, especially in large-scale scenarios, remains a critical challenge.

**Model Consistency** Ensuring consistency across models at different nodes is complex, particularly with asynchronous updates and heterogeneous data distributions. Independent updates can cause model drift and misalignment in learning objectives [156]. Approaches such as AFL allow asynchronous model updates but introduce delays, gradient staleness, and inconsistency, slowing convergence and reducing accuracy [151]. Effective consistency management is essential, especially in heterogeneous environments where nodes vary in data distributions, computational power, and connectivity.

**Fault Tolerance and Robustness** In decentralized systems, each node functions independently, making fault tolerance essential to address node failures or network issues. While decentralized structures reduce vulnerability to single-point failures, larger scales increase the risk of node failures disrupting learning [157]. For instance, MARL could see disrupted collaboration due to node failure. Mechanisms for rapid recovery or adaptive operation adjustments are crucial to ensuring robustness and reliability in decentralized learning systems.

**Generalization Across Diverse Data** Client data in decentralized learning systems is often heterogeneous and unevenly distributed, challenging model generalization, particularly in knowledge- and result-sharing settings [158]. Diverse data sources and characteristics across clients make creating a generalizable model difficult. For example, in knowledge distillation, the student model may struggle to generalize from a global model trained on heterogeneous data. Similarly, in result-sharing, the final outcomes heavily depend on local data characteristics, potentially leading to inconsistent performance. Achieving robust generalization while preserving privacy is a fundamental challenge in decentralized learning.

**○ Gap 12.** How can we design scalable, privacy-preserving, and communication-efficient decentralized AI algorithms that ensure model consistency, fault tolerance, and robust generalization across diverse, heterogeneous environments?

### B. Code Verification

In the DeAI lifecycle, the algorithm code-design phase is fully managed by the task proposer and remains unregulated, introducing potential risks. Task creators may inadvertently or deliberately integrate unauthorized models or libraries, leading to model training failures or vulnerabilities that threaten system security [159]. In blockchain-enabled distributed learning environments, such vulnerabilities can compromise node integrity, expose sensitive data, or allow unauthorized access, while certain attacks may exploit smart contracts, undermining the network's overall integrity and reliability [160], [161]. To safeguard a fully decentralized AI system, it is essential to establish a dedicated code verification committee responsible for reviewing, testing, and validating all submitted code.

1) *Challenges in Traditional Code Verification:* In a traditional organizational context, such as a corporate environment, source code is typically defined by developers and then subjected to automated verification tools or peer reviews. Team members examine each other's code to identify issues, enhance quality, and ensure adherence to standards [162], [163]. This process can occur in formal review meetings or more informally through pull requests. However, traditional code verification presents several inherent challenges:

**Subjective Evaluation and Lack of Consensus.** Traditional code verification might be subjective, relying heavily on human judgment, leading to inconsistent evaluations. Evaluators bring personal interpretations of standards, preferences, and experience, resulting in varying outcomes. This subjectivity complicates consensus on code quality and risks compromising the reliability and consistency of the verification process [162], [164].

**Limited Transparency and Impartiality in Verification Decisions.** Traditional verification lacks robust, auditable mechanisms for transparent and impartial decision-making. Without clear documentation on why certain code was accepted or rejected, developers may find it difficult to understand and trust verification outcomes. Additionally, biases or conflicts of interest can affect decisions, particularly in environments with complex team dynamics or hierarchical influences, thereby compromising objectivity [165]–[167].

**Susceptibility to Collusion and Compromised Integrity.** Small groups of validators handling code verification pose risks of collusion, whereby validators may approve or reject code based on personal or political motivations rather than technical merit. This susceptibility to collusion can allow substandard or even harmful code to pass through verification, thereby affecting the task's functionality and security [168].

**Inefficiency and Lack of Accountability in Code Verification.** Traditional code verification can be slow, particularly

in large or distributed teams, as reviews are often sequential, leading to bottlenecks and delays [165]. Moreover, many traditional systems lack mechanisms to monitor validator performance and hold them accountable for verification decisions, which may lead to inconsistencies in standards and compromises in code quality and security.

#### 2) Blockchain-enabled Decentralized Code Verification:

**Objective and Consistent Evaluation through Consensus Mechanisms.** Blockchain-enabled decentralized code verification provides a robust solution to address the challenges of traditional verification methods by leveraging transparency, distributed consensus, and incentive mechanisms. This approach mitigates subjectivity by establishing objective criteria that all validators follow, ensuring consistent and fair evaluations [23]. By standardizing evaluations within a blockchain framework, organizations can reduce the influence of personal biases or varying expertise among validators, resulting in reliable code reviews.

**Transparency and Verifiability of Validators.** In a decentralized code verification committee, each validator's decision is permanently recorded within the blockchain, creating a transparent, auditable, and traceable review process. This transparency mitigates potential biases and conflicts of interest, as stakeholders can review decision histories. Immutable records within the blockchain ensure that all verification actions are retained, making it straightforward to track decisions, validators involved, and justifications.

**Anti-Collusion and Impartiality through Distributed Validation.** Blockchain's decentralized structure enables code reviews across multiple independent nodes, making collusion among validators challenging. This is because final decisions require consensus across a broad validator network, inherently reducing the risk of collusion or corruption. Protocols such as random validator selection or penalties for collusive behavior further deter manipulation, ensuring an impartial verification process [169], [170].

**Efficient and Parallel Verification Process.** Blockchain technology supports parallel validation, allowing multiple validators to review code simultaneously, thereby accelerating the verification process and avoiding sequential bottlenecks. Consensus mechanisms aggregate decisions swiftly, enabling faster feedback for developers and promoting a more agile and responsive verification cycle. This parallel approach not only enhances productivity but also reduces delays, thereby improving overall development timelines [171].

**Reputation Systems and Incentives for Responsible Validation.** Blockchain frameworks can incorporate reputation scoring and stake-based incentives, rewarding validators for accuracy and fairness while penalizing poor performance. Validators demonstrating consistent quality gain higher reputations, enhancing their credibility and influence within the network, while those with biased or substandard reviews may face penalties. This system enforces accountability, encourages adherence to high standards, and promotes responsible validation behavior across the network [172].

**○ Gap 13.** How to design blockchain-enabled decentralized code verification frameworks that ensure code security and operational efficiency in distributed learning systems?

## X. SUPPORTING FIGURES

Figure 3 demonstrates the escalating trends in large-scale AI model development. It highlights that computational power requirements are rapidly increasing, models are becoming significantly larger, and the volume of data used for training has surged dramatically.

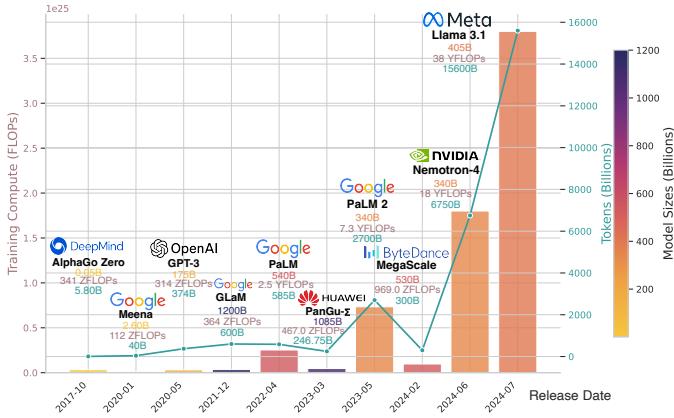


Fig. 3: Trends in the development of large-scale AI models, showcasing Training Compute Costs (bar chart), Tokens (or Data points) Counts (line plot), and Model Sizes (heatmap). Data sourced directly from [173].

## XI. SECURITY CONCERNs AND MITIGATIONS IN DEAI

In the following, we discuss the security concerns and mitigations for existing DeAI.

### A. Malicious Third-Party Package Manager and Private Key Leakage

While blockchain protocols are designed to be secure and tamper-resistant, the tools and applications that interact with them can introduce unexpected vulnerabilities. DeAI platforms such as Bittensor are not immune to such risks. A notable example occurred on July 2, 2024, when Bittensor experienced a significant security breach exploiting vulnerabilities in its package management system. Specifically, a malicious actor uploaded a compromised version (6.12.2) of the Bittensor package to the PyPi Package Manager [138].

The malicious package masqueraded as a legitimate Bittensor update but contained code designed to steal unencrypted private keys (coldkeys) from users. When users downloaded this compromised version and performed operations involving key decryption—such as staking, transferring funds, or other wallet operations—the malicious code transmitted their decrypted keys to a remote server controlled by the attacker. This breach allowed the attacker to gain unauthorized access to users' wallets and transfer funds without their consent. This

attack highlighted a critical security loophole: while the underlying blockchain protocol remained secure, vulnerabilities in third-party tools and dependencies became points of failure that compromised the network's security [139].

### B. Centralization

Moreover, the Bittensor team's response raised concerns about centralization. In an effort to mitigate the attack, the team placed the Opentensor Chain Validators behind a firewall and activated safe mode on Subtensor, effectively halting all transactions temporarily [138]. While this action was intended to protect users, it underscored the level of centralized control that the team holds over the supposedly decentralized network, potentially conflicting with the principles of decentralization inherent in blockchain technology.

To further address both the security vulnerabilities and centralization concerns, the Bittensor team introduced the Child Hotkeys feature as a mitigation strategy [174]. This feature allows a hotkey (used for staking and validation operations) to delegate a portion or all of its staked TAO tokens to one or more child hotkeys. By decentralizing responsibilities across multiple child hotkeys, the risk associated with a single point of failure, e.g., private key leakage, is reduced. If one child hotkey is compromised, it does not affect others or the parent hotkey, enhancing overall network security. Additionally, child hotkeys enable validators to distribute validation tasks across different subnets, mitigating centralization by dispersing control and reducing the influence of any single validator. While this approach aims to enhance both security and decentralization within the network, its effectiveness remains to be empirically validated over time.

### C. Collusion

In addition to security vulnerabilities, concerns have been raised about collusion within Bittensor's governance structure. The root network, composed of the top validators by delegated stake, plays a crucial role in determining the distribution of TAO tokens and the overall governance of the platform [14]. This concentration of power can lead to collusion or centralized decision-making, contradicting the decentralized ethos of blockchain and deAI projects.

To address these concerns, the Bittensor community proposed the introduction of Dynamic TAO (dTAO) as outlined in the BIT001 proposal [175]. Dynamic TAO aims to decentralize the governance process by allowing all TAO holders to participate directly in decision-making. By staking TAO through intermediary pools to obtain Dynamic TAO tokens specific to each subnet, participants can influence the allocation of resources and incentives based on market-driven mechanisms rather than relying on a centralized root network. This approach is intended to align the interests of individual stakeholders with the overall health and decentralization of the network.

While these mitigation strategies are promising, concerns over centralization and other security issues remain theoretical and await empirical validation. Ongoing monitoring,

community engagement, and potential future incidents will provide more data to assess the effectiveness of Dynamic TAO and similar approaches in truly decentralizing control and enhancing security in DeAI platforms.