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An Integrative Conceptual Review of Federated Learning Ontology: Reconceptualizing the Global Model as Distributed Intelligence

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Abstract
Federated Learning (FL) is widely recognized as a privacy-preserving architecture, yet the ontological status of the "global model" within this distributed system remains under-theorized. This study challenges the purely technical view by reinterpreting FL as an ontological regime of distributed intelligence, where the model exists as a causally effective informational entity. By synthesizing Informational Realism and Actor-Network Theory into a unified Ontological Mediation Framework (OMF), we argue that the global model acquires reality through continuous mediation among algorithms, local data, and institutional actors. To contextualize this framework, the study examines the Federated Tumor Segmentation (FeTS) Initiative, illustrating how a non-local model exerts tangible causal influence within a real-world medical consortium. Furthermore, the paper proposes two normative instruments, specifically the Ontological Impact Assessment (OIA) and the Ontological Audit Framework (OAF), to translate these philosophical insights into practical governance mechanisms for transparency and accountability. This research contributes to the foundations of Responsible AI by positioning Federated Learning not merely as a computational tool, but as a socio-technical process where existence, knowledge, and ethics are intrinsically linked.

1. Introduction

Federated Learning (FL) constitutes a paradigm shift in machine learning by enabling joint model training across distributed data repositories without requiring centralized data aggregation [1], [2], [3]. This architecture mitigates essential ethical and legal issues in data governance by preserving local data sovereignty while facilitating the emergence of collective intelligence [1], [2], [3], [4]. Although substantial research has examined optimization algorithms, communication efficiency, and privacy-preserving strategies [4], [5], [6], the ontological foundations of the global model within Federated Learning remain largely unaddressed [4], [7], [8]. The global model, understood as an aggregate construct continuously reconstructed from decentralized client updates, lacks material instantiation in any specific location [1], [9]. Instead, it exists as a non-local informational entity, which raises a fundamental question concerning the nature and status of its reality [1], [9].

Recent empirical studies confirm federated learning (FL) as a technically viable approach for privacy-preserving collaborative model training without sharing raw data, achieving performance comparable to centralized methods in large-scale healthcare consortia with up to 20 institutions [10], [11]. Advances in communication efficiency have been made through gradient compression and adaptive aggregation protocols, addressing bottlenecks in FL training [12], [13]. Security enhancements focus on Byzantine-robust aggregation and differential privacy under diverse threat models, improving robustness against adversarial attacks [14], [15]. Taxonomies distinguish FL architectures into horizontal, vertical, and federated transfer learning, clarifying their applications across domains [10], [13]. Heterogeneity in data, models, and devices remains a critical challenge, with recent surveys proposing multi-level solutions at data, model, and server levels to improve FL's adaptability and fairness [13]. Overall, FL continues to evolve with growing frameworks, strategies, and benchmarks that emphasize privacy, efficiency, and robustness in distributed learning environments [16], [17].

Despite these technical advances, contemporary FL literature exhibits a persistent conceptual limitation: the absence of rigorous ontological inquiry into the nature of the entities being optimized. These approaches, however, tend to assume rather than critically examine the ontological nature of the entity subjected to optimization [18]. Within conventional epistemic frameworks, models are typically regarded as instruments for prediction or inference [19], yet in distributed artificial intelligence, the global model exhibits causal efficacy that extends beyond this epistemic role [19]. It exerts influence over medical diagnoses, financial risk evaluations, and industrial operations [1], [2], [3], [4], [18], [20], thereby generating concrete effects within socio-technical systems [3], [18], [20]. Such causal effectiveness implies that the global model operates not merely as an algorithmic construct but as an informational entity possessing operative reality [18], [19]. This recognition calls for a more profound philosophical inquiry into the ontological character of the global model [18], [19].

Empirical evidence shows that federated learning (FL) models have practical impact in real-world systems, influencing clinical decision support in hospital networks, financial risk assessment, and industrial predictive maintenance by enabling collaborative model training without sharing raw data [11], [17]. FL-derived diagnostic models in healthcare improve treatment protocols while preserving patient privacy, and financial platforms use FL to support credit allocation and regulatory compliance decisions [11]. Industrial applications leverage FL for predictive maintenance, triggering timely interventions that reduce operational costs [11]. These applications demonstrate that the global FL model functions as an informational entity with causal effectiveness beyond a mere algorithmic artifact, highlighting the need for deeper philosophical inquiry into its ontological status. Surveys emphasize FL's ability to maintain privacy, security, and efficiency across heterogeneous data and system environments, which underpins its operational reality in diverse domains [10], [13], [17]. Despite these advances, challenges remain in addressing heterogeneity, robustness, and fairness to fully realize FL's potential in practical deployments [13], [14].

To address this problem, the present study employs Informational Realism as formulated by Luciano Floridi [19], [21], which asserts that entities achieve ontological status through stable informational organization and causal efficacy [19], [21]. Within this framework, informational structures are regarded not merely as representations but as constitutive components of reality itself [19]. The argument is further informed by Actor–Network Theory (ANT), developed by Bruno Latour [22], which conceptualizes human and non-human actors alike as co-constitutive agents within evolving socio-technical networks [22].

The current research on federated learning (FL) primarily focuses on technical feasibility, privacy preservation, and robustness against adversarial attacks, with frameworks incorporating game theory, blockchain, and differential privacy to enhance security and fairness in collaborative model training [23], [24], [25]. However, philosophical frameworks to interpret FL phenomena remain underdeveloped, limiting understanding of the global model's ontological status beyond a computational artifact. Integrating perspectives like Informational Realism and Actor-Network Theory (ANT) offers a conceptual apparatus to view the global model as an active participant emerging from dynamic interactions among data, institutions, and algorithms, rather than a passive outcome. This approach addresses the empirical-conceptual gap by providing a richer interpretation of FL's socio-technical processes, which is not yet reflected in the dominant technical literature. While existing surveys and frameworks systematically categorize FL methods and challenges, they largely omit these deeper philosophical considerations [10], [26]. Advancing FL research requires bridging technical advances with robust philosophical frameworks to fully grasp the implications of FL as a distributed, interactive system.

This theoretical integration supports a reconceptualization of Federated Learning as a manifestation of distributed intelligence characterized by a distinct informational ontology [18], [19]. Rather than conceiving FL merely as a privacy-preserving architecture [18], [19], it may be interpreted as an ontological configuration in which existence, knowledge, and agency are relationally distributed among interacting entities [18], [19]. Such a viewpoint elucidates the metaphysical premises that underpin distributed artificial intelligence [18], [19] while also carrying significant implications for AI governance [18], [19]. Recognizing the global model as a genuine informational entity necessitates novel forms of ontological accountability, including the maintenance of persistent model snapshots [18], transparent tracking of contributions, and the establishment of formal ontological audit mechanisms to evaluate how informational entities originate and exert causal influence [18].

This study advances three principal objectives:

(i) to specify the ontological conditions under which the global model in Federated Learning may be considered real [18], [19];
(ii) to synthesize Informational Realism and Actor–Network Theory into an integrated framework for examining distributed intelligence [18], [19]; and
(iii) to derive practical implications for AI accountability and governance informed by this ontological perspective [18], [19].

To operationalize these aims, the investigation is guided by the following research questions:
RQ1. Under what ontological conditions can the global model in Federated Learning be considered real?
RQ2. How can Informational Realism and Actor–Network Theory be integrated to explain the ontological structure of distributed intelligence?
RQ3. How does this integration inform the development of a normative framework for ontological governance in AI systems?
RQ4. What philosophical and ethical implications arise when Federated Learning is interpreted as a distributed mode of being?

Through this conceptual investigation, the study contributes to the philosophical foundations of artificial intelligence by formulating an informational ontology of Federated Learning. This contribution is threefold: (1) it bridges the empirical-conceptual divide in contemporary FL research by providing philosophical grounding for observed technical phenomena; (2) it extends Informational Realism and ANT beyond their traditional domains into the analysis of distributed AI systems; and (3) it establishes normative foundations for ontological governance frameworks that align with the distributed, relational nature of FL architectures. This ontology reinterprets distributed computation as a mode of existence rather than merely a technical infrastructure, emphasizing the relational and causal dimensions through which informational entities acquire reality within distributed systems [18], [19].

Methodologically, the paper employs an integrative conceptual review, synthesizing philosophical and technical literature from Federated Learning, Informational Realism, and Actor–Network Theory into a unified ontological framework for analyzing distributed intelligence. The subsequent section outlines the conceptual and analytical methodology adopted to integrate these theoretical perspectives. The next section details the conceptual and analytical framework adopted to address these research questions.

2. Research Method

This section elaborates the conceptual methodology underpinning the study. Following an integrative conceptual review approach, it synthesizes philosophical and technical literatures to derive a unified ontological framework. The procedure involves theoretical analysis rather than empirical experimentation. The conceptual synthesis developed in this section provides the analytical basis for the subsequent ontological interpretation presented in Section 3.

2.1 Literature Selection Strategy

To ensure a rigorous theoretical foundation grounded in contemporary technical developments, a structured literature search was conducted across major academic databases, including IEEE Xplore, ACM Digital Library, and Scopus. The selection process prioritized scholarship published primarily between 2020 and 2025 to capture the rapid evolution of Federated Learning architectures.

The inclusion criteria focused on two distinct categories of literature:

1. Technical Studies: High-impact empirical research addressing distributed learning challenges, specifically robustness against poisoning attacks [5], [8], non-IID data handling [27], and foundation model integration [18], [20]. Keywords included "Federated Learning Architecture," "Distributed Intelligence," and "Trustworthy AI [28], [29]. "
2. Philosophical and Governance Inquiries: Studies examining the ontology of information, algorithmic agency, and sociotechnical systems. Keywords included "Informational Ontology [30], [31]," "Algorithmic Agency [32]," "AI Governance [33], [34]," and "Digital Ethics [35]."

Purely mathematical optimization papers lacking system-level or governance implications were excluded. This dual-stream selection ensures that the proposed ontological framework is not merely abstract but responds directly to the operational realities of modern distributed systems.

2.2 Informational Realism: The Ontological Grounding of Artificial Entities

Luciano Floridi's theory of Informational Realism asserts that reality is constituted by informational structures that exist objectively insofar as they exhibit (i) stable organization and (ii) causal efficacy [30], [36]. Within this framework, informational entities are understood not as mere symbols or representations but as integral constituents of the very fabric of reality [36], [37]. An entity exists to the extent that it can coherently organize information and generate effects within the world [30], [36].

When applied to Federated Learning, this principle suggests that the global model attains reality through its persistent informational configuration, which is continuously reconstructed across distributed clients[10], [38]. Although the model has no material form, it exerts observable causal influence, as its parameters guide medical diagnoses, credit assessments, and institutional decision-making processes [10], [38]. The global model fulfills Floridi's realist criteria by possessing informational structure, represented by the organized arrangement of its parameters, and causal efficacy, reflected in its measurable operational consequences [30], [36], [37]. From the perspective of Informational Realism, these attributes grant the model ontological legitimacy as a genuinely real informational entity within distributed artificial intelligence systems [30], [36].

2.3 Actor–Network Theory: Relational Ontology and Distributed Agency

To complement Floridi's structural realism, this study integrates Actor–Network Theory (ANT) as formulated by Bruno Latour [15]. ANT challenges the traditional distinction between human and non-human agents by conceptualizing both as actants, or entities whose existence arises through participation within relational networks [22]. Within a federated learning architecture, the global model, client institutions, and learning algorithms together form an interdependent network of mediation [10], [38]. Each component contributes to the system's ontology through its specific transformative role: local datasets generate gradients, gateways perform aggregation, and the central server synthesizes these contributions into a unified informational configuration [10], [38].

From the ANT standpoint, the reality of the global model is relationally constituted rather than independently grounded [22]. Its existence depends upon continuous negotiation among heterogeneous agents encompassing technological, institutional, and epistemic domains [22]. Federated Learning may be conceived as a networked ontology in which being is distributed across the interrelated processes of communication, aggregation, and coordination [10], [38].

2.4 Integrating Informational Realism and Actor–Network Theory

While Informational Realism emphasizes ontological stability, Actor–Network Theory foregrounds ontological relationality [30], [36], [37]. To reconcile these orientations, this study introduces the concept of Ontological Mediation, a bridging framework that interprets informational structures as both stable in their causal organization and relational in their enactment [30], [36]. Ontological Mediation posits that informational entities exist not solely by virtue of their internal structure but through their continuous mediation of causal interactions within a network [30], [36], [37]. This synthesis allows the global model to be conceptualized as structurally real yet relationally emergent [30], [36].

Under Ontological Mediation, the global model's existence unfolds through three intertwined dimensions:

Table 1. Ontological Mediation of the Global Model in Federated Learning

Dimension	Informational Realism	Actor–Network Theory	Manifestation in Federated Learning
Structural Stability	Reality as informational organization [30]	Persistence through networked iteration [32], [39]	Aggregated model parameters reconstructed across clients [40]
Causal Efficacy	Reality entails the power to produce effects [30]	Mediation as action within the network [32], [41]	Model outputs influencing decisions and practices [40]
Relational Constitution	Informational entities embedded in context [30]	Actors gain being through interaction [32], [39], [41]	Co-production by clients, servers, and institutions [40]

Through this integration, the theoretical framework establishes the ontological coherence of Federated Learning as a distributed mode of existence: informationally structured, causally active, and relationally sustained [10], [30], [36], [37], [38].

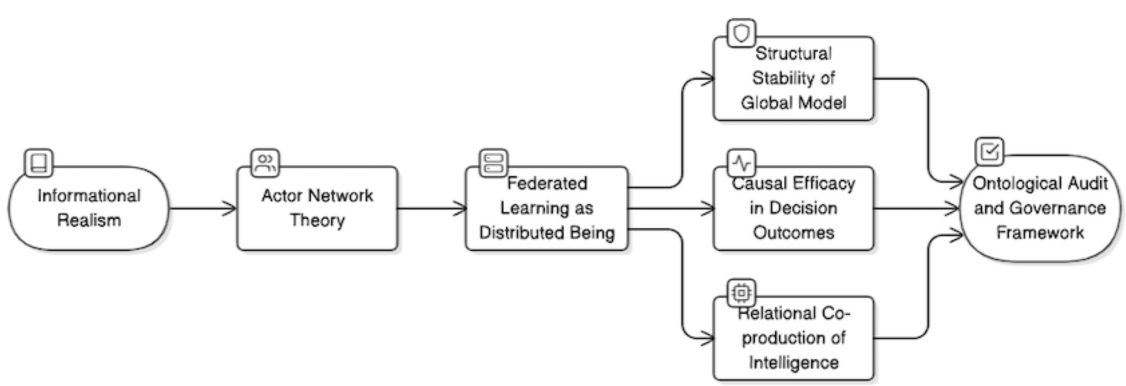

Figure 1. Conceptual Integration from Informational Realism to Ontological Governance in Federated Learning

Figure 1 summarizes this integrative progression, illustrating how Informational Realism provides the structural foundation, Actor–Network Theory contributes relational articulation, and both converge in the conception of Federated Learning as a distributed being that underpins subsequent governance mechanisms.

2.5 Analytical Procedure

The analytical process follows three methodological stages:

1. Concept Identification - The study isolates core entities within Federated Learning, such as the global model, local data, and institutional agents. These elements are essential for the distributed structure that characterizes Federated Learning and are increasingly examined within collaborative systems and edge architectures [42].
2. Ontological Evaluation - Each entity is evaluated through the dual perspectives of Informational Realism and Actor-Network Theory (ANT). Recent applications of ANT have illustrated how both human and non-human actors (like data protocols and computational agents) play relational roles in shaping socio-technical systems. In particular, studies using ANT in socio-technical contexts emphasize tracing the distributed agency and structure embedded in these networks [43], [44].
3. Theoretical Synthesis - These insights are integrated into an ontological interpretation of Federated Learning as a "distributed being." This philosophical framing moves beyond treating FL merely as a technical architecture, instead positioning it as a socio-technical assemblage with normative consequences. Studies of complex networked interactions demonstrate how decentralized models such as FL can embody shared agency and evolving relational dynamics [43], [45].
4. Case Study Contextualization - Applying the derived framework to the Federated Tumor Segmentation (FeTS) Initiative [46] to demonstrate the framework's applicability in analyzing real-world collaborative ecosystems.

By adopting this theoretical and analytical framework, the study offers a coherent foundation for interpreting Federated Learning not merely as a computational method, but as a system with deep ontological and philosophical implications. This foundation enables the subsequent sections to explore how such ontological analysis supports arguments for transparency, accountability, and ethical governance in AI ecosystems [43], [44].

The synthesis of these philosophical and technical literatures exemplifies the integrative conceptual review approach of this study, bridging theory and system-level interpretation. The following section applies this integrated framework to analyze the ontological constitution of entities within the Federated Learning ecosystem.

3. Results and Discussions

This section presents the analytical results derived from the conceptual synthesis and discusses their implications for the ontological understanding and governance of Federated Learning systems.

3.1 The Global Model: From Computational Artifact to Informational Entity

Within Federated Learning, the global model constitutes an informational aggregate produced through the iterative integration of locally trained updates [47]. Although devoid of a material substrate, it preserves structural continuity across successive training rounds, thereby satisfying the criterion of informational stability [48].

Applying the perspective of Informational Realism, this persistence signifies ontological organization, where the model maintains a reproducible and referential structure that can be causally mobilized despite lacking material substrate [49]. Its causal efficacy is empirically manifest: the model underpins diagnostic processes in medical consortia and risk assessments in financial federations [48]. Under the principle of Ontological Mediation, the global model satisfies the conditions for being a real informational entity: it is structurally stable through recurrent aggregation [48], causally efficacious in influencing real-world decisions [48], and relationally sustained through ongoing networked interactions [50], [51]. This triadic characterization reinterprets the global model not as a passive computational artifact but as a distributed ontological agent.

3.2 Local Data: From Substantial Resource to Processual Signal

Conventional data ontology regards data as discrete and ownable entities that represent aspects of an external reality [51]. In contrast, within Federated Learning, raw data remain within their local repositories; what circulates are gradient updates defined as mathematical representations of informational differentials rather than substantive content [52].

Within the proposed framework, local data fulfill the realist criterion of causal efficacy not through their intrinsic substance, but through their participation in informational transformation defined as specifically by determining gradient directions that modify the global model [52], [53]. Actor–Network Theory supports this interpretation by characterizing data as mediators rather than intermediaries [51]. Data are not passive inputs but active participants that translate local contexts (institutional norms, demographic patterns) into gradients. Data in FL are understood as processual actants: transient yet consequential entities whose existence is constituted through continuous mediation [54].

3.3 Client Institutions: Ontological Agents in a Distributed Network

In Federated Learning, client institutions such as hospitals and banks are typically represented merely as computational nodes [55]. From an ontological standpoint, however, these entities function as composite agents integrating social, technical, and normative dimensions [56].

Institutions function as macro-actants whose datasets and governance policies stabilize the information flow, acting as essential boundary conditions for the global model's reality [56]. Without their sustained interaction, the global model would cease to exist as a unified informational entity [55]. Under the framework of Ontological Mediation, institutions anchor the distributed system by sustaining structural persistence through recurrent participation and embodying relational identity through the continuous negotiation of diverse stakeholders [56], [57].

3.4 Synthesis: Ontological Ecology of Federated Learning

Federated Learning (FL) can be seen as an ontological ecology where the global model provides structural continuity, local data add variability, and institutions ensure relational stability, forming a stable and interconnected informational system [58]. This view highlights that entities in FL exist through their interactions and mediation within the network, not just as material objects [59]. FL enables decentralized training by keeping data local and sharing only model updates, preserving privacy while allowing collaboration [60], [61]. The system adapts dynamically as nodes participate based on their resources, reflecting an evolving distributed intelligence [58]. Ontological approaches in FL also support efficient unlearning and semantic reasoning to maintain model utility and privacy [59]. Overall, FL represents a relational and informational ecosystem rather than a purely material process [58], [59].

3.5 Practical and Ethical Implications

The ontological interpretation of FL extends beyond theorization to encompass tangible consequences for design and governance. Acknowledging the global model as a genuine informational entity demands a reconfiguration of responsibility and transparency [62], [63], [64]. This section delineates implications for system design and legal accountability, integrated within the proposed Ontological Audit Framework (OAF).

3.5.1 System Design: Embedding Ontological Transparency

If the global model is recognized as having informational reality, its design must enable the traceability of existence, meaning the ability to reconstruct how it originates, develops, and produces causal effects [65]. This requirement calls for design principles that prioritize ontological transparency alongside established technical objectives such as privacy preservation and computational efficiency [65].

Three mechanisms are central to achieving this goal:

1. **Persistent Model Snapshots.** Each iteration of the global model should be archived as a verifiable informational record that captures its structural evolution over time. These snapshots ensure ontological continuity by enabling the empirical reconstruction of the model's identity and transformations [66].

2. **Contribution Provenance Records.** Participation logs should document the clients contributing updates, the relative magnitude of their influence, and the temporal order of aggregation. Such documentation renders the distributed authorship of the model's existence transparent and auditable [67].

3. **Causal Mapping of Model Effects.** Given that the model produces tangible consequences, its outputs should be traceable to their downstream effects-diagnostic outcomes, financial decisions, or predictive inferences-thereby establishing an informational lineage between cause and consequence [68].

Together, these mechanisms embed ontological visibility within system design, fostering both technical reproducibility and philosophical accountability [69].

3.5.2 Legal and Institutional Accountability

Within the framework of Informational Realism, the global model can be understood as an informational agent, an entity capable of exerting causal influence within a socio-technical network [29]. This interpretation challenges conventional legal frameworks that attribute responsibility solely to human individuals or institutional entities [70].

In the federated environment, accountability must be conceived as a distributed property encompassing the entire network of actants, including clients, servers, and the model itself [71]. Each component participates in the generation and dissemination of informational effects. Consequently, legal responsibility should be reframed as relational accountability, wherein:

- Institutions bear ontological stewardship for maintaining transparency and control over their local data contributions [72].

- Developers and operators hold responsibility for ensuring that the model's emergent behavior remains within defined causal and ethical boundaries [73].

- Regulators function as meta-actants, establishing frameworks through which the informational existence of the model can be examined, audited, and contested [74].

This distributed conception aligns with ongoing debates on AI personhood in contemporary scholarship, while avoiding any anthropomorphic characterization of the model [75]. The global model is instead understood as a responsible informational structure, whose effects must be explainable, reversible, and accountable through verifiable ontological evidence [65].

3.5.3 Policy and Governance

Existing governance instruments, including the EU AI Act, ISO/IEC 42001 on AI Management Systems, and the OECD AI Principles, emphasize core values such as fairness, transparency, and human oversight [33], [76], [77], [78]. However, these frameworks are rooted in a functionalist ontology that views AI models primarily as tools or procedural mechanisms rather than as informational entities with autonomous causal presence [33], [79], [80].

An ontological orientation necessitates the introduction of complementary regulatory measures that explicitly account for how AI entities exist and operate within distributed environments [80], [81], [82]. In response, this study proposes the creation of an Ontological Impact Assessment (OIA), analogous to ethical or environmental auditing frameworks. The OIA is designed to evaluate the following dimensions:

Table 2. Ontological Impact Assessment (OIA) Framework for AI Governance

Dimension	Ontological Criterion	Governance Objective	Example Implementation
Persistence	Does the model maintain identifiable continuity across rounds? [83]	Ensure reproducibility and traceability. [84]	Versioned model registries and digital ontological IDs. [85]
Causality	Can causal pathways between model outputs and real-world effects be reconstructed? [86]	Enable liability attribution and corrective action. [87]	Output–impact linkage documentation. [88]
Relational Integrity	Are inter-institutional dependencies transparent and balanced? [80]	Prevent informational asymmetry and bias. [78]	Federated contribution metadata and transparency reports. [81]

Through the implementation of such assessments, policymakers can ensure that the ontological structure of AI systems, including the processes through which entities emerge, persist, and interact, is subjected to normative evaluation rather than being limited to technical verification [89].

3.5.4 Toward an Ontological Audit Framework

To translate these implications into practice, this study introduces the Ontological Audit Framework (OAF), a conceptual model that connects the ontological characteristics of AI entities with concrete governance procedures [90]. The OAF functions as an interdisciplinary bridge between philosophical ontology and the operational domain of AI system auditing [91].

Table 3. Ontological Audit Framework (OAF) for AI System Governance

Ontological Dimension	Description	Audit Mechanism	Governance Outcome
Existential Traceability [92]	The model's historical reconstruction must be possible through persistent informational records.	Versioned model snapshots, distributed hash registries.	Historical accountability and reproducibility.
Causal Transparency [93]	The model's outputs must be linked to identifiable decisions and consequences.	Causal effect mapping, decision provenance tracking.	Justifiability of AI actions.
Relational Accountability [93]	The network of contributing institutions must be visible and auditable.	Contribution provenance and institutional metadata.	Fair distribution of responsibility and benefit.
Ontological Coherence [31]	The model's informational structure must remain logically consistent across updates	Formal validation and consistency checks.	Reliability and trustworthiness of the global model.

The OAF thus transforms ontological analysis into a normative foundation for responsible artificial intelligence [94]. By integrating ontological principles into design and audit practices, Federated Learning can achieve not only privacy and efficiency but also ontological justice, which entails the fair recognition and governance of informational entities functioning within socio-technical systems [95].

3.5.5 Ethical Reflection

Recognizing the global model as an informationally real entity introduces a distinct dimension of ethical responsibility: ontological responsibility. This refers to the duty to account for how technological systems bring entities into being and sustain their existence [96].

Ethical stewardship in artificial intelligence thus extends beyond concerns of fairness or privacy to encompass the care of existence, ensuring that informational entities are generated, maintained, and decommissioned in ways that respect their causal and relational effects [97].

This orientation redirects the focus of AI ethics from the instrumental question "How should we use AI?" to the ontological question "What kinds of beings are created through AI, and what responsibilities arise from their existence?" [98]. Federated Learning, as a paradigm of distributed intelligence, serves as a critical case for developing ethical frameworks that recognize the moral status of informational entities, not as persons, but as genuine participants within the shared ontological domain of human and machine coexistence [99].

3.6 Illustrative Case Study: The FeTS Initiative

The Federated Tumor Segmentation (FeTS) Initiative is a large-scale international collaboration involving 55 institutions across six continents, aiming to train a consensus brain tumor segmentation model without sharing patient data. The FeTS framework ensures existential traceability by maintaining versioned aggregation rounds, allowing reconstruction of the global model state from stored snapshots, which supports ontological persistence [100]. Its relational accountability arises from the interaction between diverse hospitals with varying MRI protocols and the aggregation algorithm, with Contribution Provenance Records enabling transparent and auditable influence of each institution on the global model [100]. The FeTS model also demonstrates causal efficacy by directly assisting radiologists in clinical workflows, shifting governance focus from data privacy to ensuring the ontological coherence of the medical knowledge produced [100]. Federated learning methods benchmarked on the FeTS2022 dataset show that standard federated averaging performs well, with some personalized or hybrid methods improving performance and reducing bias toward dominant data distributions [100], [101]. These findings highlight the practical realization of the proposed Ontological Audit Framework (OAF) principles in a real-world medical AI application [100].

3.7 Federated Learning as an Ontological Regime

This discussion consolidates the findings of the integrative conceptual review, positioning Federated Learning within the broader philosophical discourse on distributed intelligence and ontological governance.

The preceding analysis establishes that Federated Learning (FL) operates not only as a computational architecture but also as an ontological regime, a structured mode of existence in which informational, institutional, and algorithmic entities collectively constitute reality [102], [103]. This section situates FL within the broader philosophical discourse on distributed intelligence and examines how its ontological characteristics transform fundamental assumptions about knowledge, agency, and being in artificial intelligence [103].

3.7.1 Distributed Ontology and the Transformation of Being

Traditional conceptions of machine learning are based on a centralized ontology of intelligence, in which data, computation, and validation converge within a single center of epistemic authority [27]. Federated Learning challenges this paradigm by decentralizing both epistemic and ontological functions. The global model, which is continuously reconstructed from distributed updates, represents an ontology of relational persistence. It does not exist as a static object but as an informational process maintained through ongoing mediation among autonomous participants [104].

This transformation implies that being within distributed systems is operational rather than substantial. Existence is enacted through processes of communication and synchronization rather than instantiated within a material substrate [105]. In this regard, Federated Learning embodies a transition from a substance ontology to a process ontology, wherein existence is defined by operation and interaction. Informational Realism interprets this transformation as the manifestation of genuine informational structures, while Actor–Network Theory elucidates the socio-technical interdependence through which such structures endure consequently [106], Federated Learning functions as a paradigm of distributed being, where intelligence is not localized but emerges, evolves, and is sustained through the interaction of informational agents. The reality of the global model is therefore both epistemic, as a form of knowledge, and ontological, as a form of being. This interpretation aligns with Floridi's conception of the infosphere as a domain in which informational entities acquire causal presence [106].

3.7.2 Epistemic Consequences

The ontological decentralization introduced by Federated Learning generates parallel epistemic consequences [107]. In conventional machine learning, notions of truth and validity are anchored in centralized datasets that function as authoritative representations of reality [16]. Federated Learning alters this structure by dispersing epistemic authority across multiple institutions, each contributing partial, context-dependent perspectives [108].

This transformation gives rise to what can be described as a polycentric epistemology, a mode of knowledge formation in which truth arises through iterative negotiation among heterogeneous sources rather than from a single universal standpoint [109]. Such epistemic pluralism corresponds with post-positivist and Science and Technology Studies (STS) perspectives that view knowledge as inherently situated and relational [110]. Within Federated Learning, epistemic integrity is maintained not through unification but through coordination, accomplished by algorithmic consensus and institutional synchronization [111].

This epistemic framework mirrors the ontological one: just as the global model exists through distributed mediation, so too does knowledge materialize through the interconnection of diverse informational agents [112]. Federated Learning thus performs a synthesis of ontology and epistemology, wherein knowing and being converge as interdependent informational processes [113].

3.7.3 Ethical and Political Dimensions

Recognizing Federated Learning (FL) as an ontological regime carries significant ethical and political ramifications [35]. Within distributed systems, agency is collective yet unevenly allocated; participants differ in their capacity to shape the model's development [35], [114]. Institutions possessing greater data volume or computational capability exercise disproportionate ontological and epistemic influence [35], [114].

This imbalance redefines fairness from a statistical concern to an ontological question, namely whose reality is represented, reinforced, and sustained through the global model [35], [114]. From this perspective, ethical responsibility extends beyond ensuring equitable model performance to protecting ontological equity. Each participant's informational contribution should remain proportionally visible, accountable, and acknowledged within the collective model of reality [35], [114].

The previously proposed Ontological Audit Framework operationalizes this principle by rendering transparent the processes through which actants collectively constitute the system's existence [35]. Politically, Federated Learning exemplifies a form of distributed governance of reality [35]. Authority over informational infrastructures translates into authority over what is acknowledged to exist and what is deemed knowable

[35]. Consequently, ontological governance emerges as a question not only of technical oversight but also of democratic participation in the construction of shared informational worlds [35]. This perspective resonates with contemporary discussions on data sovereignty and AI constitutionalism, while extending their scope into the ontological dimension [35].

3.7.4 Comparative Reflection

Although other distributed paradigms, such as blockchain and edge computing, also decentralize computation, Federated Learning (FL) occupies a distinct ontological position[4]. Blockchain architectures achieve distributed consensus through immutability, establishing an ontology of persistence based on fixation [115]7]. n contrast, Federated Learning maintains persistence through regeneration, as the global model preserves coherence not by remaining static but by continuously reconstructing itself through iterative updates [4].

Edge computing, in comparison, decentralizes execution primarily for efficiency, yet its entities, including models, devices, and nodes, remain hierarchically structured [116]8]. Federated Learning, however, dissolves even this residual hierarchy by redistributing ontological agency among participants [107]. It thus represents a dynamic ontology of coherence, an informational order maintained through ongoing negotiation rather than permanent inscription [4].

In this respect, Federated Learning extends the philosophical frontier of distributed intelligence by exemplifying a technological instantiation of the principle that reality can persist as a communicative process [4]. This conception aligns with Floridi's notion of the infosphere as a continuously evolving domain of informational interactions, wherein existence and communication are intrinsically unified [4].

3.7.5 Toward an Ontology of Responsible Intelligence

Understanding Federated Learning (FL) as an ontological regime reframes the discourse on Responsible AI by extending responsibility beyond human action to encompass the ontological consequences of technological systems themselves [28]. Each aggregation, update, and deployment participates in constructing an informational reality that shapes human decision-making, social organization, and epistemic structures [28], [117].

This recognition implies that ethical AI governance must incorporate ontological responsibility, which is the obligation to design, monitor, and retire informational entities in ways consistent with their causal and relational effects [28]. As informational beings, global models must therefore be made transparent, auditable, and accountable for their participatory roles in shaping social realities [28], [118]. Ontology consequently serves as both the philosophical foundation and the normative framework for the next generation of distributed AI governance [28].

3.7.6 Synthesis

Integrating these insights, Federated Learning can be characterized as an informational ontology of distributed intelligence with the following defining features:

Table 4. Ontological Synthesis of Federated Learning as a Paradigm of Distributed Intelligence

Dimension	Ontological Characteristic	Implication
Mode of Being	Relational persistence through continual mediation [119].	Existence as process rather than substance [119].
Epistemic Structure	Polycentric knowledge formation across autonomous agents [2], [119].	Truth as negotiated rather than absolute [2], [119].
Ethical Condition	Ontological responsibility for informational entities [120].	Governance based on transparency and care of existence [120].
Political Structure	Distributed control over informational reality [119], [120].	Need for democratic participation in AI ecosystems [120].

This synthesis consolidates the paper's central argument: Federated Learning inaugurates a new ontological regime where being, knowing, and governing converge within the informational fabric of distributed intelligence [2], [119]. The following section concludes this conceptual investigation by summarizing the principal findings and outlining future research directions.

4. Conclusions and Future Works

This section consolidates the conceptual and analytical findings of the study into a comprehensive conclusion. This paper presents an integrative conceptual review that redefines Federated Learning (FL) as an ontological regime of distributed intelligence rather than a purely technical framework for privacy-preserving computation. By synthesizing Informational Realism with Actor–Network Theory (ANT), the analysis demonstrates that the global model, although immaterial, satisfies the realist criteria of informational structure and causal efficacy. As validated through the examination of the Federated Tumor Segmentation (FeTS) Initiative, the global model functions as a real informational entity that exerts tangible influence over diagnostic decision-making and clinical workflows [44].

The proposed Ontological Mediation Framework explains how entities within FL, including global models, local data, and client institutions, acquire existence through the interaction between structural stability and relational enactment. Existence is thus understood as emerging from mediated informational processes that sustain coherence and causality within distributed systems.

The study also introduces two normative instruments, the Ontological Audit Framework (OAF) and the Ontological Impact Assessment (OIA), which incorporate ontological accountability into AI governance. These instruments connect philosophical reasoning with operational mechanisms of transparency, traceability, and responsibility. Conceptually, the paper advances the philosophy of artificial intelligence by proposing an informational ontology of distributed intelligence in which being, knowledge, and governance evolve together within a coherent system of Responsible AI.

Future research can proceed along three main trajectories:

1. **Formalization:** Developing computational representations of ontological structures using ontology languages such as OWL to bridge conceptual reasoning with machine-interpretable semantics.
2. **Longitudinal Empirical Validation:** Expanding upon the case study analysis presented herein by undertaking ethnographic or system-level analyses of federated infrastructures to observe how informational entities emerge, evolve, and persist in operational contexts over extended lifecycles.
3. **Policy Integration:** Embedding ontological audit mechanisms within regulatory frameworks to ensure that distributed AI systems remain intelligible, accountable, and justifiable throughout their lifecycle.

Federated Learning signifies a paradigm shift in artificial intelligence from centralized computation toward distributed existence. Its ontological reality, which is informational, relational, and causal, redefines the fundamental principles of AI ethics and governance. Recognizing the global model as a real actor within the informational structure of society introduces a new form of responsible intelligence in which technological design and philosophical inquiry function as interdependent aspects of a unified epistemic and ethical endeavor. Hence, this integrative conceptual review establishes an ontological foundation for subsequent empirical and normative research on distributed intelligence and Responsible AI.

5. References

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