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(54) **AI AGENT DECISION PLATFORM WITH DEONTIC REASONING**

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Publication Classification

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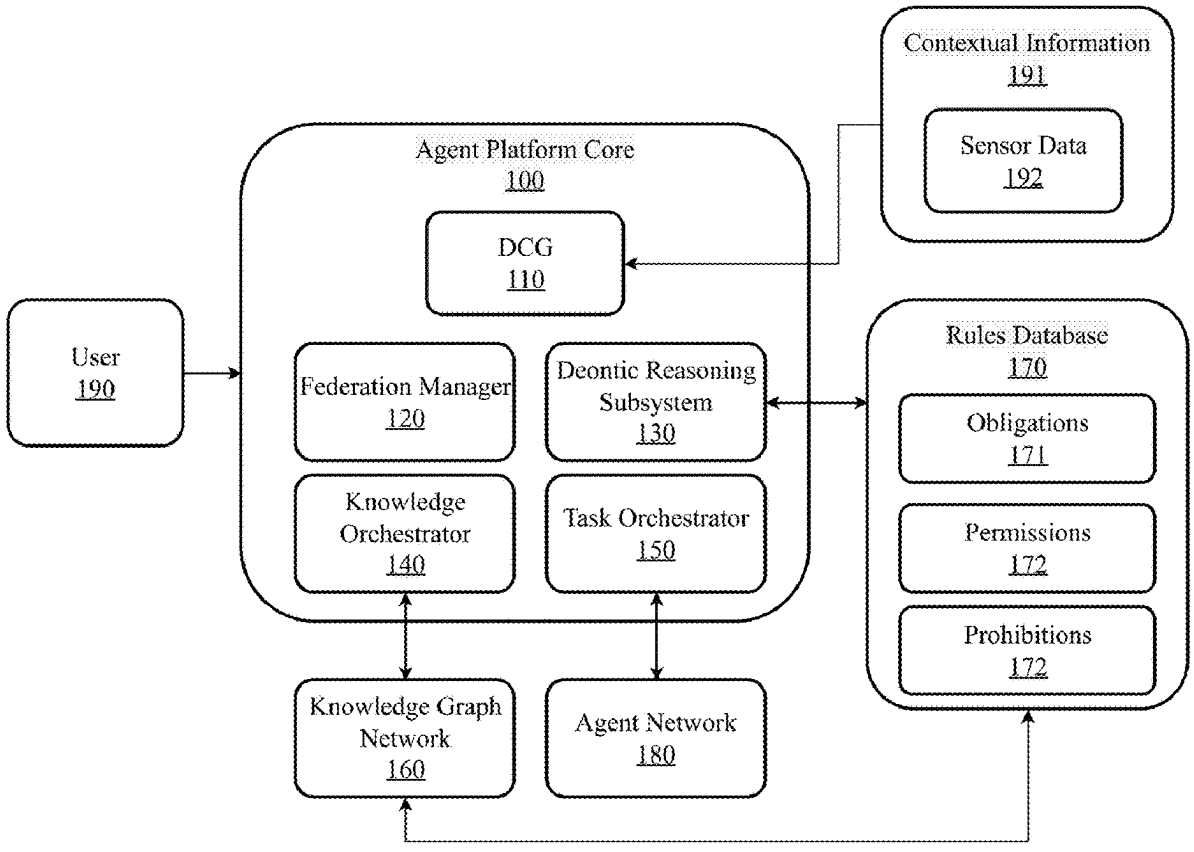
G06N 3/042 (2023.01)

(52) **U.S. Cl.**

CPC ***G06N 3/047*** (2023.01); ***G06N 3/042*** (2023.01)

(57) **ABSTRACT**

A system and method for extending AI-enhanced decision platforms with deontic and normative reasoning capabilities that enhance adjustably autonomous decision-making through a novel integration of symbolic and neural approaches. The invention uses hierarchical and fuzzy deontic logic implementations alongside connectionist AI/ML to manage obligations, permissions, and prohibitions while maintaining observer awareness to achieve goals while incorporating knowledge across multiple expert domains. The system employs dynamic event and spatio-temporal knowledge graphs along with debate mechanisms, enabling high-assurance automated reasoning while preserving explainability through neuro-symbolic integration. In at least one embodiment, the invention operates through a federated distributed computational graph architecture that allows for arbitrary scaling while maintaining coherence, consistency and supporting compound workflows. The invention provides a framework for AI systems to make logically consistent, ethically-aware decisions by combining deontic reasoning with multi-agent coordination, token space communications and knowledge, including on intermediate results, enabling automated decision-making for a variety of applications.



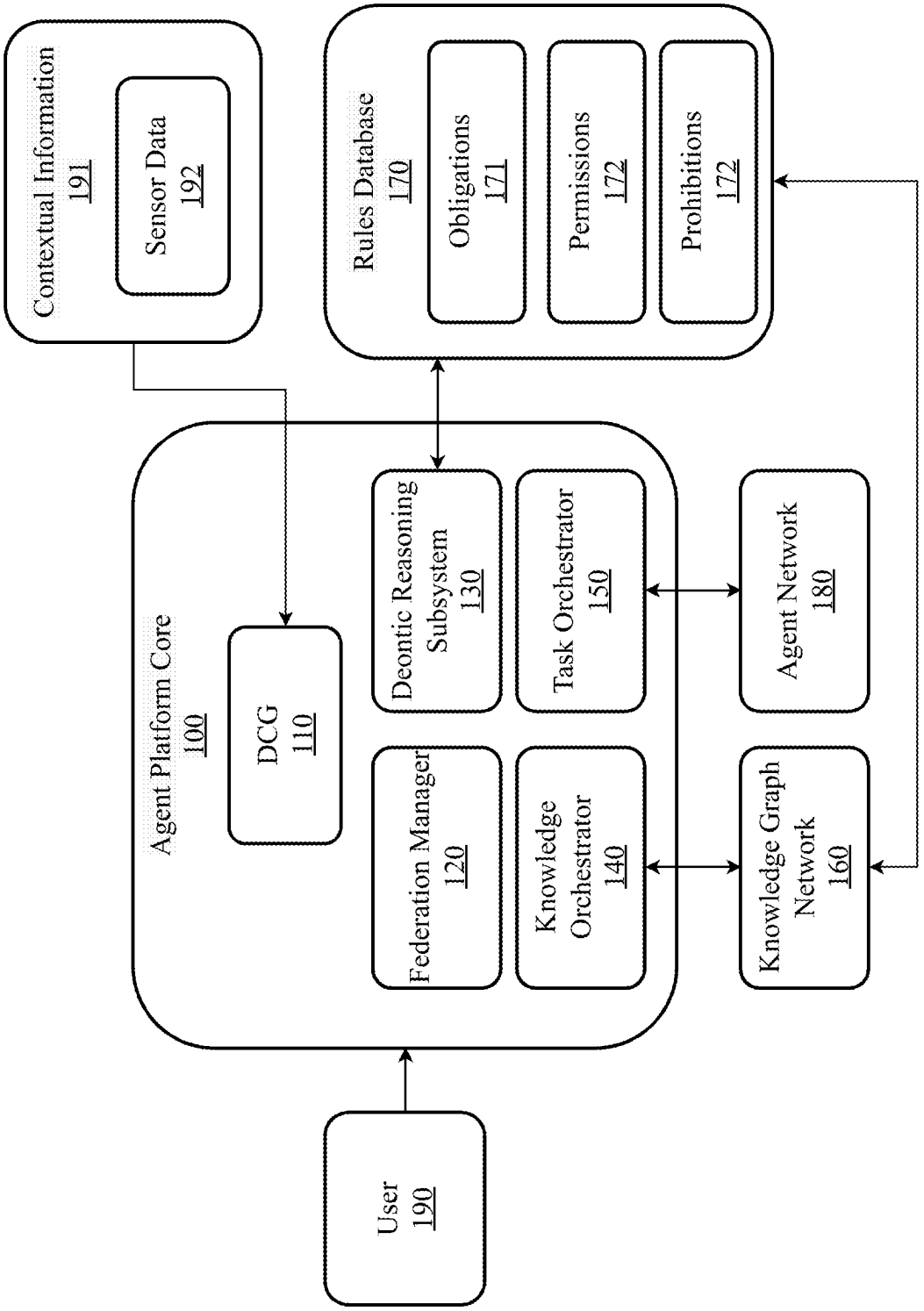

Contextual Information
191
Sensor Data
192
Rules Database
170
Obligations
171
Permissions
172
Prohibitions
172
Agent Platform Core
100
DCG
110
Deontic Reasoning Subsystem
130
Task Orchestrator
150
Agent Network
180
Federation Manager
120
Knowledge Orchestrator
140
Knowledge Graph Network
160
User
190

FIG. 1

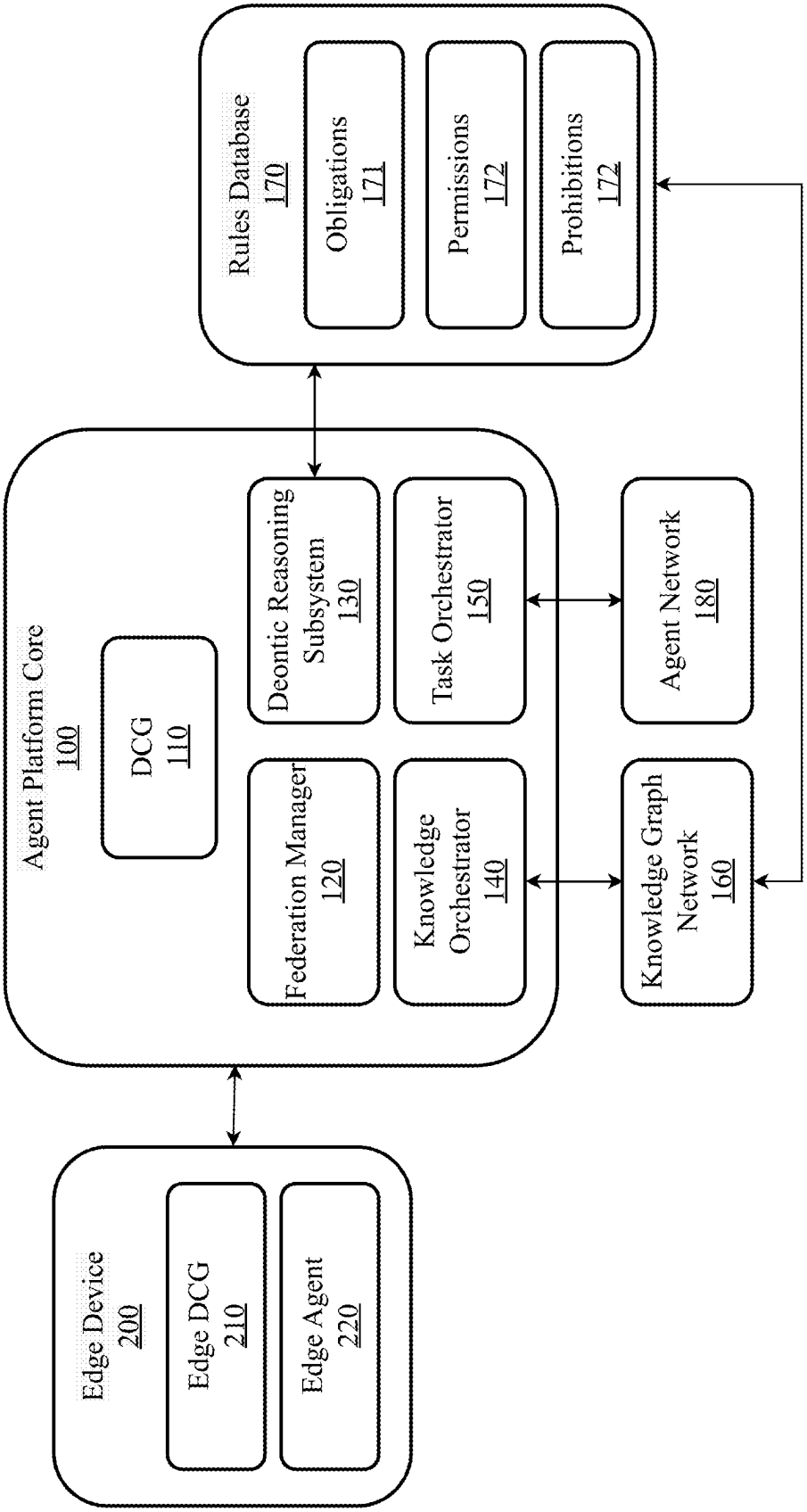

Rules Database
170
Obligations
171
Permissions
172
Prohibitions
172
Agent Platform Core
100
DCG
110
Deontic Reasoning Subsystem
130
Task Orchestrator
150
Federation Manager
120
Knowledge Orchestrator
140
Agent Network
180
Knowledge Graph Network
160
Edge Device
200
Edge DCG
210
Edge Agent
220

FIG. 2

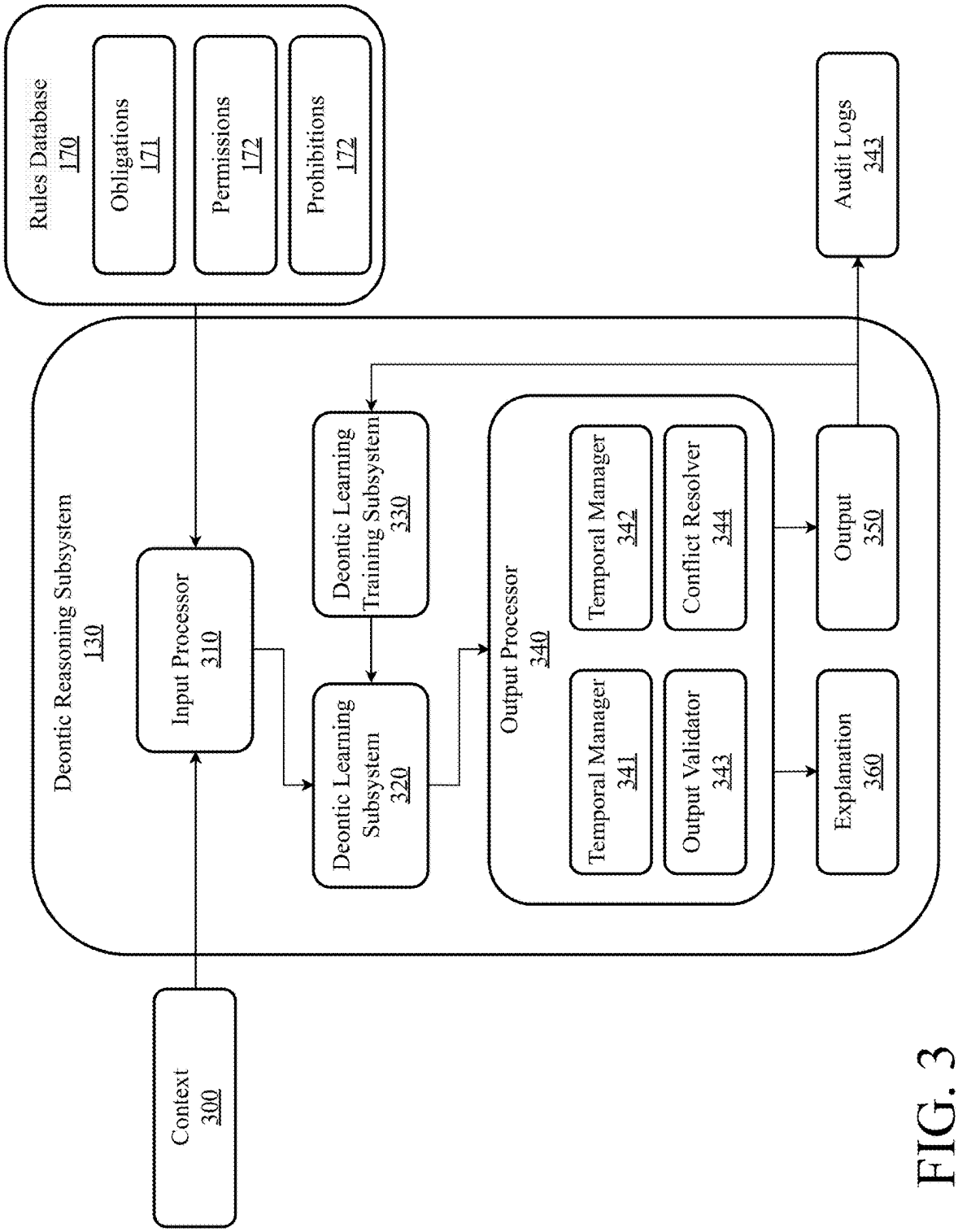

Rules Database
170
Obligations
171
Permissions
172
Prohibitions
172
Audit Logs
343
Deontic Reasoning Subsystem
130
Input Processor
310
Deontic Learning
Training Subsystem
330
Deontic Learning
Subsystem
320
Output Processor
340
Temporal Manager
342
Conflict Resolver
344
Output
350
Temporal Manager
341
Output Validator
343
Explanation
360
Context
300

FIG. 3

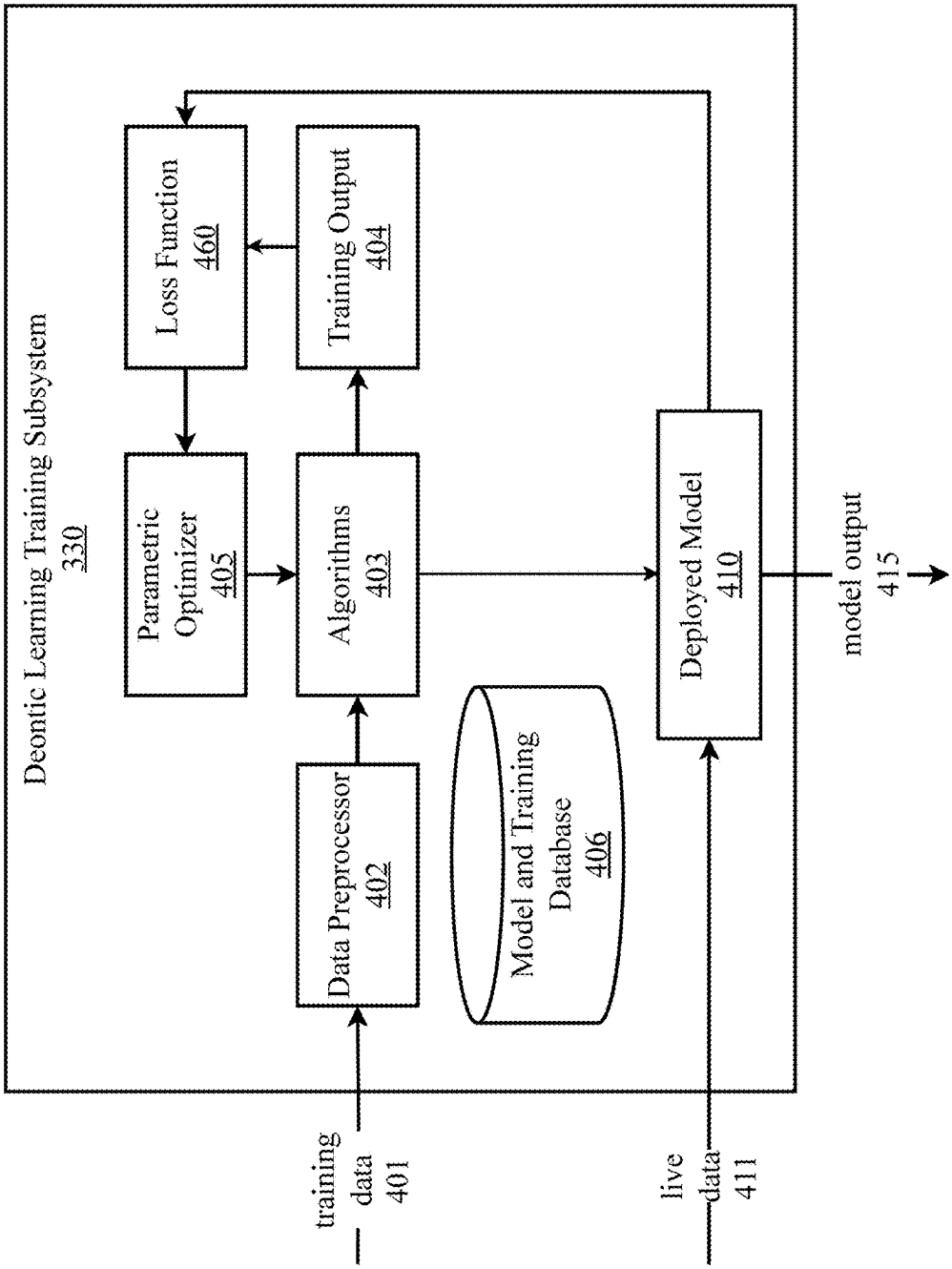

Deontic Learning Training Subsystem
330
Loss Function
460
Training Output
404
Parametric Optimizer
405
Algorithms
403
Deployed Model
410
model output
415
Data Preprocessor
402
Model and Training Database
406
training data
401
live data
411

FIG. 4

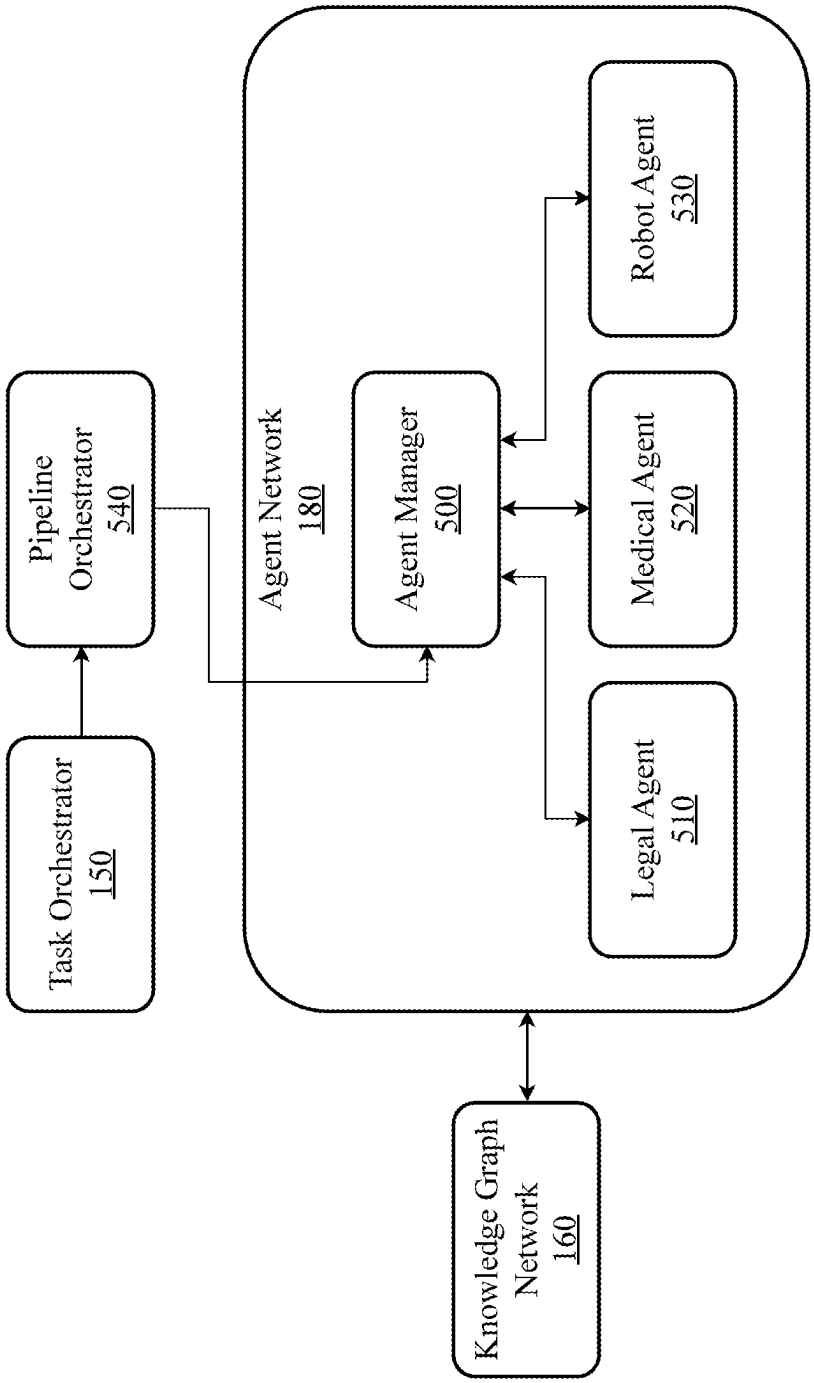

Task Orchestrator
150
Pipeline
Orchestrator
540
Agent Network
180
Agent Manager
500
Legal Agent
510
Medical Agent
520
Robot Agent
530
Knowledge Graph
Network
160

FIG. 5

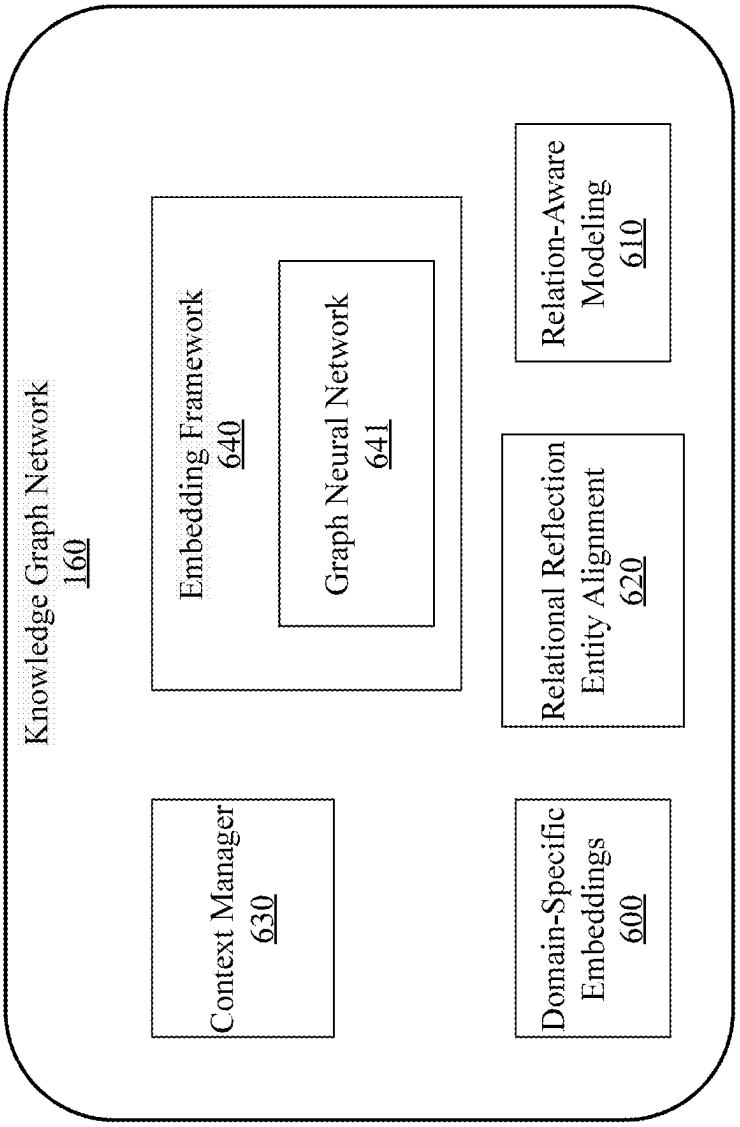

Knowledge Graph Network
160
Embedding Framework
640
Graph Neural Network
641
Relation-Aware
Modeling
610
Relational Reflection
Entity Alignment
620
Context Manager
630
Domain-Specific
Embeddings
600

FIG. 6

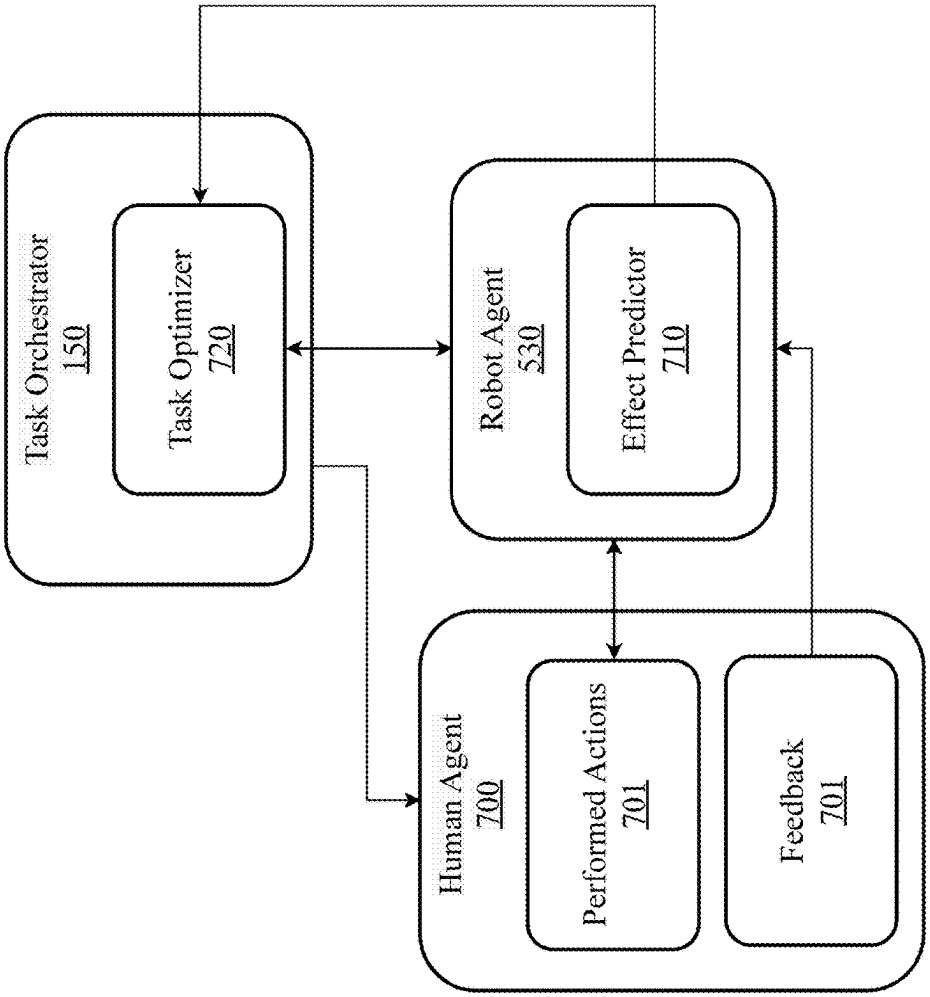

Task Orchestrator
150
Task Optimizer
720
Robot Agent
530
Effect Predictor
710
Human Agent
700
Performed Actions
701
Feedback
701

FIG. 7

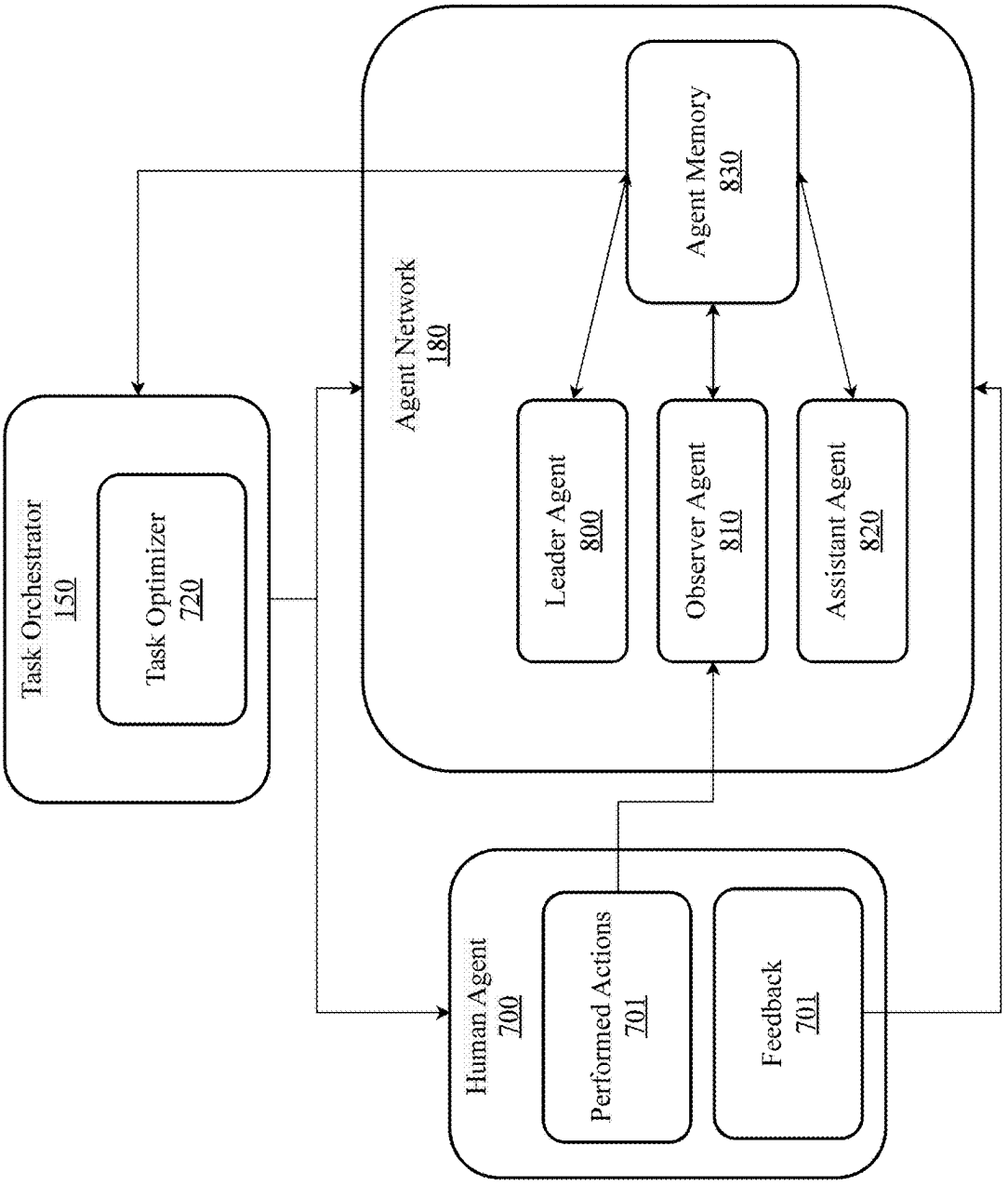

Task Orchestrator
150
Task Optimizer
720
Agent Network
180
Agent Memory
830
Leader Agent
800
Observer Agent
810
Assistant Agent
820
Human Agent
700
Performed Actions
701
Feedback
701

FIG. 8

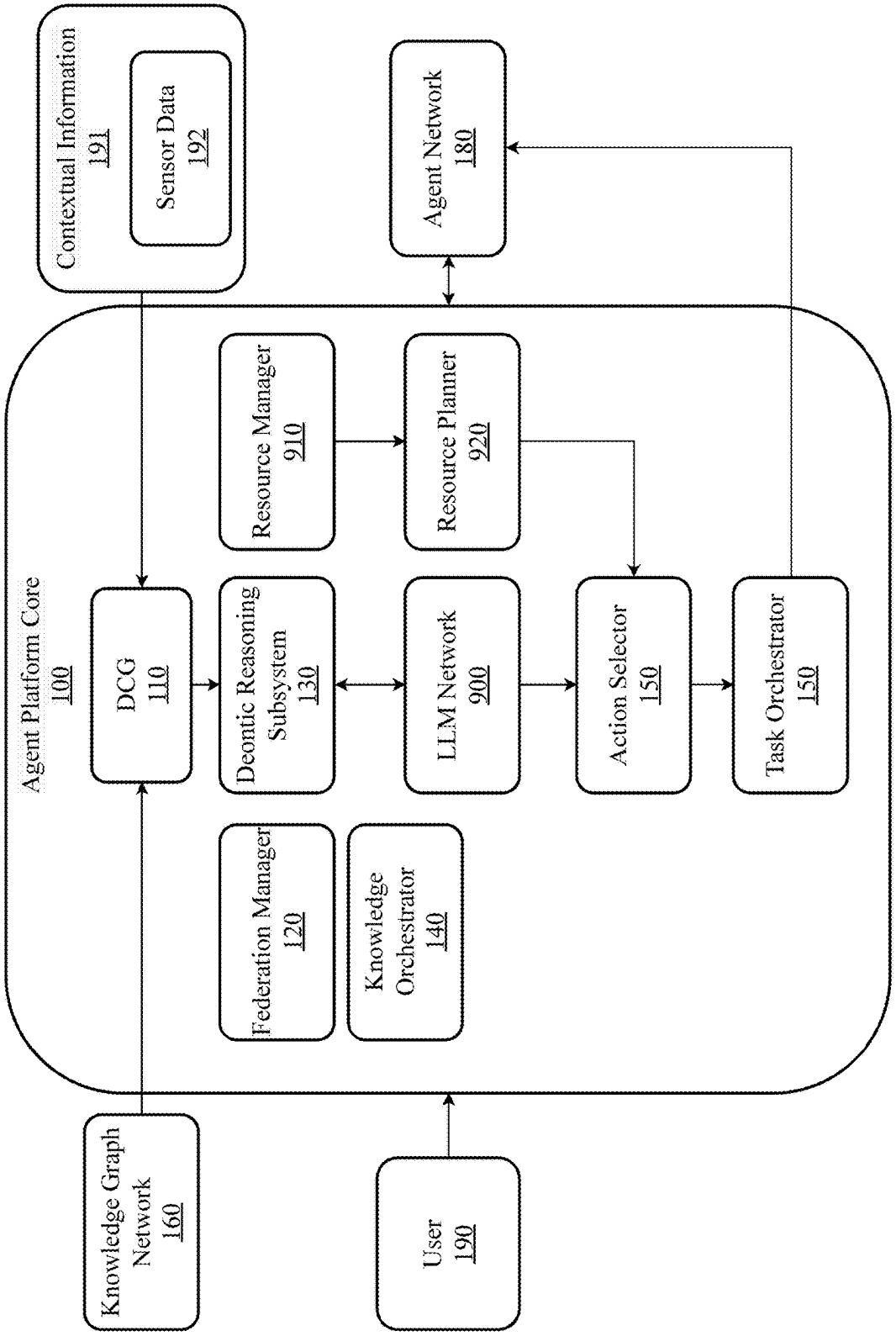

Contextual Information
191
Sensor Data
192
Agent Network
180
Agent Platform Core
100
Resource Manager
910
Resource Planner
920
DCG
110
Deontic Reasoning Subsystem
130
LLM Network
900
Action Selector
150
Task Orchestrator
150
Federation Manager
120
Knowledge Orchestrator
140
Knowledge Graph Network
160
User
190

FIG. 9

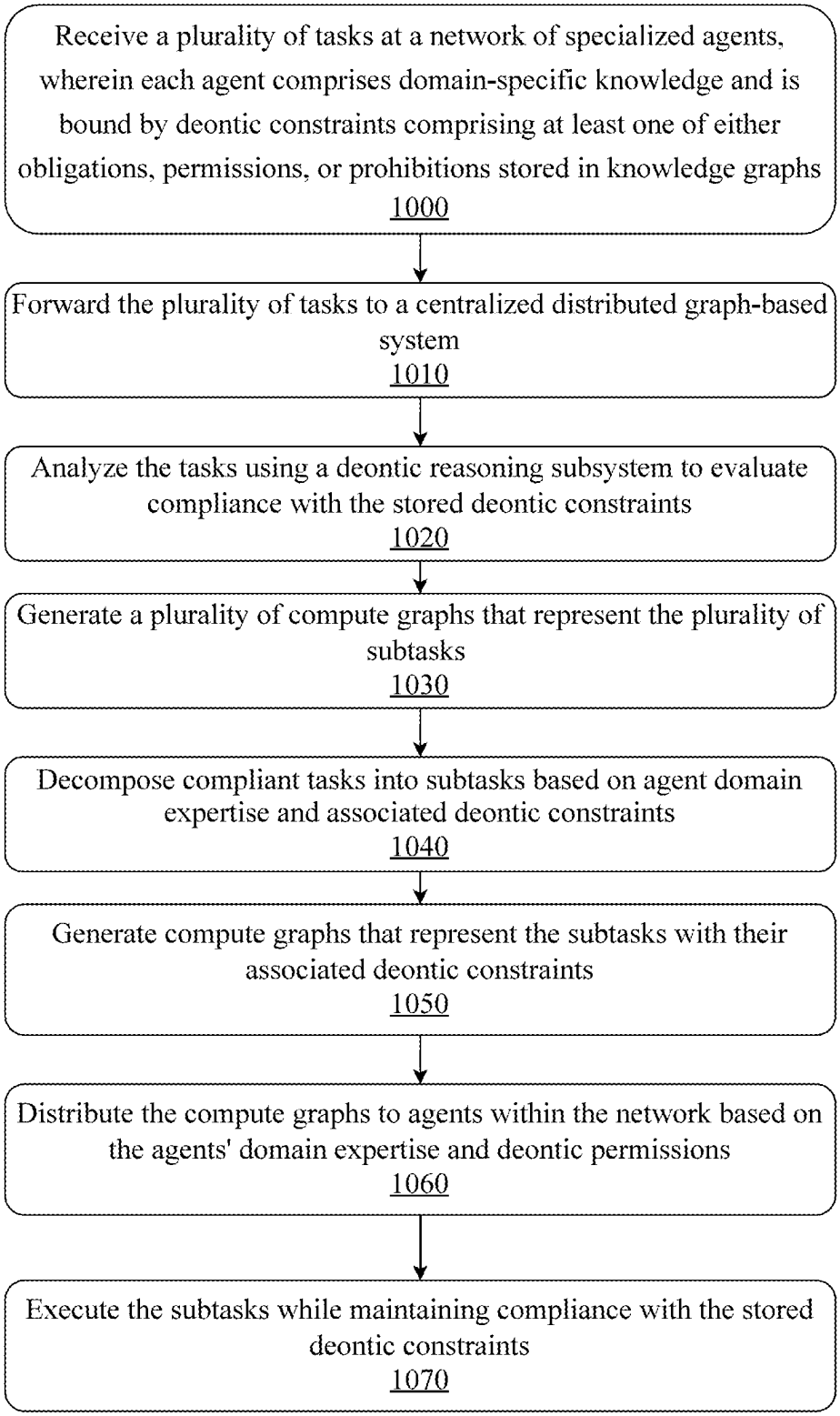

Receive a plurality of tasks at a network of specialized agents, wherein each agent comprises domain-specific knowledge and is bound by deontic constraints comprising at least one of either obligations, permissions, or prohibitions stored in knowledge graphs
1000
Forward the plurality of tasks to a centralized distributed graph-based system
1010
Analyze the tasks using a deontic reasoning subsystem to evaluate compliance with the stored deontic constraints
1020
Generate a plurality of compute graphs that represent the plurality of subtasks
1030
Decompose compliant tasks into subtasks based on agent domain expertise and associated deontic constraints
1040
Generate compute graphs that represent the subtasks with their associated deontic constraints
1050
Distribute the compute graphs to agents within the network based on the agents' domain expertise and deontic permissions
1060
Execute the subtasks while maintaining compliance with the stored deontic constraints
1070

FIG. 10

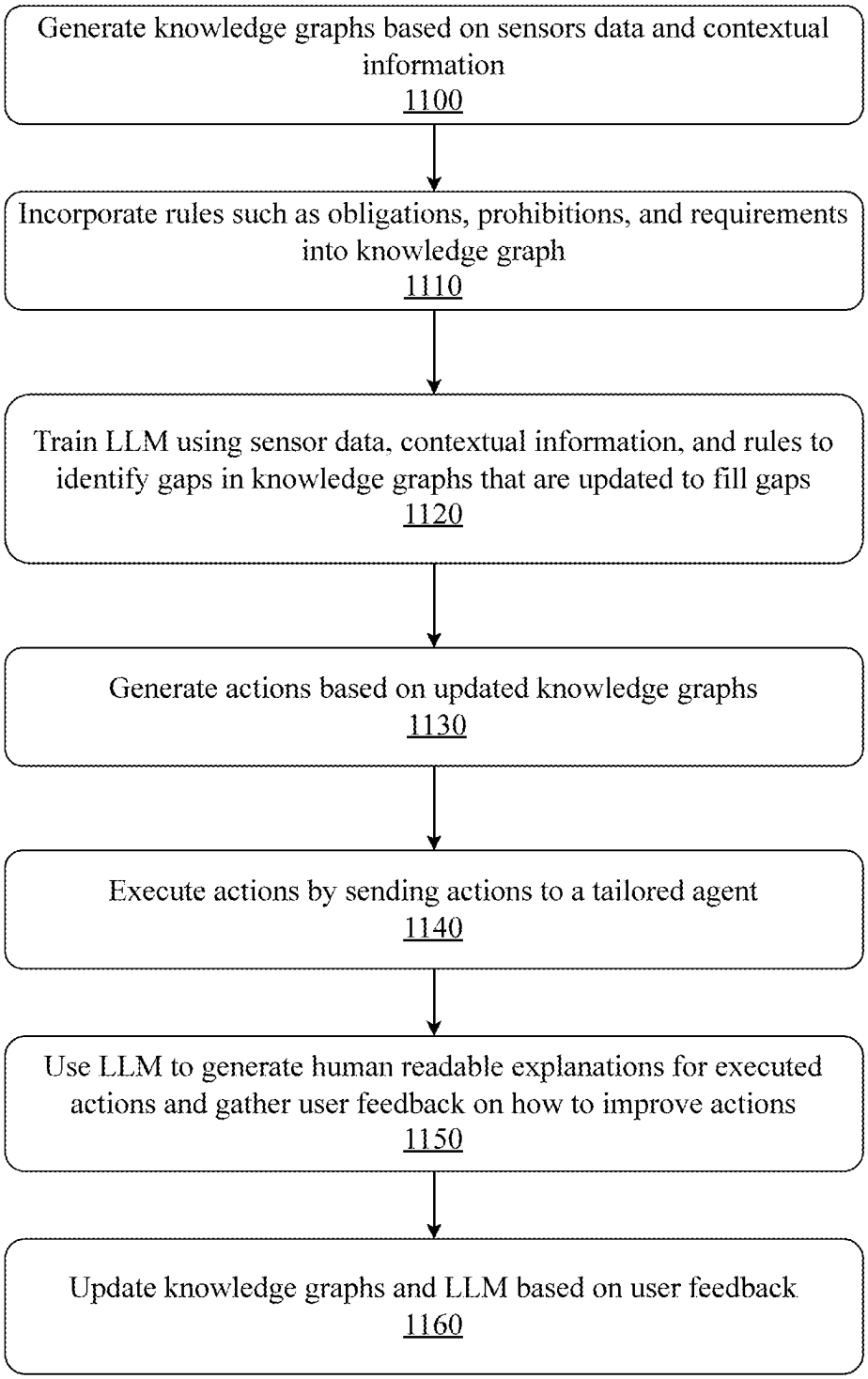

Generate knowledge graphs based on sensors data and contextual information
1100
Incorporate rules such as obligations, prohibitions, and requirements into knowledge graph
1110
Train LLM using sensor data, contextual information, and rules to identify gaps in knowledge graphs that are updated to fill gaps
1120
Generate actions based on updated knowledge graphs
1130
Execute actions by sending actions to a tailored agent
1140
Use LLM to generate human readable explanations for executed actions and gather user feedback on how to improve actions
1150
Update knowledge graphs and LLM based on user feedback
1160

FIG. 11

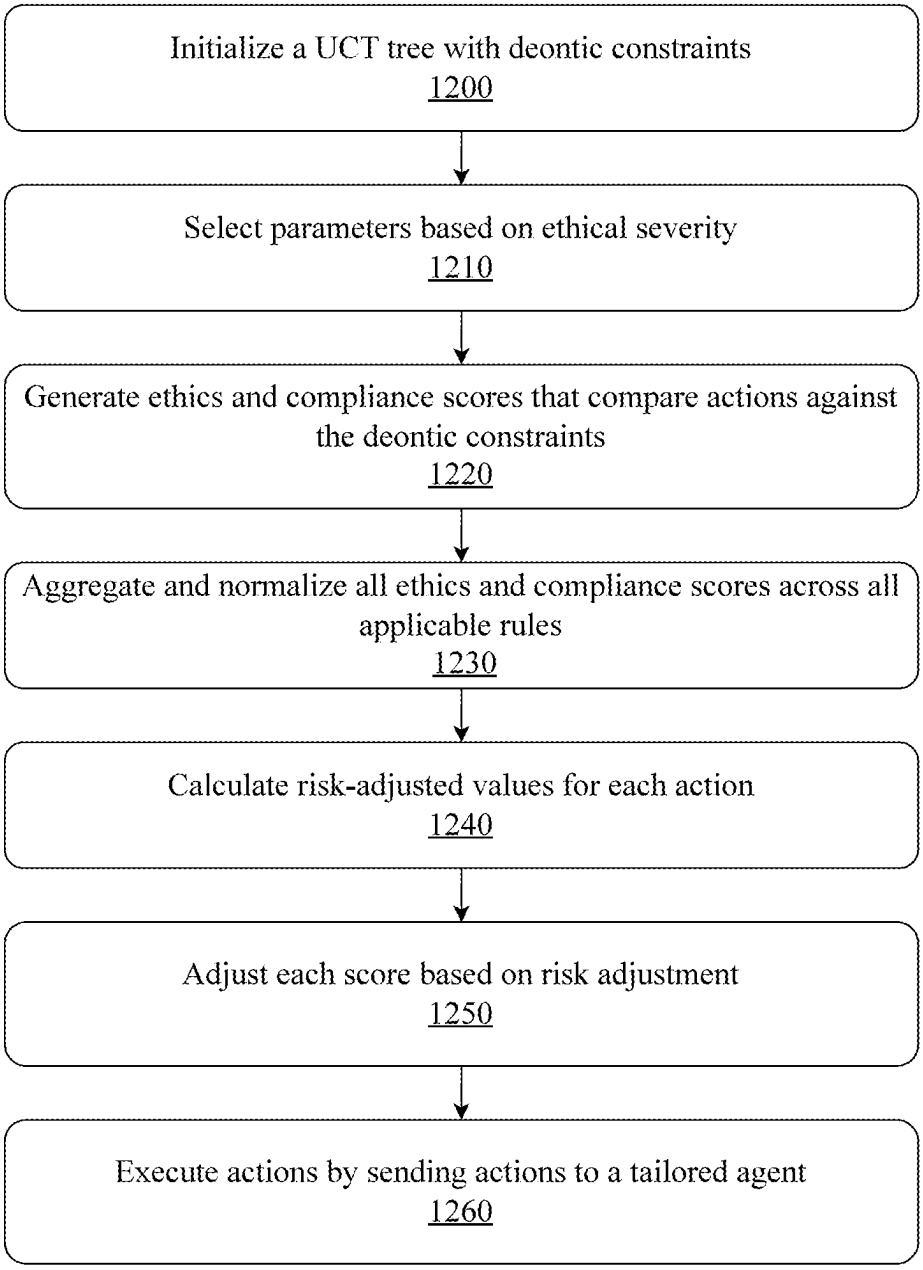

Initialize a UCT tree with deontic constraints
1200
Select parameters based on ethical severity
1210
Generate ethics and compliance scores that compare actions against the deontic constraints
1220
Aggregate and normalize all ethics and compliance scores across all applicable rules
1230
Calculate risk-adjusted values for each action
1240
Adjust each score based on risk adjustment
1250
Execute actions by sending actions to a tailored agent
1260

FIG. 12

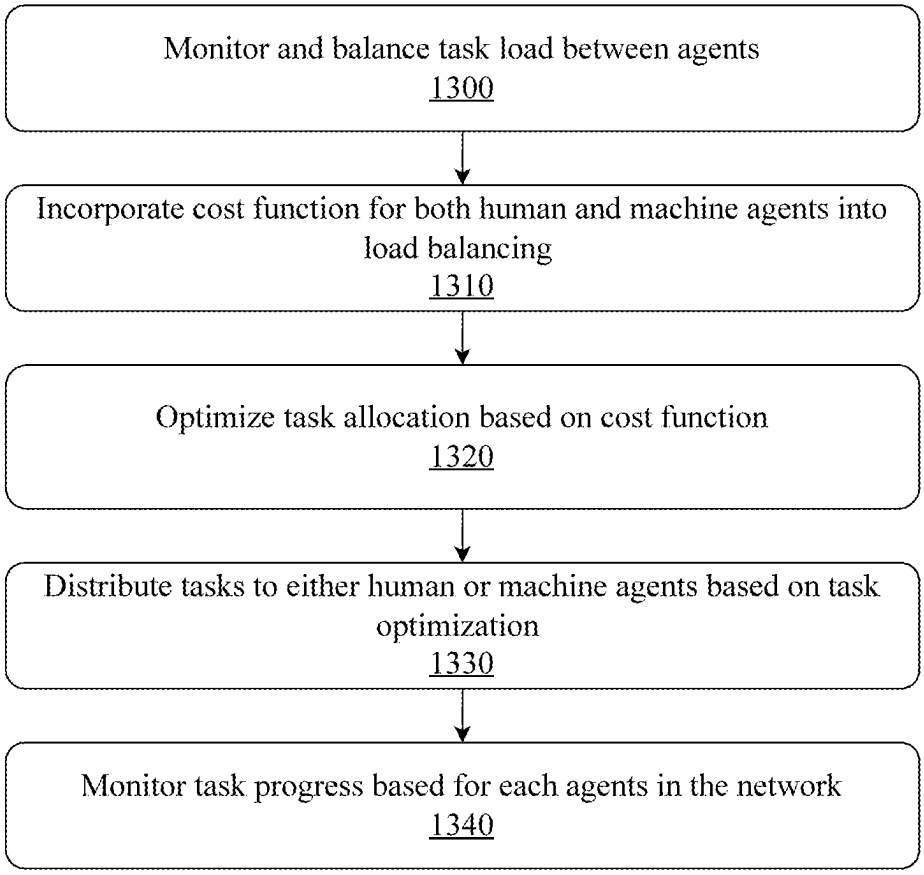

Monitor and balance task load between agents
1300
Incorporate cost function for both human and machine agents into load balancing
1310
Optimize task allocation based on cost function
1320
Distribute tasks to either human or machine agents based on task optimization
1330
Monitor task progress based for each agents in the network
1340

FIG. 13

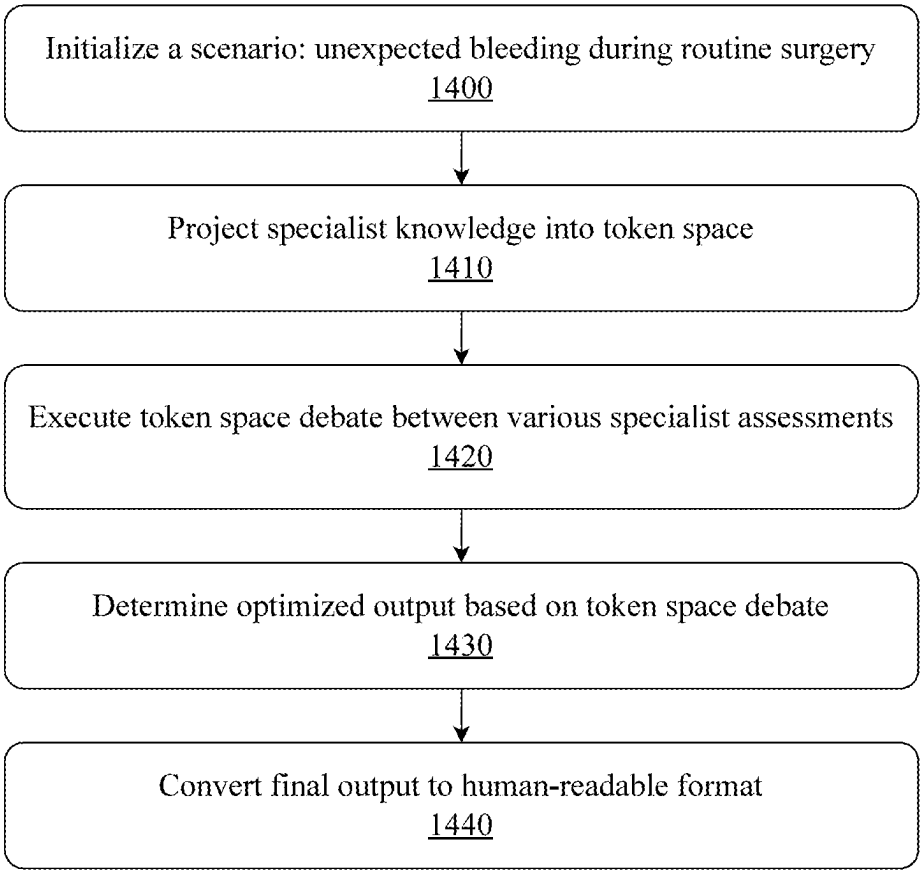

Initialize a scenario: unexpected bleeding during routine surgery
1400
Project specialist knowledge into token space
1410
Execute token space debate between various specialist assessments
1420
Determine optimized output based on token space debate
1430
Convert final output to human-readable format
1440

FIG. 14

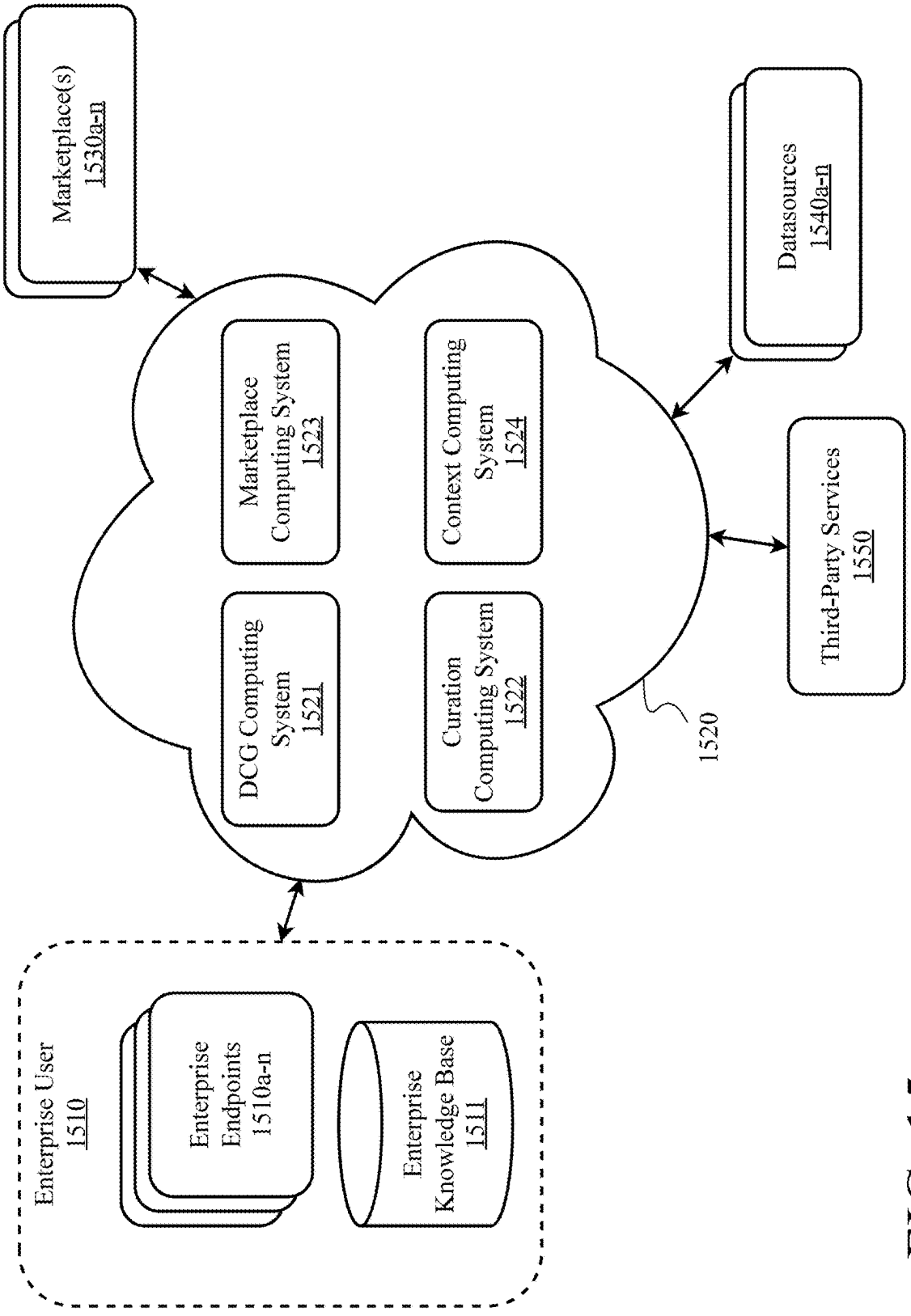

Marketplace(s)
1530a-n
Datasources
1540a-n
Marketplace
Computing System
1523
Context Computing
System
1524
DCG Computing
System
1521
Curation
Computing System
1522
1520
Third-Party Services
1550
Enterprise User
1510
Enterprise
Endpoints
1510a-n
Enterprise
Knowledge Base
1511

FIG. 15

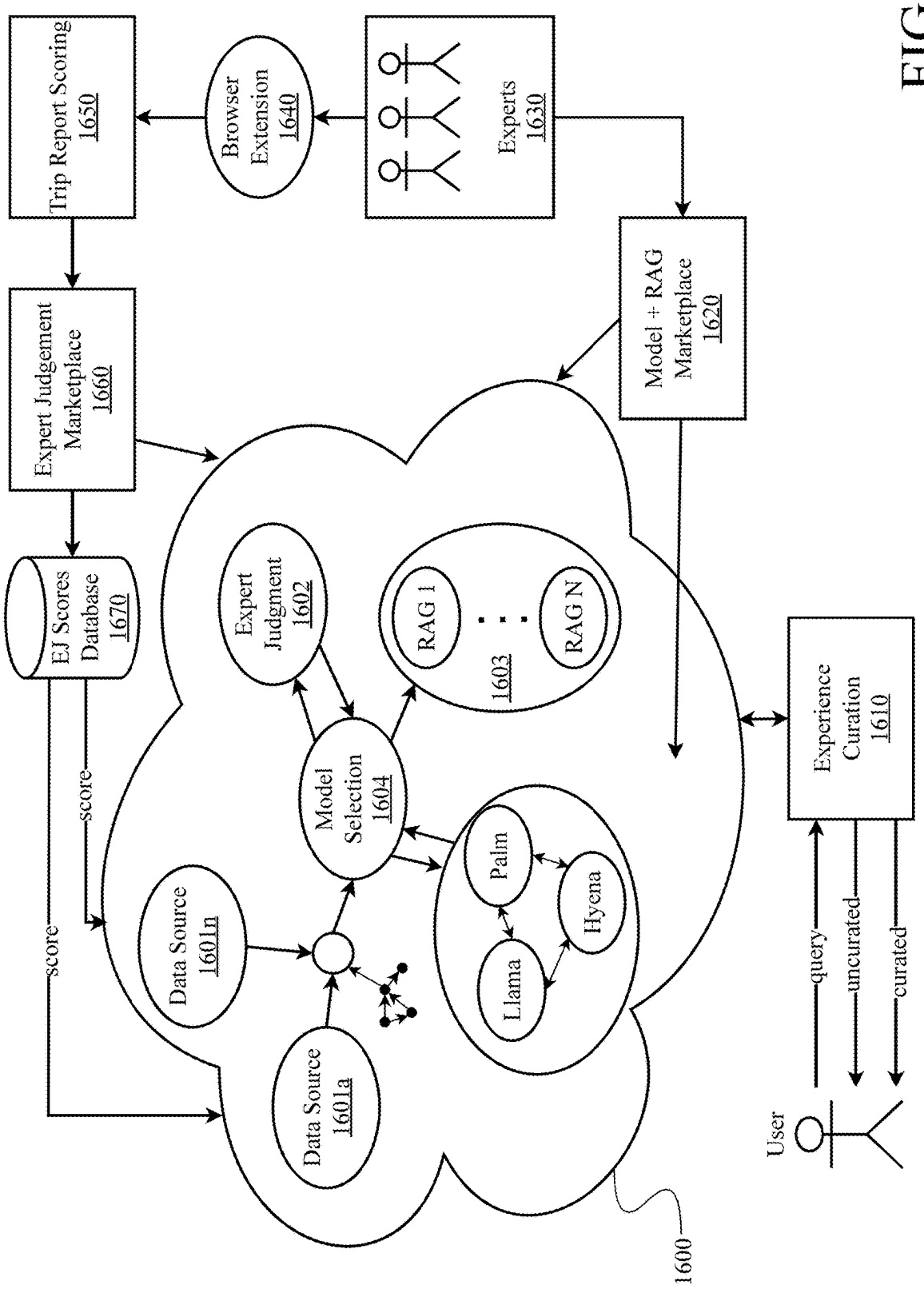

Trip Report Scoring 1650
Browser Extension 1640
Experts 1630
Expert Judgement Marketplace 1660
Model + RAG Marketplace 1620
EJ Scores Database 1670
Expert Judgment 1602
RAG 1
RAG N
1603
Model Selection 1604
Palm
Hyena
Llama
Data Source 1601n
Data Source 1601a
score
score
score
Experience Curation 1610
query
uncurated
curated
User
1600

FIG. 16

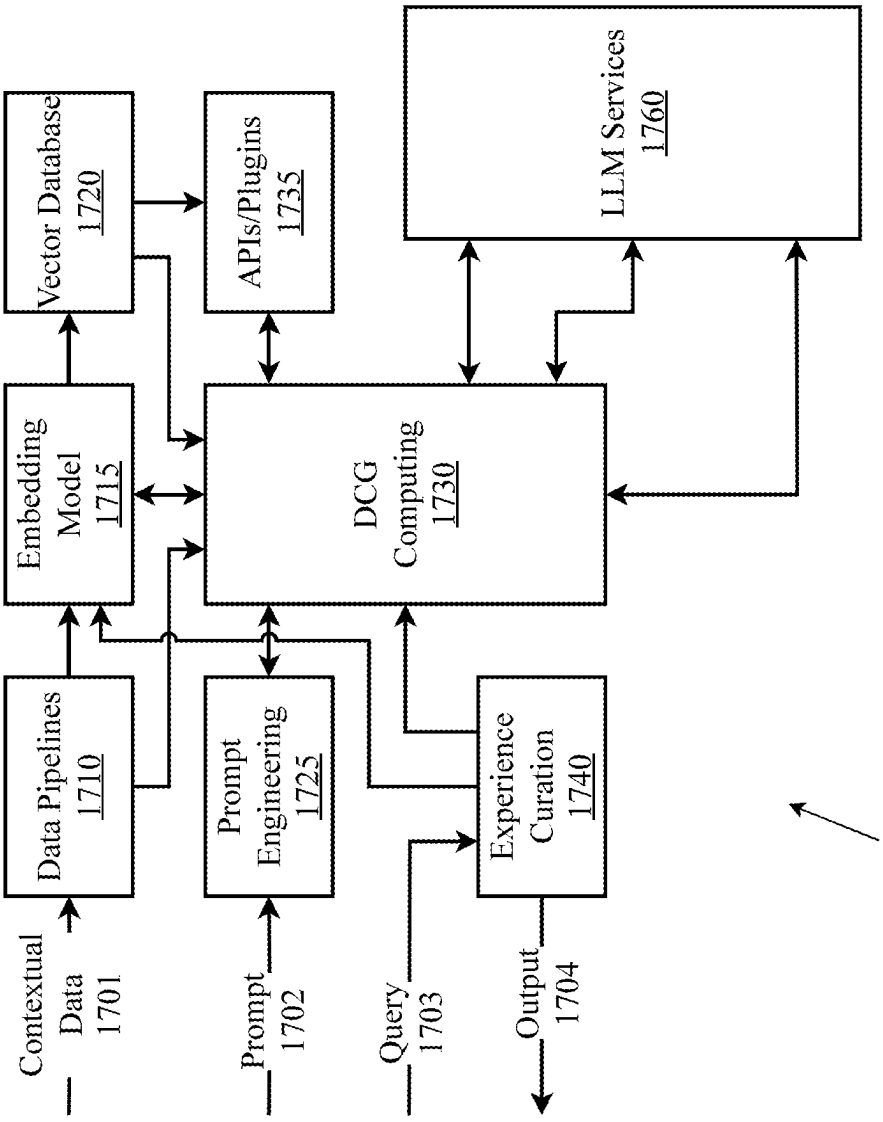

Vector Database
1720
APIs/Plugins
1735
LLM Services
1760
Embedding
Model
1715
DCG
Computing
1730
Data Pipelines
1710
Prompt
Engineering
1725
Experience
Curation
1740
1700
Contextual
Data
1701
Prompt
1702
Query
1703
Output
1704

FIG. 17

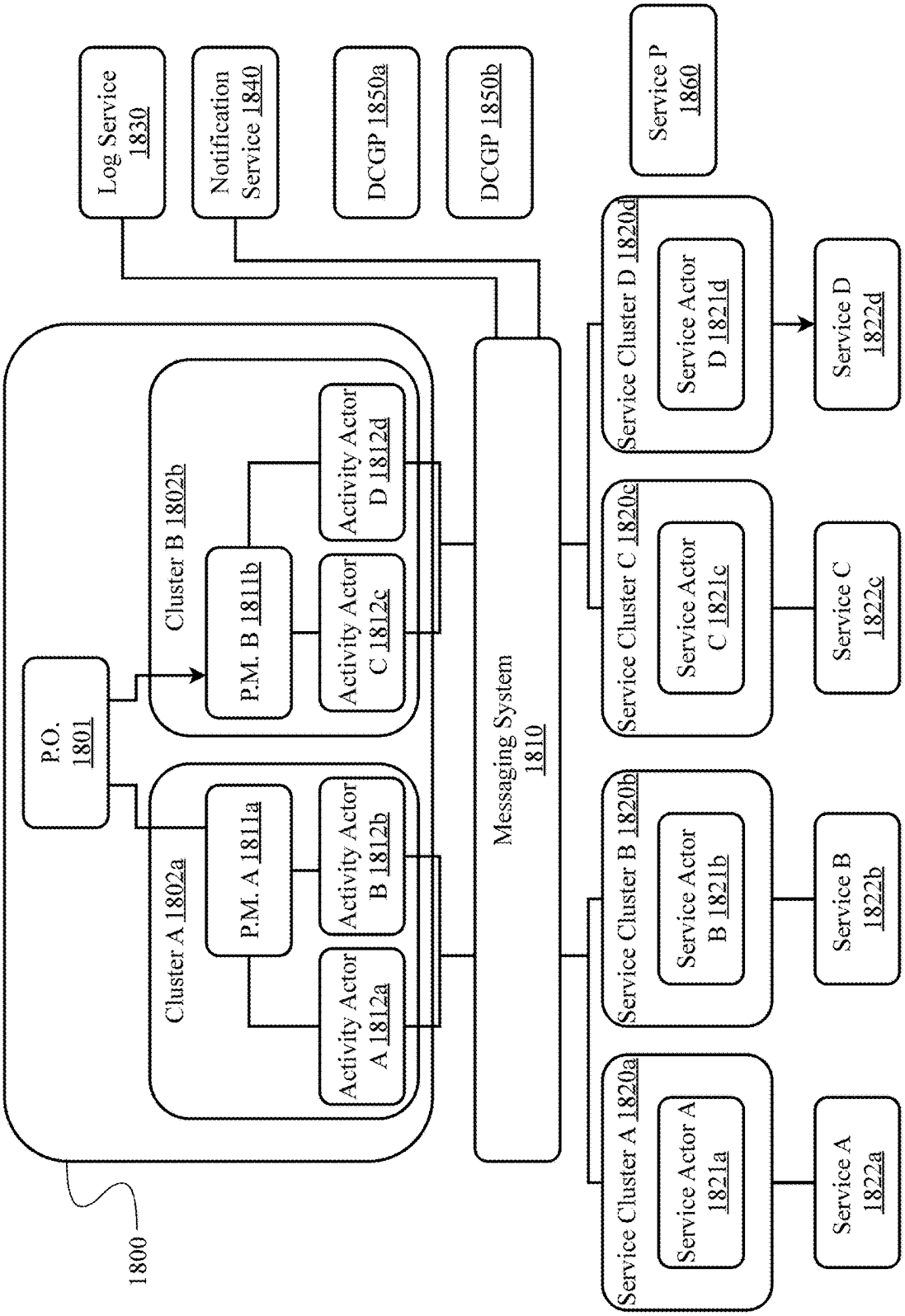

1800
P.O. 1801
Cluster A 1802a
P.M. A 1811a
Activity Actor A 1812a
Activity Actor B 1812b
Cluster B 1802b
P.M. B 1811b
Activity Actor C 1812c
Activity Actor D 1812d
Log Service 1830
Notification Service 1840
DCGP 1850a
DCGP 1850b
Service P 1860
Messaging System 1810
Service Cluster A 1820a
Service Actor A 1821a
Service A 1822a
Service Cluster B 1820b
Service Actor B 1821b
Service B 1822b
Service Cluster C 1820c
Service Actor C 1821c
Service C 1822c
Service Cluster D 1820d
Service Actor D 1821d
Service D 1822d

FIG. 18

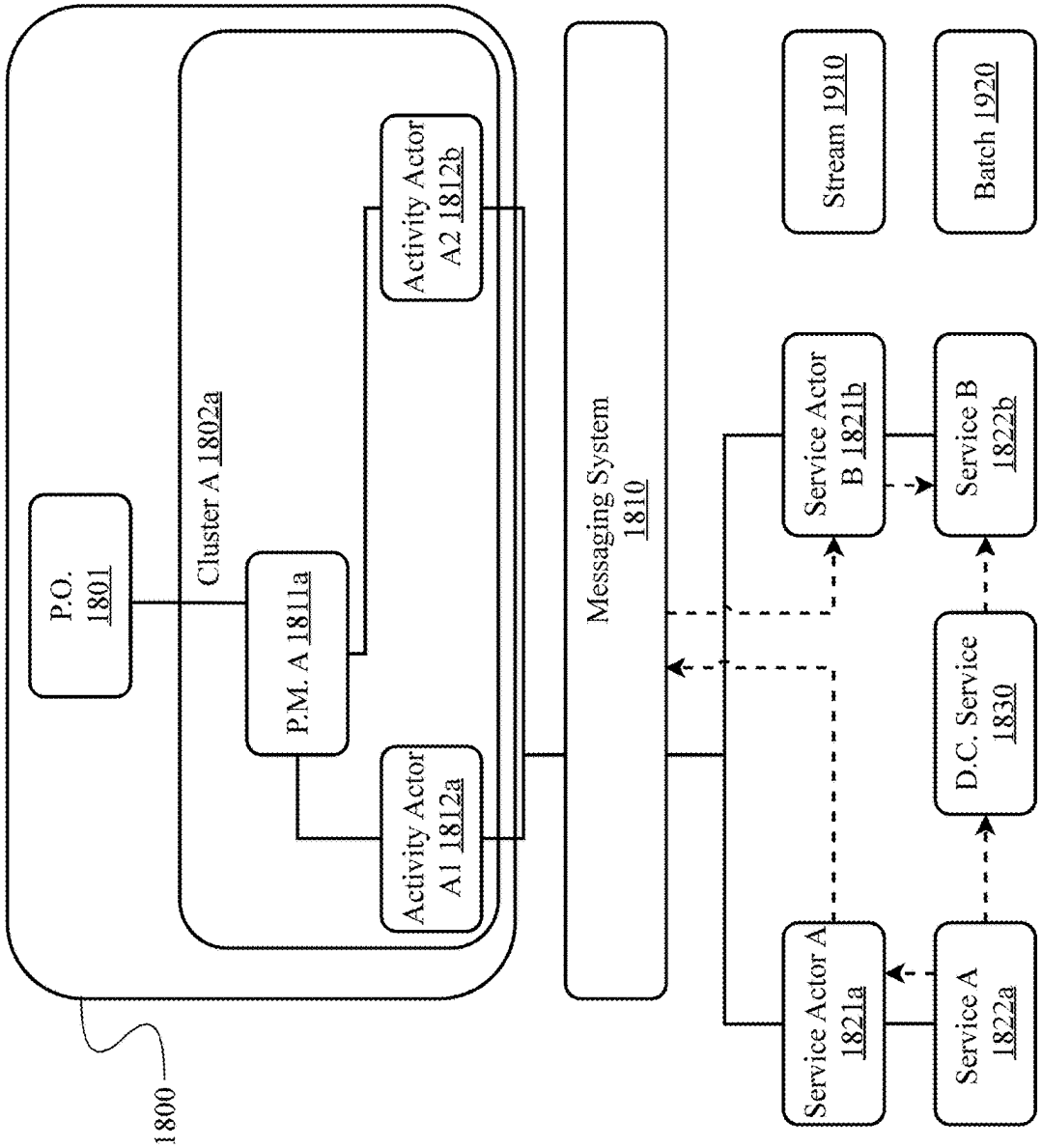

1800
P.O. 1801
Cluster A 1802a
P.M. A 1811a
Activity Actor A1 1812a
Activity Actor A2 1812b
Messaging System 1810
Service Actor A 1821a
Service Actor B 1821b
Service A 1822a
Service B 1822b
D.C. Service 1830
Stream 1910
Batch 1920

FIG. 19

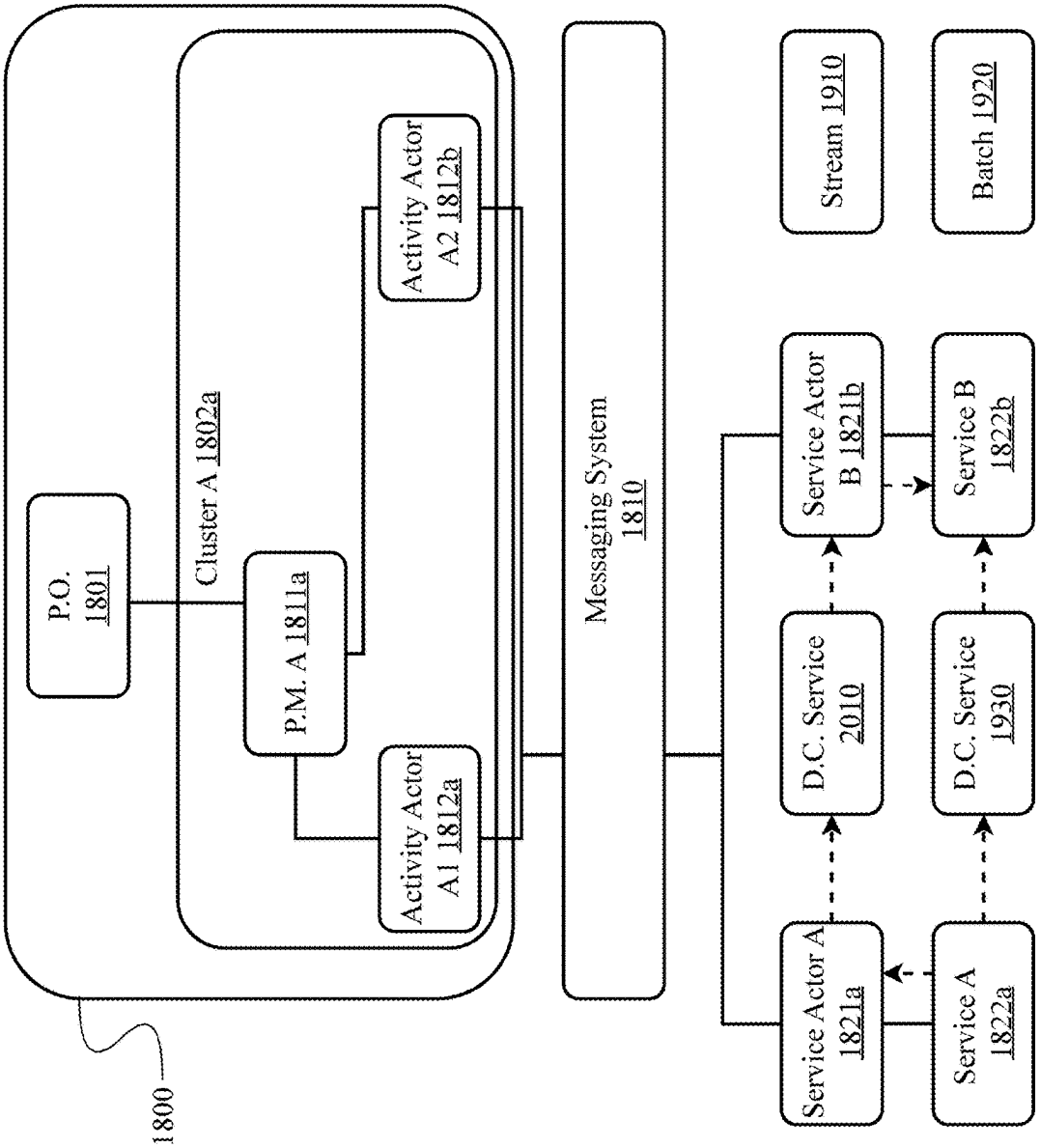

1800
P.O. 1801
Cluster A 1802a
P.M. A 1811a
Activity Actor A1 1812a
Activity Actor A2 1812b
Messaging System 1810
Service Actor A 1821a
Service A 1822a
D.C. Service 2010
D.C. Service 1930
Service Actor B 1821b
Service B 1822b
Stream 1910
Batch 1920

FIG. 20

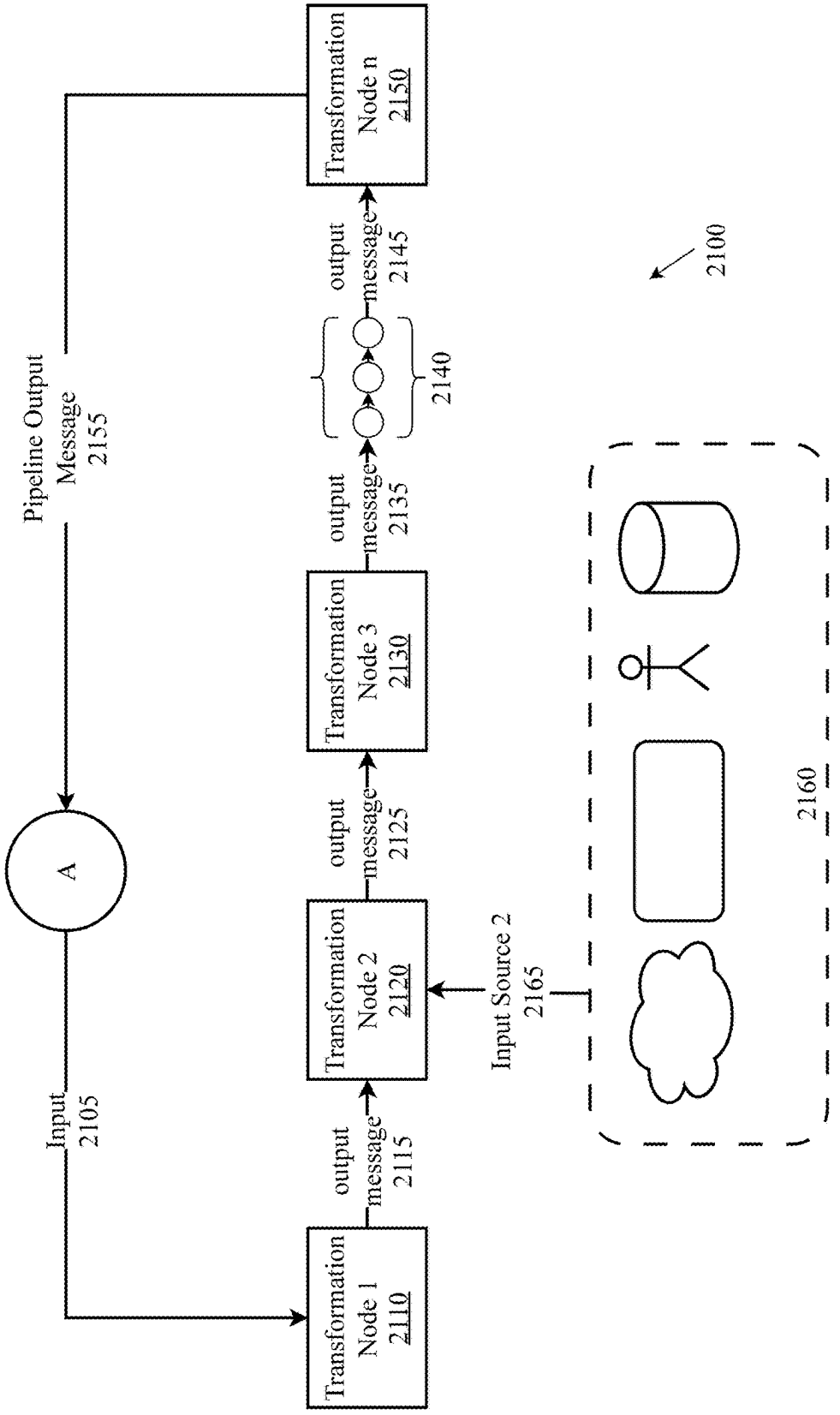

Input
2105
A
Pipeline Output
Message
2155
Transformation
Node 1
2110
output
message
2115
Transformation
Node 2
2120
output
message
2125
Transformation
Node 3
2130
output
message
2135
2140
output
message
2145
Transformation
Node n
2150
Input Source 2
2165
2160
2100

FIG. 21

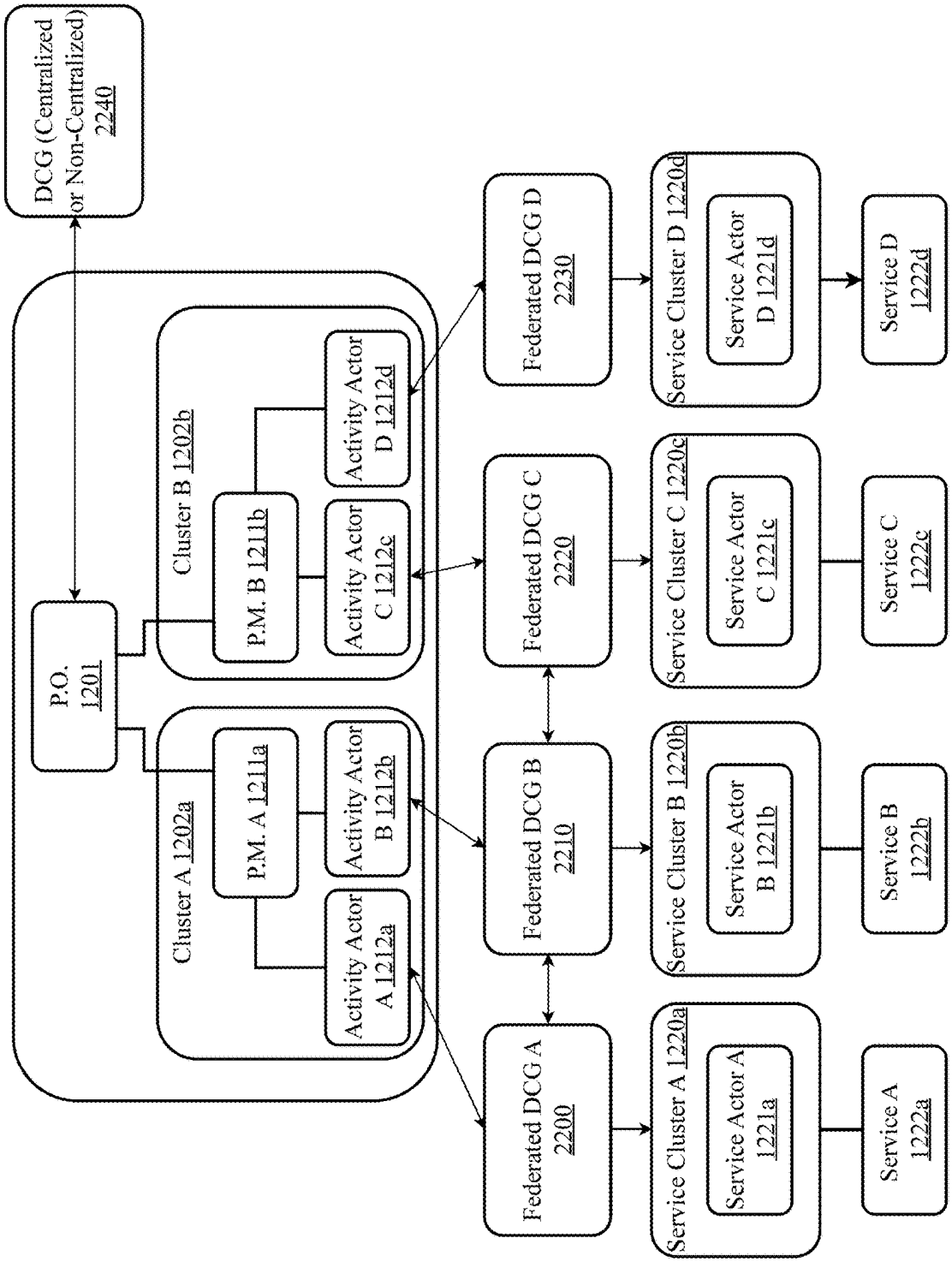

DCG (Centralized or Non-Centralized) 2240
P.O. 1201
Cluster A 1202a
P.M. A 1211a
Activity Actor A 1212a
Activity Actor B 1212b
Cluster B 1202b
P.M. B 1211b
Activity Actor C 1212c
Activity Actor D 1212d
Federated DCG A 2200
Federated DCG B 2210
Federated DCG C 2220
Federated DCG D 2230
Service Cluster A 1220a
Service Actor A 1221a
Service A 1222a
Service Cluster B 1220b
Service Actor B 1221b
Service B 1222b
Service Cluster C 1220c
Service Actor C 1221c
Service C 1222c
Service Cluster D 1220d
Service Actor D 1221d
Service D 1222d

FIG. 22

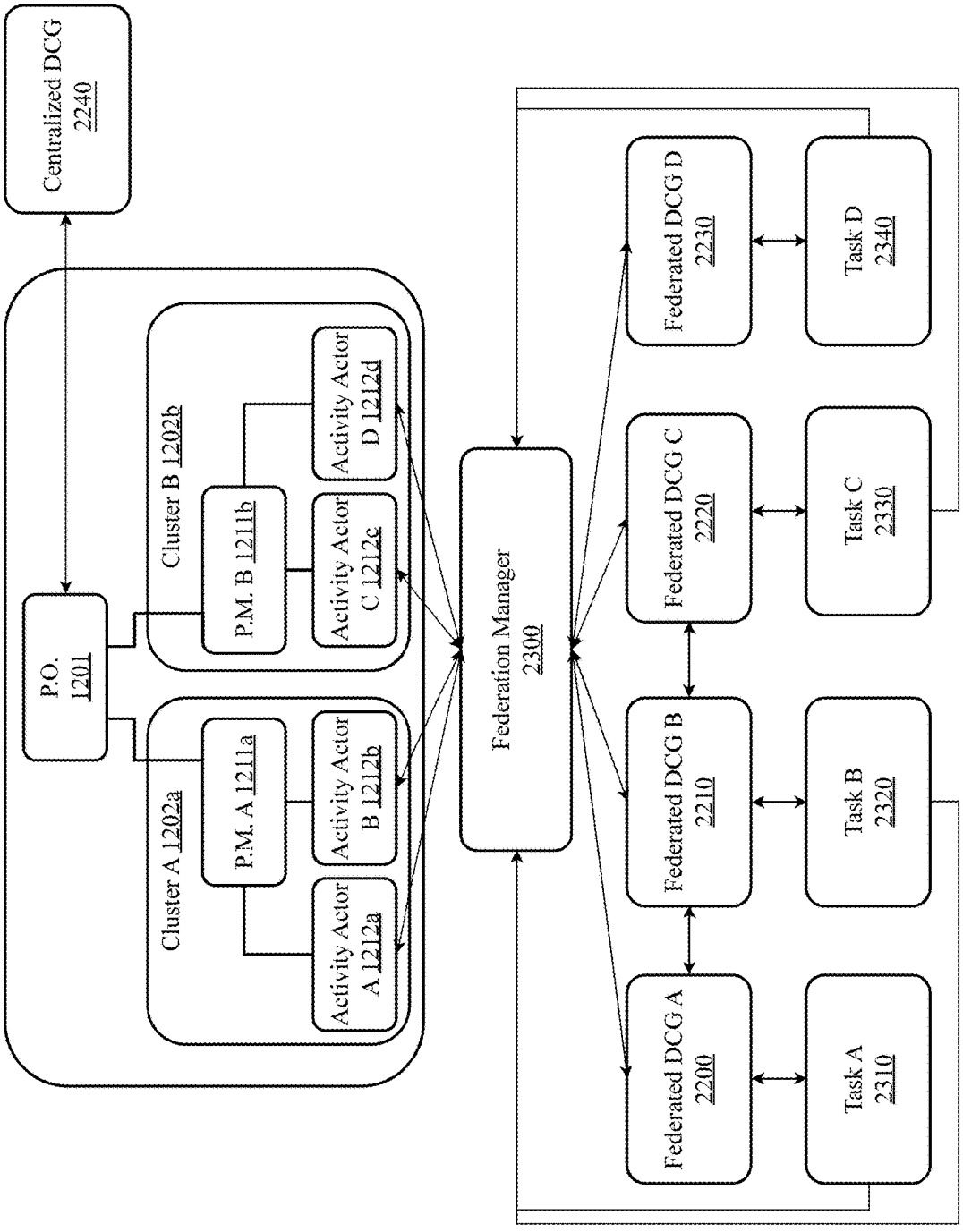

Centralized DCG
2240
P.O.
1201
Cluster A 1202a
P.M. A 1211a
Activity Actor A 1212a
Activity Actor B 1212b
Cluster B 1202b
P.M. B 1211b
Activity Actor C 1212c
Activity Actor D 1212d
Federation Manager
2300
Federated DCG A
2200
Federated DCG B
2210
Federated DCG C
2220
Federated DCG D
2230
Task A
2310
Task B
2320
Task C
2330
Task D
2340

FIG. 23

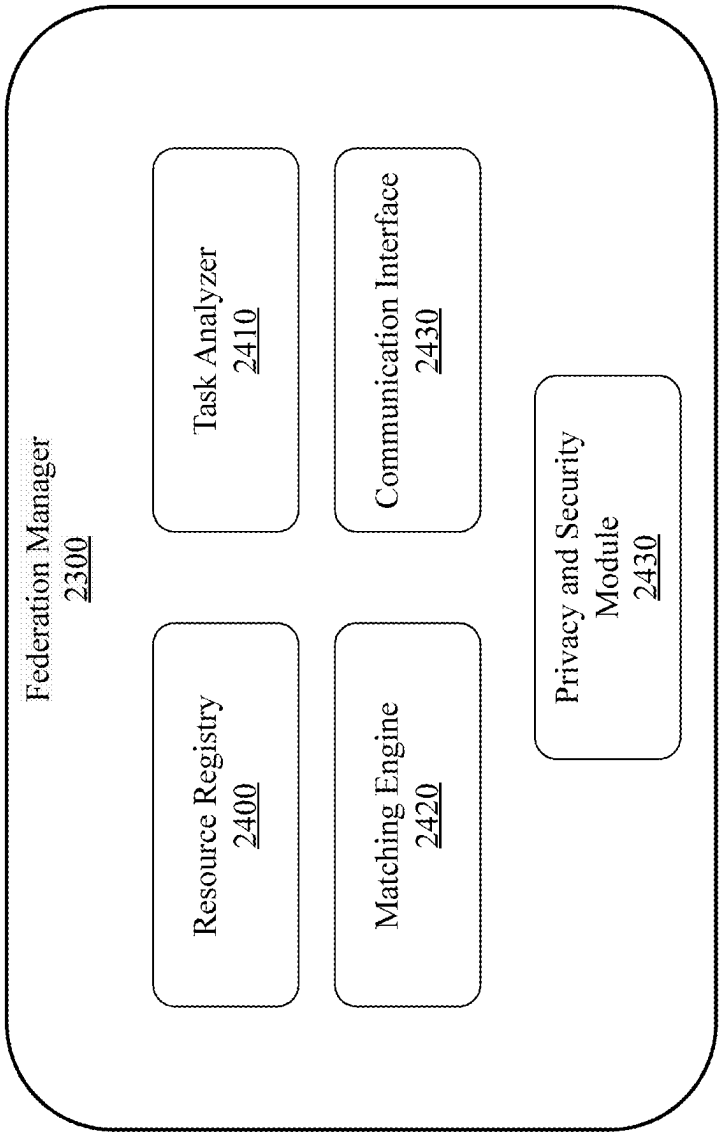

Federation Manager
2300
Resource Registry
2400
Task Analyzer
2410
Matching Engine
2420
Communication Interface
2430
Privacy and Security
Module
2430

FIG. 24

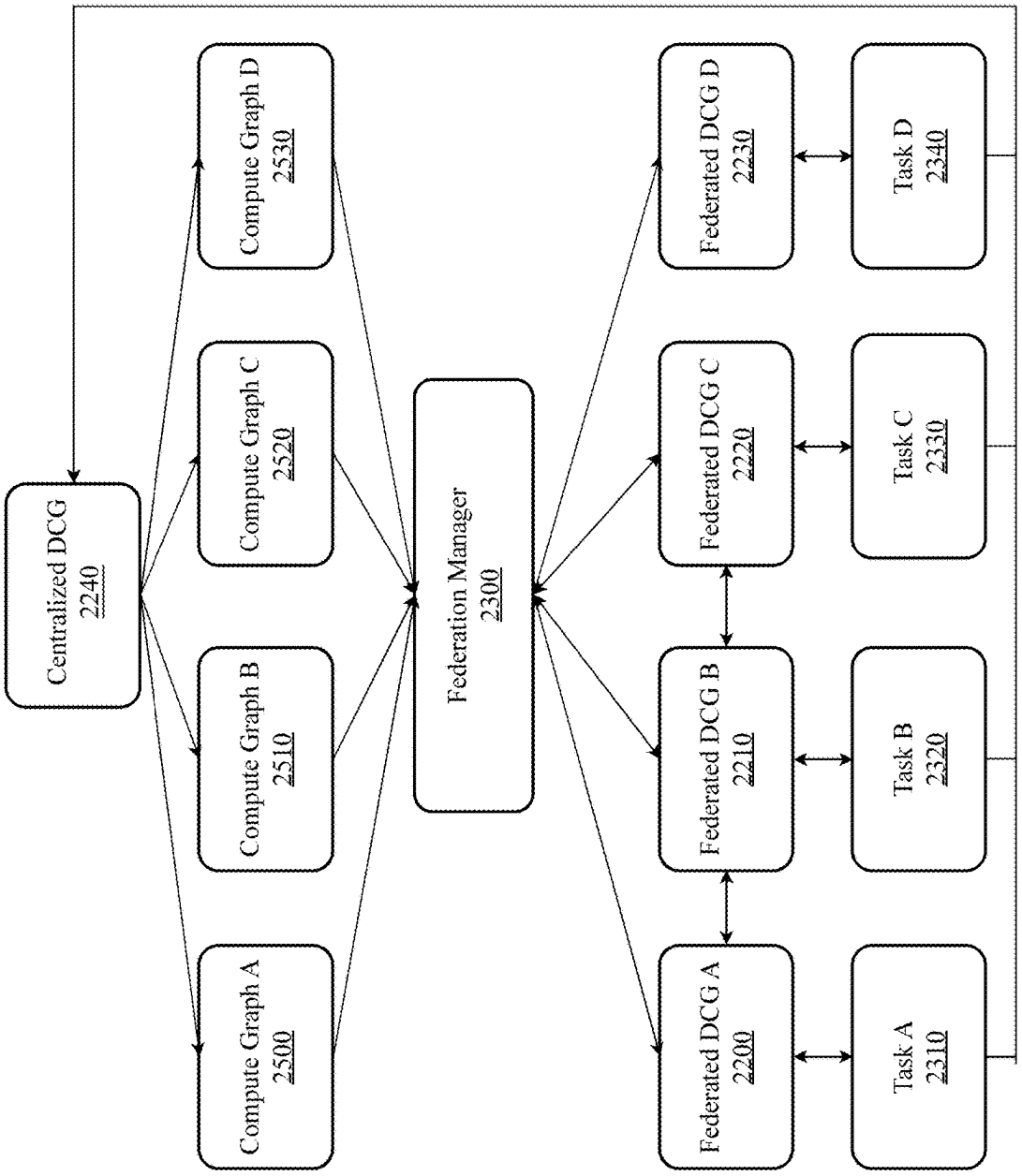

Centralized DCG
2240
Compute Graph A
2500
Compute Graph B
2510
Compute Graph C
2520
Compute Graph D
2530
Federation Manager
2300
Federated DCG A
2200
Federated DCG B
2210
Federated DCG C
2220
Federated DCG D
2230
Task A
2310
Task B
2320
Task C
2330
Task D
2340

FIG. 25

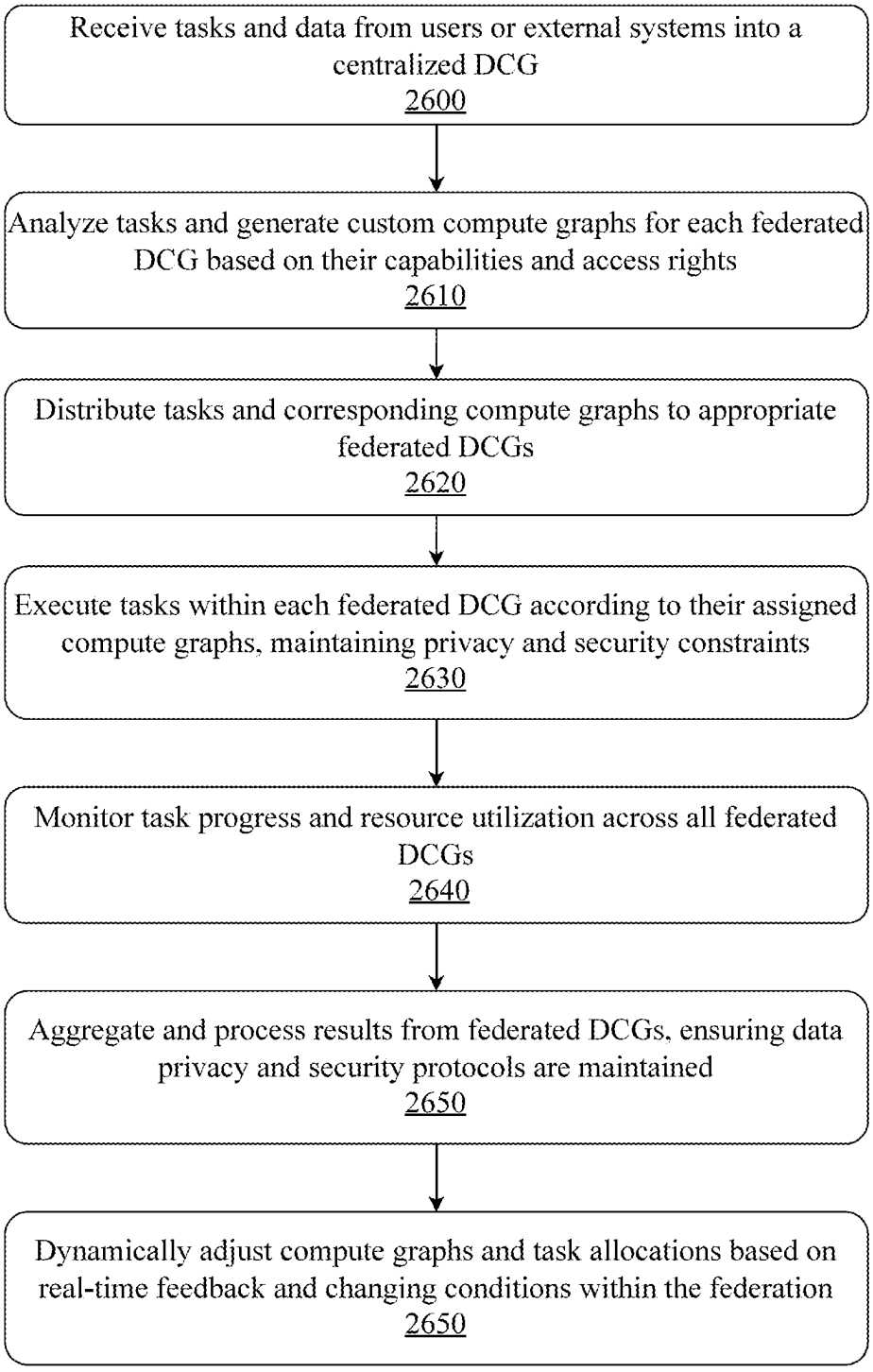

Receive tasks and data from users or external systems into a centralized DCG
2600
Analyze tasks and generate custom compute graphs for each federated DCG based on their capabilities and access rights
2610
Distribute tasks and corresponding compute graphs to appropriate federated DCGs
2620
Execute tasks within each federated DCG according to their assigned compute graphs, maintaining privacy and security constraints
2630
Monitor task progress and resource utilization across all federated DCGs
2640
Aggregate and process results from federated DCGs, ensuring data privacy and security protocols are maintained
2650
Dynamically adjust compute graphs and task allocations based on real-time feedback and changing conditions within the federation
2650

FIG. 26

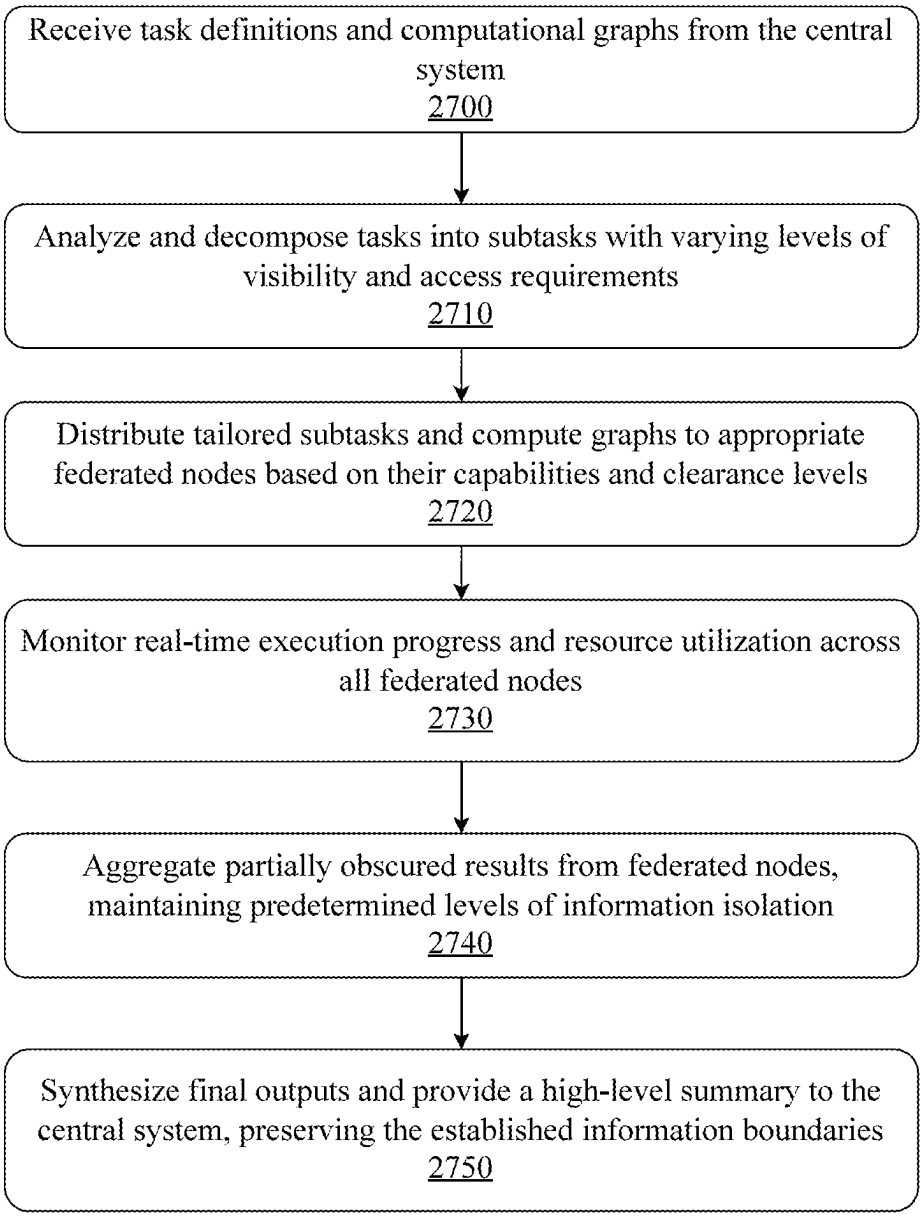

Receive task definitions and computational graphs from the central system
2700
Analyze and decompose tasks into subtasks with varying levels of visibility and access requirements
2710
Distribute tailored subtasks and compute graphs to appropriate federated nodes based on their capabilities and clearance levels
2720
Monitor real-time execution progress and resource utilization across all federated nodes
2730
Aggregate partially obscured results from federated nodes, maintaining predetermined levels of information isolation
2740
Synthesize final outputs and provide a high-level summary to the central system, preserving the established information boundaries
2750

FIG. 27

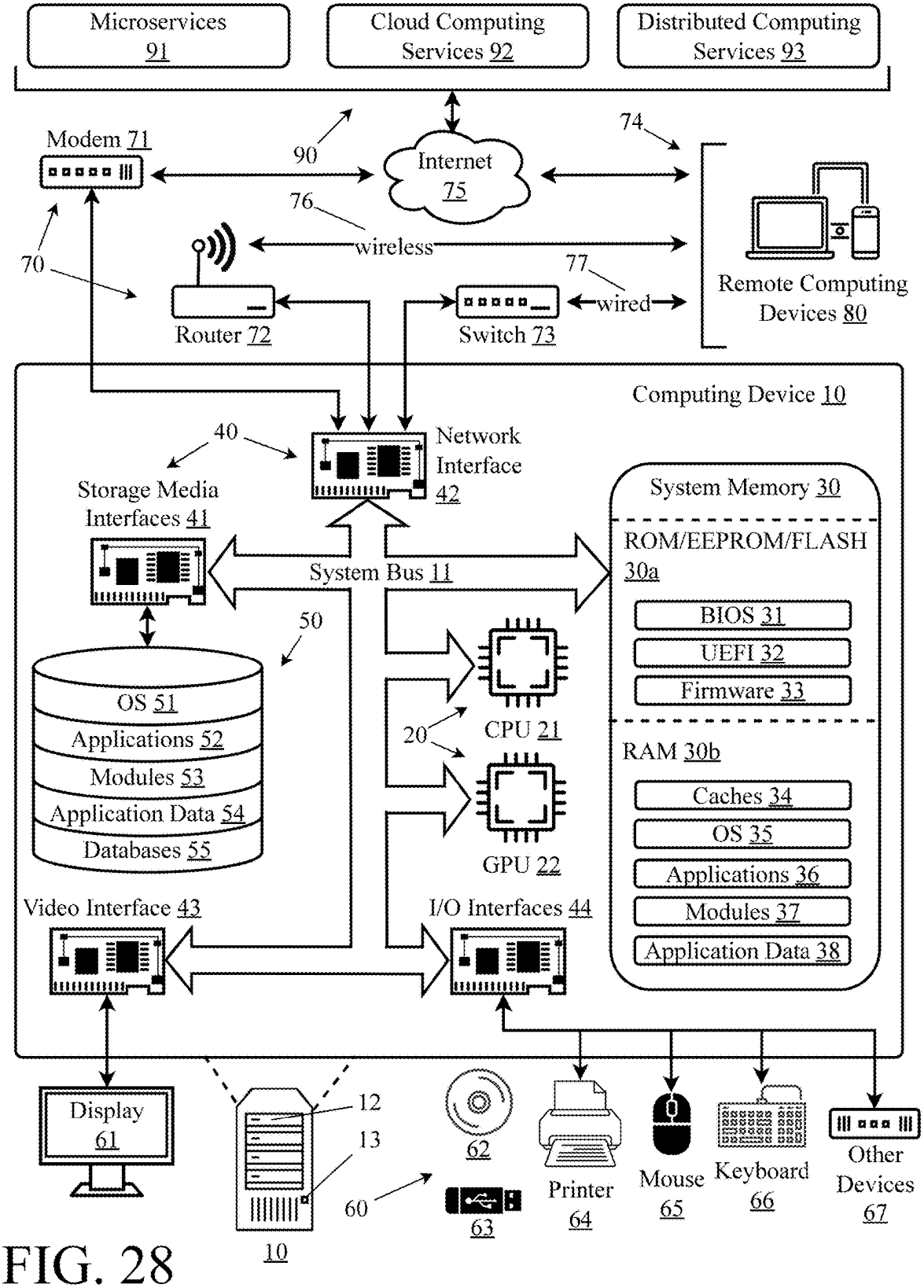

Microservices 91
Cloud Computing Services 92
Distributed Computing Services 93
Modem 71
90
Internet 75
74
76
wireless
70
77
wired
Router 72
Switch 73
Remote Computing Devices 80
Computing Device 10
40
Network Interface 42
Storage Media Interfaces 41
System Memory 30
ROM/EEPROM/FLASH 30a
BIOS 31
UEFI 32
Firmware 33
System Bus 11
50
OS 51
Applications 52
Modules 53
Application Data 54
Databases 55
20
CPU 21
GPU 22
RAM 30b
Caches 34
OS 35
Applications 36
Modules 37
Application Data 38
Video Interface 43
I/O Interfaces 44
Display 61
12
13
62
60
63
10
Printer 64
Mouse 65
Keyboard 66
Other Devices 67

FIG. 28

AI AGENT DECISION PLATFORM WITH DEONTIC REASONING

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] Priority is claimed in the application data sheet to the following patents or patent applications, each of which is expressly incorporated herein by reference in its entirety:

[0002] Ser. No. 18/656,612

[0003] 63/551,328

BACKGROUND OF THE INVENTION

Field of the Art

[0004] The present invention relates to federated large-scale cloud and edge computing, and more particularly to federated distributed graph-based computing platforms designed to enhance artificial intelligence based on enabled compliant decision-making, user experiences, and intelligent automation capabilities using deontic reasoning capabilities for individuals and groups across heterogeneous computing environments, including but not limited to cloud infrastructures, managed data centers, edge computing nodes, wearable/mobile devices, embedded devices, and robotics. By leveraging federated neurosymbolic AI architectures, this invention ensures scalable, ethically aligned AI interactions within dynamic multi-agent ecosystems while maintaining compliance with regulatory, operational, and security constraints.

Discussion of the State of the Art

[0005] The increasingly rapid evolution of artificial intelligence systems and computing experiences, particularly in multi-agent and distributed computing environments, has highlighted challenges in coordinating AI agent behaviors while ensuring ethical, legal, and operational compliance, especially across multiple devices, roles, and personas. Traditional approaches to AI agent goal specification, analysis, reasoning, action facilitation, policy adherence, and coordination typically rely on rigid rule-based (expert systems, explicitly encoded logic) systems or purely neural-based architectures, neither of which adequately addresses the need for flexible yet principled decision-making in complex real-world scenarios or addresses role-specific, task-specific, and other contextual factors core to improving outcomes and meeting ultimate human and application-level goals and objectives. The emergence of large language models (LLMs) and other AI technologies has further complicated this landscape by introducing powerful but potentially unpredictable agents that require careful oversight, ethical compliance layers, and constraint mechanisms, yet still lack acceptable levels of explainability, predictability, or trustworthiness and regularly demonstrate hallucination, inconsistency, or security vulnerabilities.

[0006] Current AI agent platforms or agentic applications primarily focus on task orchestration and completion and resulting completion and efficiency metrics, without robust mechanisms for encoding and enforcing obligations, permissions, and prohibitions that govern agent behavior (e.g., autonomous decision-making consistency), agent-in-application behavior (e.g., how agents interact with various applications), and emergent risks and states created when building or operating compound agentic systems and application at scale. While some systems implement basic rule-following capabilities (e.g., verification of schemas, keyword and category checks, schematization and serialization checks, or content blocks) or retrieval-augmented generation (RAG) and rule setups, they typically lack the sophistication to handle complex normative reasoning and iterative problem-solving with the context and continuity that many important real-world applications demand. This is powerfully evidenced by ongoing gap analysis in explainability, unlearning, jailbreaking, and hallucination or falsehood research for individual or mixtures of agents with or without chain-of-thought or other iterative attempts at reasoning-like behavior. This limitation becomes particularly acute in scenarios involving multiple agents operating across different jurisdictions, regulatory frameworks, and ethical contexts, and is further complicated when agents interact as part of larger applications or when mixtures of compound agents and applications and people interact with one another with varied degrees of the data flow process, data and model provenance, or even participants making decision-making provenance and traceability unlikely or untrusted.

[0007] Most existing agent coordination systems rely either on centralized control and orchestration architectures that create bottlenecks, scalability limitations, and single points of failure, or on decentralized approaches that struggle to maintain consistent provenance, traceability, explainability, and behavioral alignment across the system (in both single-agent and multi-agent contexts). The challenge of balancing individual agent or team autonomy with system-wide governance constraints and goals remains largely unresolved. Furthermore, these systems often lack the ability to adapt their constraints dynamically or to adjust themselves to meet practical objectives, especially if those objectives are specified informally such as via natural language and not expressly declared objective functions, in response to changing contexts, and they struggle to reason about the implications of their actions across different temporal and operational scales. These limitations become particularly apparent when systems operate in conditions dissimilar or contradictory to their training datasets, or when they face adversarial activity from other actors, whether in-part or wholly human or artificial or agentic applications.

[0008] What is needed is a federated neurosymbolic compound agentic platform that seamlessly integrates deontic logic and normative reasoning capabilities with modern AI technologies, enabling principled yet flexible agent enabled behavior and adjustable automation in complex, real-world environments. Such a system must be capable of managing distributed agent interactions efficiently while maintaining rigorous compliance with ethical, legal, and operational constraints, all while scaling effectively across heterogeneous computing environments and dynamically adapting to evolving regulatory and operational requirements.

SUMMARY OF THE INVENTION

[0009] Accordingly, the inventor has conceived and reduced to practice, an AI agent decision platform with deontic and normative reasoning. The agent platform represents an innovative approach to multi-agent coordination that combines deontic reasoning and normative reasoning with sophisticated knowledge exchange mechanisms. At its core, the platform employs domain-specific expert agents—including legal, medical, robotic, observer, and leadership agents—each maintaining domain-specific expertise and

unique knowledge bases while operating within a framework of ethical constraints. These agents collaborate within a dynamic framework of ethical constraints, enabling rapid geometric debate and decision-making while preserving semantic relationships and ethical boundaries and a mix of agent-specific, group-specific, or platform level knowledge corpora. The platform's federation manager coordinates agent activities while a deontically informed role-based knowledge orchestrator maintains semantic consistency and contextual relevance across the system's distributed knowledge graphs and analysis processes.

[0010] What sets this platform apart is its implementation of advanced orchestration across multiple tiers and tessellations of compute-enabled devices alongside observer-aware processing and dynamic responsibility allocation. Agents can assume different roles based on task requirements and cognitive load assessments (e.g., for themselves, a group of agents or bots, a paired human or groups of people, or blends), with sophisticated monitoring systems ensuring optimal task distribution between human and machine agents or groups. The platform incorporates advanced resource management capabilities that balance computational needs with overarching goals and context alongside broader longstanding and situation-specific ethical considerations, while maintaining explainability and decision-making or chain-of-thought provenance through generated human-readable outputs or human-understandable outputs (which may be stored or compressed into non-human readable forms). By integrating large language models with deontic reasoning, normative reasoning, and semantic knowledge representations distilled from broader simulated, synthetic and empirical observations, the platform enables agents to engage in collegiate-style debates and knowledge exchange, mimicking practical academic or applied discourse to observer, orient, decide, and act on an ongoing while maintaining strict ethical compliance and operational efficiency across changing active sets of considerations with varied finite time horizons of interest.

[0011] According to a preferred embodiment, a computing system for an AI agent decision platform with deontic and normative reasoning, the computing system comprising: one or more hardware processors configured for: receiving a plurality of tasks at a network of specialized AI agents, wherein each agent comprises domain-specific knowledge and is bound by deontic constraints comprising at least one of either obligations, permissions, prohibitions, social norms, or actions and consequences stored in knowledge graphs; forwarding the plurality of tasks to a centralized distributed graph-based system incrementally or en masse; analyzing the tasks using a deontic reasoning subsystem to evaluate compliance with the stored deontic constraints from knowledge graphs; generating a plurality of potential compute graphs that represent the plurality of subtasks, which may be calculated before or at the execution time of a pipeline or pipeline step; decomposing compliant tasks into subtasks based on agent domain expertise and associated deontic or normative constraints or goals; generating compute graphs that represent the subtasks with their associated deontic constraints or goals; distributing the tasks or compute graphs to agents within the network based on the agents' domain expertise, available resources, and deontic permissions or goals (optionally to include agent-based supervision, judging or supervision agent selection and role declaration by system); and executing the subtasks while maintaining compliance with the stored deontic constraints or goals, is disclosed.

[0012] According to a preferred embodiment, a computer-implemented method for an AI agent decision platform with normative and deontic reasoning, the computer-implemented method comprising the steps of: receiving a goal or objective, determining a potential set of associated tasks, determining a data flow, process flow, and control flow for a plurality of tasks and preparing it for submission to a distributed computational graph based network of orchestration and compute nodes with at least one specialized model or agent, wherein each model or agent was trained upon or fine-tuned or is augmented by (e.g., via RAG or vector database) domain-specific knowledge and is bound by deontic constraints comprising at least one of either obligations, permissions, social norms, prohibitions, actions or consequences stored in knowledge graphs or vectorized representations; forwarding the plurality of tasks to a centralized distributed graph-based processing system; analyzing the ongoing tasks and emergent data and process flows throughout emergent pipeline execution, dynamic branching, and pruning processes using a deontic reasoning subsystem to evaluate compliance with the stored deontic constraints and goals; generating a plurality of active and potential compute graphs that represent the plurality of executed, potential, or in-execution subtasks; decomposing compliant tasks into subtasks or subgraphs based on agent domain expertise and associated deontic constraints or goals; generating compute graphs that represent the subtasks or subgraphs with their associated deontic constraints; generating additional graph layers or edges relating appropriateness of potential models or agents known to the system with various tasks to aid in agent and model selection traversals and optimization; parameterizing tasks (e.g., injecting the appropriate model or agent selection) from the available set for a given task node from scored, ranked, or constraint-satisfied entities; distributing en masse or incrementally during ongoing computation the compute graphs or subgraphs to all or a selection of models agents within the network based on availability, resource constraints, and the agents' domain expertise and deontic permissions and appropriateness metrics; and executing the subtasks while maintaining compliance and logging execution and observability details supporting provenance and performance management of resultant data and process elements with the stored deontic constraints, is disclosed.

[0013] According to a preferred embodiment, a system for an AI agent decision platform with normative or deontic reasoning, comprising one or more computers or mobile/wearables, embedded, or robotic devices with executable instructions that, when executed, cause the system to: receive a plurality of tasks directed to a network of specialized agents, wherein each agent comprises domain-specific models, knowledge, context, or training and is bound by deontic goals or constraints comprising at least one of either obligations, permissions, or prohibitions stored in knowledge graphs; forwarding the plurality of tasks to a centralized distributed graph-based system; analyze the tasks using a deontic reasoning subsystem to evaluate compliance with the stored deontic constraints; generating a plurality of compute graphs that represent the plurality of subtasks; decompose compliant tasks into subtasks based on agent domain expertise and associated deontic constraints; gener-

ate compute graphs that represent the subtasks with their associated deontic constraints; distribute the compute graphs, subgraphs, or tasks to agents within the network based on the agents' domain expertise and deontic permissions; and execute the subtasks while maintaining compliance with the stored deontic constraints, is disclosed.

[0014] According to a preferred embodiment, the system implements an optional token-space concurrency with operations, where multiple specialized agents converge on decisions with minimal latency using geometric and wave-interference mechanisms for combining and evaluating vector embeddings within a high-dimensional token space. Rather than requiring physical quantum computing hardware or quantum entanglement, these operations draw conceptual parallels from quantum superposition, treating each agent's partial states (e.g., constraints, risk indicators, or subtask results) like waveforms whose amplitudes and phases can constructively or destructively interfere. Each token captures both magnitude (e.g., a confidence score) and a learned phase or direction encoding the agent's current stance or domain-specific perspective, enabling rapid detection of consensus or conflicts among agents without requiring full multi-round dialogues. The system's geometric interpretation allows efficient parallel evaluation of multiple agent perspectives by encoding them as vectors in a high-dimensional space where similarity and conflicts can be detected through mathematical operations analogous to wave interference patterns. The embedding framework incorporates a graph neural network that processes and learns from complex relational data, enabling the system to capture subtle patterns and relationships through geometric operations in token space. Domain-specific embeddings implement specialized knowledge representations for different fields using techniques from relation-aware entity alignment research, operating in high-dimensional spaces that preserve semantic relationships while enabling efficient computation through quantum-inspired operations. For instance, when specialized agents must coordinate under time pressure, token-space operations allow them to exchange ephemeral "micro-updates" of their states, unifying or flagging collisions as vectors misalign. While the architecture optionally permits integration with genuine quantum computing resources for specialized optimizations or advanced search routines, the primary implementation uses classical, geometry-based methods that borrow wave-like principles to enhance how information is merged and compared at scale. The system employs these token-space operations within its collegiate-style debate framework, enabling structured argumentation between different specialized agents through rapid geometric interactions while maintaining deontic constraints. This integration extends to the system's advanced information theoretic principles, which optimize knowledge transfer between components using mutual information measurements and transfer entropy calculations to quantify and optimize information flow between different knowledge domains. By coupling this quantum-inspired token-space concurrency with the deontic reasoning subsystem, the platform ensures any partial agreement emerging from geometric unification respects obligations, permissions, and prohibitions before finalizing actions, while maintaining the sophisticated causal entropy measurements used to understand and maintain causal relationships within the knowledge structure.

[0015] According to a preferred embodiment, while the system can utilize standard LazyGraphRAG approaches for basic retrieval tasks, it implements a significantly enhanced spatiotemporal and event-capable variant that fundamentally extends beyond traditional LazyGraphRAG capabilities. This enhanced implementation adds several key innovations: 1) a sophisticated event knowledge graph (EKG) that treats events as first-class nodes complete with timestamps, participants, triggers, outcomes and location references; 2) a spatiotemporal knowledge graph (STKG) that integrates both temporal and spatial dimensions where nodes and edges carry spatial coordinates plus temporal intervals, enabling phenomena like movements of vehicles or changes in climate data to be represented; 3) a multi-layered knowledge graph that implements specialized node types including entity nodes and deontic nodes, with edges labeled for relationships like "Applies to", "overrides or ConflictsWith, " and "TemporalValidity"; and 4) a deontic reasoning subsystem that enforces obligations, permissions, and prohibitions at each retrieval step. Unlike traditional LazyGraphRAG which primarily focuses on chunk-based text retrieval with minimal overhead, this enhanced variant enables true real-time, event-driven intelligence and advanced location and time-based retrieval through deep integration of EKG and STKG features. The system supports iterative expansions that factor in both textual relevance and spatiotemporal constraints, yielding a more nuanced, multi-dimensional retrieval experience that unifies textual evidence with numeric or geometry-based properties in the same knowledge retrieval pass. Through this comprehensive enhancement of the base LazyGraphRAG approach, the system achieves capabilities essential for complex real-world applications requiring sophisticated spatiotemporal reasoning and ethical compliance that would be impossible with standard LazyGraphRAG implementations alone.

[0016] According to an aspect of an embodiment, the agents may be human or non-human agents.

[0017] According to an aspect of an embodiment, the agents receive feedback and adjust task allocation based on the feedback.

[0018] According to an aspect of an embodiment, knowledge graphs are updated based on a plurality of contextual data and sensor data.

[0019] According to an aspect of an embodiment, sensor data includes but is not limited to Internet of Things (IoT) data, medical device data, wearable device data, video data, and image data.

BRIEF DESCRIPTION OF THE DRAWING FIGURES

[0020] FIG. **1** is a block diagram illustrating an exemplary system architecture for an AI agent decision platform with deontic reasoning.

[0021] FIG. **2** is a block diagram illustrating an exemplary system architecture for an AI agent decision platform with deontic reasoning that can be configured with edge devices.

[0022] FIG. **3** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, a deontic reasoning subsystem.

[0023] FIG. **4** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, a deontic learning training subsystem.

[0024] FIG. **5** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, an agent network.

[0025] FIG. **6** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, a knowledge graph network.

[0026] FIG. **7** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning wherein an agent can predict and optimize actions based on user feedback and contextual information.

[0027] FIG. **8** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning and agents organized in a hierarchy that store task and action information.

[0028] FIG. **9** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning and an integrated LLM network capable of managing resources.

[0029] FIG. **10** is a flow diagram illustrating an exemplary method for an AI agent decision platform with deontic reasoning that can be configured with edge devices.

[0030] FIG. **11** is a flow diagram illustrating an exemplary method for updating knowledge graphs based on incoming sensor and contextual information.

[0031] FIG. **12** is a flow diagram illustrating an exemplary method for integrating deontic constraints into UCT planning.

[0032] FIG. **13** is a flow diagram illustrating an exemplary method of an AI agent decision platform with deontic reasoning with task optimization and monitoring.

[0033] FIG. **14** is a flow diagram illustrating an exemplary method for integrating specialized knowledge into a knowledge graph and leveraging the platform in a simulated routine surgery.

[0034] FIG. **15** is a block diagram illustrating an exemplary system architecture for a distributed generative artificial intelligence reasoning and action platform, according to an embodiment.

[0035] FIG. **16** is a block diagram illustrating an exemplary aspect of a distributed generative AI reasoning and action platform incorporating various additional contextual data.

[0036] FIG. **17** is a diagram illustrating incorporating symbolic reasoning in support of LLM-based generative AI, according to an aspect of a neuro-symbolic generative AI reasoning and action platform.

[0037] FIG. **18** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph, according to one aspect.

[0038] FIG. **19** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph, according to one aspect.

[0039] FIG. **20** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph, according to one aspect.

[0040] FIG. **21** is a block diagram of an architecture for a transformation pipeline within a system for predictive analysis of very large data sets using a distributed computational graph computing system.

[0041] FIG. **22** is a block diagram illustrating an exemplary system architecture for a federated distributed graph-based computing platform.

[0042] FIG. **23** is a block diagram illustrating an exemplary system architecture for a federated distributed graph-based computing platform that includes a federation manager.

[0043] FIG. **24** is a block diagram illustrating an exemplary component of a federated distributed graph-based computing platform that includes a federation manager, the federation manager.

[0044] FIG. **25** is a block diagram illustrating an exemplary system architecture for a federated distributed graph-based computing platform that includes a federation manager where different compute graphs are forward to various federated distributed computation graph systems.

[0045] FIG. **26** is a flow diagram illustrating an exemplary method for a federated distributed graph-based computing platform.

[0046] FIG. **27** is a flow diagram illustrating an exemplary method for a federated distributed graph-based computing platform that includes a federation manager.

[0047] FIG. **28** illustrates an exemplary computing environment on which an embodiment described herein may be implemented.

DETAILED DESCRIPTION OF THE INVENTION

[0048] The inventor has conceived and reduced to practice an AI agent decision platform incorporating normative and deontic reasoning capabilities. The platform represents a sophisticated AI-enhanced decision system that seamlessly integrates ethical reasoning with distributed computing, enabling automated decision-making across multiple domains in complex, federated, and resource-constrained environments. At its core, the system employs a novel fusion of symbolic and neural approaches, utilizing quantum-inspired token space operations and advanced information theoretic principles in certain embodiments to achieve both logical consistency and operational efficiency. The platform's federated distributed computational graph (DCG) architecture facilitates seamless scaling, while its integrated semantic knowledge corpora-governed by role-based and deontic access constraints enables system components, individual constituent models, and agents to maintain system-wide compliance, preserve privacy, enforce ethical constraints, and manage knowledge relationships. This architecture further supports knowledge corpora development and curation within appropriate access pools.

[0049] A key innovation is the platform's ability to coordinate numerous and distinct specialized agents (which may also have additional heterogeneity such as in their embeddings, input or output formats, resource use or needs, execution costs, license terms, ethical restrictions, other legal use restrictions such as export bans or sale restrictions) through a collegiate-style knowledge exchange framework that enables structured debates and dynamic ongoing task, computational subgraph formulation, allocation, and dissemination. The system maintains sophisticated observer-aware processing capabilities that ensure appropriate perspective and context across different knowledge domains, spatial localities and contexts, or temporal frames. Through its integration of large language models, other AI/ML techniques modeling simulation, spatiotemporal and event

enhanced knowledge graphs with supporting vector databases and structured/unstructured databases (e.g., SQL, noSQL, graph, document, key value), and normative and deontic reasoning, the platform can handle complex scenarios requiring cross-domain expertise while maintaining strict reasoning processes, threshold based sufficiency scoring, analysis and data fidelity monitoring, role or team-level ethical, normative data and model compliance and auditability. Resource management and task optimization are handled through advanced mechanisms that consider both computational efficiency and ethical implications, enabling the system to balance operational requirements with moral constraints. The result is a highly adaptable, ethically-sound decision-making platform that can operate across various domains while maintaining transparency, accountability, and logical consistency).

[0050] The present invention addresses fundamental limitations in traditional machine learning and artificial intelligence approaches to AI-enhanced decision-making and automation processes. While neural network-based systems excel at pattern recognition and general task completion, they struggle with providing verifiable logical reasoning and guaranteed correctness in decision-making processes. This limitation becomes particularly acute in scenarios requiring explicit reasoning about obligations, permissions, and prohibitions—the domain of deontic logic. By combining normative and deontic reasoning capabilities with modern AI-based or enhanced reasoning and planning technologies, the system achieves both the flexibility of machine learning, AI methods and the verifiable correctness of formal logical systems. The system further extends its capabilities through the incorporation of variants of formal logic, which enhance formal logic and rule performance beyond historical norms. For example, the system can extend standard rule-based languages (such as Datalog or Vadalog, which typically operate with existential rules or tuple-generating dependencies) to a fuzzy setting by implementing arbitrary t-norms in place of classical conjunctions in rule bodies. The system may also incorporate advanced logical frameworks including dyadic existential rules for Datalog, or similar extensions for other formal logic languages such as Vadalog, DDlog, Prolog, Logica, Yedalog, Answer Set Programming (including Potassco), Mercury, or Curry. This implementation enables sophisticated reasoning capabilities while maintaining computational efficiency and logical consistency across the platform's distributed architecture. Specifically, the system implements dyadic decomposable sets that provide decidable query answering while maintaining polynomial data complexity for various rule classes. The platform leverages the key properties of dyadic pairs of tuple-generating dependencies (TGDs), where one component contains head-ground rules that generate only ground facts, and the other component belongs to an underlying decidable class of rules. This architectural choice ensures that query evaluation complexity remains within PTIME for data complexity when the underlying class exhibits polynomial data complexity, and within EXPTIME for combined complexity when there is an exponential gap between data and combined complexities. The system's implementation of dyadic existential rules allows it to systematically decompose complex rule sets into more manageable components while preserving decidability and computational efficiency properties. The platform employs an evolved hybrid approach to selectively formalize rule-based knowledge and reasoning, combining mixtures and debate between AI agents, specialized models, authoritative data sources, structured expert judgment, and corpora of rulesets to maintain rigorous yet adjustable logical consistency while handling the complexity and scale of real-world applications. The system's architecture ensures that all decisions are optimal not only from an operational perspective but also provably compliant with defined ethical and regulatory constraints, priorities, and objectives. This compliance is verified through multiple mechanisms including formalized checks, consensus or model blends, accumulated evidence/agreement, model-based expert judgment or debate, and selective crowdsourcing with supplemental human experts. This architectural approach has significant implications for both trustworthiness and explainability scoring, rating, estimation, and risk determination for individual transformations, subgraphs, or full end-to-end data and process flows, particularly when orchestrated through federated distributed computational graphs. The system ensures that rules, data flow, control flow, and execution topologies (both explicit and implicit) across federated resources can be analyzed through a priori or pre-mortem analysis, during execution, and through post-hoc evaluation to verify that individual transformation steps (such as persistence, query, model execution/evaluation, retraining, and rule evaluation) are answerable. The system can therefore evaluate characteristics of individual transformations, subgraphs, or full pipelines including computational complexity estimation, resource utilization, evaluation time, cost, processing nature (e.g., transactional guarantees such as at-least-once versus exactly-once or none), and decidability of model response or query answering.

[0051] Many advanced features disclosed in the parent patent applications may be used with one or more embodiments. Neuro-symbolic integration addresses a fundamental challenge in AI by combining connectionist and symbolic approaches. The system recognizes that foundational large language models (like GPT-3 and GPT-4) are connectionist AI models with neural network architectures containing billions of parameters, but lack explicit symbolic representations or rules. To bridge this gap, the system integrates both approaches by combining the pattern-recognition strengths of deep neural networks with explicit symbolic reasoning capabilities. The architectural components reflect this hybrid approach through a specialized structure that combines connectionist elements (deep neural networks with millions to billions of parameters organized in interconnected layers) with symbolic systems. These neural networks employ distributed representation, where each neuron contributes to representing multiple features or concepts simultaneously, while the symbolic component maintains explicit representations of symbols and rules. The system then maps these learned representations to symbolic concepts and rules through a sophisticated integration process. This allows for both learning from massive amounts of data through the neural components while maintaining explicit knowledge representation through the symbolic elements. Unlike traditional connectionist models that struggle with hallucination, this integration enables the system to validate outputs against established knowledge bases, providing more reliable and verifiable results. The logic-based knowledge graphs serve as a foundation for maintaining and reasoning about these symbolic relationships, while the neural components handle pattern recogni-

tion and learning from unstructured data. The system implements a sophisticated approach to combining neural and symbolic processing through several key interconnected mechanisms. At its foundation, the system maps learned patterns to symbolic rules through a carefully orchestrated multi-step process. This begins with obtaining diverse input data, including enterprise knowledge and expert knowledge, which is processed through embedding models to create vectorized datasets. These vectorized datasets serve as training data for machine learning models that learn complex representations of the underlying patterns and relationships. The learned representations are then systematically mapped to symbolic concepts and rules, creating a crucial bridge between connectionist learning approaches and symbolic reasoning frameworks. This mapping process enables the system to translate the distributed representations learned by neural networks into explicit symbolic forms that can be manipulated using logical reasoning. The system's capabilities are significantly enhanced through RAG (Retrieval-Augmented Generation) integration, which provides a sophisticated mechanism for incorporating external knowledge sources and contextual data into the processing pipeline. The RAG functionality serves as a powerful tool for knowledge enhancement, allowing organizations to leverage proprietary datasets in a controlled manner. For example, a medical research company can share valuable information with other institutions through RAG-based augmentation rather than providing direct access to raw training data. The RAG marketplace described in the parent patent application enables the buying and selling of these knowledge augmentation capabilities, creating an ecosystem for knowledge sharing while protecting proprietary information. The RAG system can store vectorized context in specialized vector databases like Pinecone, enabling efficient retrieval and incorporation of relevant contextual information during processing. The other major component involves combining pattern matching with logical reasoning through an advanced neuro-symbolic architecture. This integration allows the system to leverage both the powerful pattern recognition capabilities of neural networks and the structured logical reasoning of symbolic systems. The platform implements this through a feedback loop where symbolic reasoning outputs are incorporated back into the neural network to refine learned representations over time. This bidirectional flow of information enables the system to perform sophisticated reasoning tasks while maintaining the ability to learn from and adapt to new data. The architecture supports various reasoning techniques, including logic rules and inference engines, which can be applied to the symbolic representations derived from the neural network's learned patterns. This combination allows the system to handle both the uncertainty and pattern recognition strengths of neural networks while maintaining the explicit reasoning capabilities of symbolic systems. The integration of these mechanisms is orchestrated through a distributed computational graph (DCG) that manages complex workflows and data pipelines. The DCG can dynamically select, create, and incorporate trained models with external data sources and marketplace components, enabling flexible deployment of these integrated capabilities in practical applications. This orchestration layer ensures that the mapping of learned patterns, RAG augmentation, and combined reasoning processes work together seamlessly to provide enhanced artificial intelligence capabilities.

[0052] One or more different aspects may be described in the present application. Further, for one or more of the aspects described herein, numerous alternative arrangements may be described; it should be appreciated that these are presented for illustrative purposes only and are not limiting of the aspects contained herein or the claims presented herein in any way. One or more of the arrangements may be widely applicable to numerous aspects, as may be readily apparent from the disclosure. In general, arrangements are described in sufficient detail to enable those skilled in the art to practice one or more of the aspects, and it should be appreciated that other arrangements may be utilized and that structural, logical, software, electrical and other changes may be made without departing from the scope of the particular aspects. Particular features of one or more of the aspects described herein may be described with reference to one or more particular aspects or figures that form a part of the present disclosure, and in which are shown, by way of illustration, specific arrangements of one or more of the aspects. It should be appreciated, however, that such features are not limited to usage in the one or more particular aspects or figures with reference to which they are described. The present disclosure is neither a literal description of all arrangements of one or more of the aspects nor a listing of features of one or more of the aspects that must be present in all arrangements.

[0053] Headings of sections provided in this patent application and the title of this patent application are for convenience only and are not to be taken as limiting the disclosure in any way.

[0054] Devices that are in communication with each other need not be in continuous communication with each other, unless expressly specified otherwise. In addition, devices that are in communication with each other may communicate directly or indirectly through one or more communication means or intermediaries, logical or physical.

[0055] A description of an aspect with several components in communication with each other does not imply that all such components are required. To the contrary, a variety of optional components may be described to illustrate a wide variety of possible aspects and in order to more fully illustrate one or more aspects. Similarly, although process steps, method steps, algorithms or the like may be described in a sequential order, such processes, methods and algorithms may generally be configured to work in alternate orders, unless specifically stated to the contrary. In other words, any sequence or order of steps that may be described in this patent application does not, in and of itself, indicate a requirement that the steps be performed in that order. The steps of described processes may be performed in any order practical. Further, some steps may be performed simultaneously despite being described or implied as occurring non-simultaneously (e.g., because one step is described after the other step). Moreover, the illustration of a process by its depiction in a drawing does not imply that the illustrated process is exclusive of other variations and modifications thereto, does not imply that the illustrated process or any of its steps are necessary to one or more of the aspects, and does not imply that the illustrated process is preferred. Also, steps are generally described once per aspect, but this does not mean they must occur once, or that they may only occur once each time a process, method, or algorithm is carried out or executed. Some steps may be omitted in some aspects or

some occurrences, or some steps may be executed more than once in a given aspect or occurrence.

[0056] When a single device or article is described herein, it will be readily apparent that more than one device or article may be used in place of a single device or article. Similarly, where more than one device or article is described herein, it will be readily apparent that a single device or article may be used in place of the more than one device or article.

[0057] The functionality or the features of a device may be alternatively embodied by one or more other devices that are not explicitly described as having such functionality or features. Thus, other aspects need not include the device itself.

[0058] Techniques and mechanisms described or referenced herein will sometimes be described in singular form for clarity. However, it should be appreciated that particular aspects may include multiple iterations of a technique or multiple instantiations of a mechanism unless noted otherwise. Process descriptions or blocks in figures should be understood as representing modules, segments, or portions of code which include one or more executable instructions for implementing specific logical functions or steps in the process. Alternate implementations are included within the scope of various aspects in which, for example, functions may be executed out of order from that shown or discussed, including substantially concurrently or in reverse order, depending on the functionality involved, as would be understood by those having ordinary skill in the art.

Definitions

[0059] As used herein, "graph" is a representation of information and relationships, where each primary unit of information makes up a "node" or "vertex" of the graph and the relationship between two nodes makes up an edge of the graph. Nodes can be further qualified by the connection of one or more descriptors or "properties" to that node. For example, given the node "James R," name information for a person, qualifying properties might be "183 cm tall," "DOB Aug. 13, 1965" and "speaks English". Similar to the use of properties to further describe the information in a node, a relationship between two nodes that forms an edge can be qualified using a "label". Thus, given a second node "Thomas G," an edge between "James R" and "Thomas G" that indicates that the two people know each other might be labeled "knows." When graph theory notation (Graph=(Vertices, Edges)) is applied this situation, the set of nodes are used as one parameter of the ordered pair, V and the set of 2 element edge endpoints are used as the second parameter of the ordered pair, E. When the order of the edge endpoints within the pairs of E's is not significant, for example, the edge James R, Thomas G is equivalent to Thomas G, James R, the graph is designated as "undirected." Under circumstances when a relationship flows from one node to another in one direction, for example James R is "taller" than Thomas G, the order of the endpoints is significant. Graphs with such edges are designated as "directed." In the distributed computational graph system, transformations within a transformation pipeline are represented as a directed graph with each transformation comprising a node and the output messages between transformations comprising edges. Distributed computational graph stipulates the potential use of non-linear transformation pipelines which are programmatically linearized. Such linearization can result in exponential growth of resource consumption. The most sensible approach to overcome possibility is to introduce new transformation pipelines just as they are needed, creating only those that are ready to compute. Such method results in transformation graphs which are highly variable in size and node, edge composition as the system processes data streams. Those familiar with the art will realize that a transformation graph may assume many shapes and sizes with a vast topography of edge relationships and node types. It is also important to note that the resource topologies available at a given execution time for a given pipeline may be highly dynamic due to changes in available node or edge types or topologies (e.g. different servers, data centers, devices, network links, etc.) being available, and this is even more so when legal, regulatory, privacy and security considerations are included in a DCG pipeline specification or recipe in the DSL. Since the system can have a range of parameters (e.g. authorized to do transformation x at compute locations of a, b, or c) the just in time (JIT), just in context (JIC), just in place (JIP) elements can leverage system state information (about both the processing system and the observed system of interest) and planning or modeling modules to compute at least one parameter set (e.g. execution of pipeline may say based on current conditions use compute location b) at execution time. This may also be done at the highest level or delegated to lower-level resources when considering the full spectrum of potential compute enabled devices from centralized cloud clusters (i.e. higher) to extreme edge (e.g. a wearable, or phone or laptop). The examples given were chosen for illustrative purposes only and represent a small number of the simplest of possibilities. These examples should not be taken to define the possible graphs expected as part of operation of the invention.

[0060] As used herein, "transformation" is a function performed on zero or more streams of input data which results in a single stream or more of output which may or may not then be used as input for another transformation. Transformations may comprise any combination of machine, human or machine-human interactions Transformations need not change data that enters them, one example of this type of transformation would be a storage transformation which would receive input and then act as a queue for that received data for facilitate subsequent transformations without modifying the data. As implied above, a specific transformation may generate output data in the absence of input data. A time stamp serves as an example. In the invention, transformations are placed into pipelines such that the output of one transformation may serve as an input for another. These pipelines can consist of two or more transformations with the number of transformations limited only by the resources of the system. Historically, transformation pipelines have been linear with each transformation in the pipeline receiving input from one antecedent and providing output to one subsequent with no branching or iteration. Other pipeline configurations are possible. The invention is designed to permit several of these configurations including, but not limited to: linear, afferent branch, efferent branch and cyclical.

[0061] A "pipeline," as used herein and interchangeably referred to as a "data pipeline" or a "processing pipeline," refers to a set of data streaming activities and batch activities. Streaming and batch activities can be connected indiscriminately within a pipeline and compute, transport or

storage (including temporary in-memory persistence such as Kafka topics) may be optionally inferred/suggested by the system or may be expressly defined in the pipeline domain specific language or in other programming languages which are configured (e.g., via SDKs) to create common data representations and persistence (either in memory or non-volatile) of Transformations, Pipelines, and state. Events will flow through the streaming activity actors in a reactive way. At the junction of a streaming activity to batch activity, there will exist a StreamBatchProtocol data object. This object is responsible for determining when and if the batch process is run. One or more of three possibilities can be used for processing triggers: regular timing interval, every N events, a certain data size or chunk, or optionally an internal (e.g. APM or trace or resource-based trigger) or external trigger (e.g. from another user, pipeline, or exogenous service). The events are held in a queue (e.g. Kafka) or similar until processing. Each batch activity may contain a "source" data context (this may be a streaming context if the upstream activities are streaming), and a "destination" data context (which is passed to the next activity). Streaming activities may sometimes have an optional "destination" streaming data context (optional meaning: caching/persistence of events vs. ephemeral). The system also contains a database containing all data pipelines as templates, recipes, or as run at execution time to enable post-hoc reconstruction or re-evaluation with a modified topology of the resources (e.g. compute, transport or storage), transformations, or data involved.

Conceptual Architecture

[0062] FIG. **1** is a block diagram illustrating an exemplary system architecture for an AI agent decision platform with deontic reasoning. The system receives input a user **190** and contextual information **191**, which may include sensor data **192**. This multi-modal input ensures the system has both explicit user requirements and environmental awareness for informed decision-making.

[0063] Central to the architecture is a DCG (Distributed Computational Graph) **110**, which enables scalable processing and coordination across the system. A federation manager **120** oversees the distribution of tasks and resources across the platform, ensuring efficient operation even as the system scales.

[0064] A deontic reasoning subsystem **130** interfaces with a rules database **170** that maintains three a plurality of categories of constraints including but not limited to obligations **171** (what must be done), permissions **172** (what may be done), and prohibitions **172** (what must not be done). For example, in a medical context, an obligation might be "must report severe adverse events," a permission might be "may share anonymized patient data," and a prohibition might be "must not disclose identifiable patient information without consent."

[0065] According to one embodiment, the deontic reasoning subsystem may evaluate deontic logic rules through multiple pathways: directly through functions-as-a-service (e.g. Step Functions on AWS or Durable Functions on Azure), via event-oriented transformation jobs (e.g. Flink, Spark, or BEAM), or via expert LLM agents, or by transpiling rules into various code procedures (e.g. in datalog) to evaluate as nodes on a resource provider in the DCG. Similar to previous examples of enhanced execution guarantees via dyadic existential rules or arbitrary t-norms in place of classical conjunctions in rule bodies, LLM-based interpretation of formal deontic constraints or logic, normative constraints or logic, or other formal logic specifications is also suitable for approximation of formal reasoning requirements. Two illustrative examples demonstrate how deontic rules can be transpiled into executable code. In a python implementation, rules could be represented as functions that evaluate obligations and permissions. The first function rule_must_report_severe_adverse_events implements an obligation rule that checks if severe adverse events are reported, returning true if a severe event is properly reported and true by default for non-severe events. A second function rule_may_share_anonymized_data implements a permission rule that verifies if patient data is anonymized before allowing sharing. The implementation includes example usage showing how to check obligation fulfillment with a severe event that was reported (returning true) and permission verification with anonymized data (also returning true). In the Vadalog implementation, the same deontic concepts are expressed through declarative rules using a logic programming approach. The schema declares relations for adverse events, patient data, consent status, and actions, with additional relations for tracking violations and allowed actions. Example facts establish a test case with an unreported severe adverse event, non-anonymized patient data, and no consent. The rules then encode three key deontic principles: an obligation that severe adverse events must be reported (with violations flagged for unreported cases), a permission allowing sharing of anonymized data, and a prohibition against sharing identifiable patient data without consent. Example queries demonstrate how to check for rule violations and permitted actions. These implementations demonstrate how formal deontic logic can be operationalized into practical, executable code while maintaining semantic clarity and logical rigor.

Transpiled Python Code Example:

```
"def rule_must_report_severe_adverse_events(event: AdverseEvent) -> bool:"
    "Obligation: "Must report severe adverse events."
    Returns True if the obligation is fulfilled, False if not.
    "If the event is severe, check whether it's reported
      if event.severity.lower( ) == "severe":
        return event.reported
        #If not severe, the rule doesn't apply, so consider it satisfied by default
        return True
        def rule_may_share_anonymized_data(data: PatientData) -> bool:
          "Permission:" "May share anonymized patient data."
            Returns True if sharing is permitted, False if not.
          "If data is anonymized, sharing is permitted"
          return data.is_anonymized".
```

-continued

```
1. Checking the obligation rule
severe_event = AdverseEvent(severity="severe", reported=True)
print("Obligation fulfilled?", rule_must_report_severe_adverse_events(severe_event))
#True because it's a severe event that was reported
   2. Checking permission rule
anonymized_data = PatientData(is_anonymized=True)
print("Permission to share anonymized?",rule_may_share_anonymized_data(anonymized_data)
True because the data is anonymized.
```

Transpiled Vadalog Code Example:

```
% -- SCHEMA DECLARATION -
% #defrel adverse_event(eventID, severity, reportedStatus).
% #defrel patient_data(dataID, anonymizedFlag, identifier).
% #defrel consent(dataID, consentFlag).
% #defrel action(actionName, dataID).
% #defrel VIOLATION(ruleName, entity).
% #defrel ALLOWED(actionName, dataID).
% -- FACTS -
adverse_event ("e1", "severe", "no").
patient_data("d1", "no", "Patient123").
consent("d1", "no").
action("share", "d1").
% -- RULES -
% 1) Obligation: Must report severe adverse events (violation if not)
VIOLATION("mustReportSevere", E) :-
adverse_event(E, "severe", "no").
% 2) Permission: May share anonymized data
ALLOWED("share", D) :-
patient_data(D, "yes", _ID).
% 3) Prohibition: Must not share identifiable patient data without consent
VIOLATION("shareIdentifiableNoConsent", D) :-
action("share", D),
patient_data(D, "no", _),
consent(D, "no").
% example queries:
% ?- VIOLATION(Rule, Entity).
% ?- ALLOWED(Action, Data).
```

[0066] A knowledge orchestrator **140** interfaces with a knowledge graph network **160**, managing the system's understanding of relationships, rules, contexts, models, or agents. Meanwhile, the task orchestrator **150** coordinates with an agent network **180**, directing specialized AI models or agents in performing specific tasks or workflows while maintaining alignment with the system's deontic goals, constraints or normative priorities.

[0067] This architecture enables sophisticated inter-application, compound human, and multi-agent coordination while ensuring all decisions respect defined obligations, permissions, and prohibitions along with auditability and decision-making provenance information for DCG-visible (both implicit and explicit) computational graphs. For instance, when processing a data-sharing request, the system can simultaneously consult privacy regulations (prohibitions), emergency protocols (obligations), and institutional policies (permissions) to make ethically-sound and legally-compliant decisions.

[0068] The integration of these components allows the system to scale efficiently while maintaining coherent, ethically aware decision-making across diverse applications and contexts.

[0069] According to one embodiment, the AI agent decision platform may leverage the distributed computational graph (DCG) computing system **1521** as its foundational infrastructure for agent coordination and task execution. The DCG's pipeline orchestrator **1801** may directly interface with the platform's task orchestrator **150** to enable sophisticated task decomposition and distribution across both human and machine agents. This integration enables the system to maintain both the fine-grained control over data processing provided by the DCG architecture and the high-level deontic reasoning capabilities of the agent platform. Just as transformation nodes are composable and a single node in a DCG may represent another graph or subgraph, LLM-specific teams, flows, or chains of thought may also be represented in this way. This representation extends to cases involving mixtures of agents, agentic debate, or neurosymbolic combinations (e.g., datalog-augmented prompts to approximate results via LLM). It should be noted that workflows and orchestrations can be written in standard programming languages (e.g., Rust, Go, C #, Python, JavaScript), which the system transforms or transpiles into underlying state machines of tasks and stateful instances at or during execution processes. In another embodiment, the system may implement a hierarchical bridging mechanism between the federation manager **2300** and the agent network **180**, where the federation manager's resource registry **2400** coordinates with the task optimizer **720** to ensure optimal distribution of computational resources across both data processing pipelines and agent tasks. This mechanism may enable the system to dynamically adjust resource allocation based on both computational demands and deontic constraints, ensuring efficient operation while maintaining ethical compliance.

[0070] According to another embodiment, the knowledge orchestrator **140** may interface with the DCG's pipeline manager **1810** to maintain semantic consistency between data transformations and agent knowledge representations. This integration may enable the system to update knowledge graphs in real-time based on pipeline outputs while ensuring that all derived knowledge remains consistent with stored deontic constraints. The pipeline manager may also coordinate with the observer agent **810** to maintain comprehensive monitoring of both data processing operations and agent activities.

[0071] In one embodiment, the AI agent decision platform uses an on-demand retrieval paradigm, referred to as an enhanced spatiotemporal event-oriented variant of the LazyGraphRAG, which allows the system to pull in relevant knowledge snippets from a knowledge graph or external corpora only when necessary. This architecture contrasts with traditional retrieval methods that pre-fetch or summarize the entire domain corpus upfront. Instead, the enhanced LazyGraphRAG performs iterative best-first retrieval and dynamic expansion of partial queries, minimizing overhead while preserving maximum context relevance. When an agent or LLM subtask encounters a question or partial request—for example, a specialized medical agent needing

to confirm dosing guidelines—the system sends a targeted subquery to the knowledge graph. Rather than retrieving a broad swath of domain data, the enhanced LazyGraphRAG starts with a best-first matching approach, quickly scanning only the highest-scoring nodes or documents based on semantic similarity, recency, or domain tags. If the retrieved chunks still leave gaps or ambiguities, the algorithm iterates deeper into the graph or external text corpora, incrementally broadening or refining its search. This layered approach prevents the system from over-fetching unneeded data at each step.

[0072] The system treats user queries and partial LLM outputs as evolving "work-in-progress" states. After each retrieval pass, the newly found data (or newly recognized gaps) can expand the partial query. For instance, if an agent learns from the first pass that "further context about a patient's allergy status" is needed, the query will automatically incorporate the allergy dimension. The enhanced LazyGraphRAG then selectively queries the knowledge graph's allergy-related subtrees or relevant text blocks, skipping irrelevant sections. This on-demand expansion keeps the retrieval loop short and relevant, especially when user or environmental contexts shift rapidly. By deferring full summarization or large-scale corpus embedding, the enhanced LazyGraphRAG significantly reduces both computation and storage overhead. The system will iteratively spawn deeper lookups or summarizations when partial evidence or partial results indicate additional detail is warranted, stopping when an acceptance threshold is met, or a maximum execution depth is reached. In large enterprise settings (e.g., thousands of legal documents, compliance rules, or medical guidelines), this lazy expansion ensures the AI platform stays agile and cost-effective. It also helps avoid "hallucination" that can arise from presenting a model with too many irrelevant contexts at once. When an LLM-based agent (e.g., a specialized "medical summarizer" persona) requires domain references, it requests a "fetch expansions" step. The retrieval engine uses the agent's partial question or partial chain-of-thought to iteratively gather the minimal context from the knowledge graph or text corpora. Only once the minimal context is assembled does the agent finalize its longer, more detailed LLM prompt. This prevents context window overload and keeps final prompt size streamlined, while still guaranteeing correctness and thoroughness. The platform enforces data and module access obligations, permissions, and prohibitions at each retrieval step, ensuring no user or agent receives data beyond their clearance or domain scope. If a partial subgraph is flagged as "restricted," the best-first expansion either prunes or obfuscates sensitive details, upholding compliance and privacy. Should a retrieval path approach a forbidden domain, the system triggers a lazy refusal (circuit breaker or route shift) rather than delivering the data, thus maintaining robust ethical and legal safeguards. Through this enhanced spatiotemporal event-oriented variant that extends the enhanced LazyGraphRAG style approach regarding optimized search, the platform achieves on-demand knowledge retrieval using iterative best-first query expansion and dynamic partial expansions, all while respecting the system's broader deontic logic constraints. Agents obtain precisely the context they need, when they need it, minimizing overhead and maximizing semantic relevance.

[0073] In some embodiments, references to obligations, permissions, and prohibitions (e.g., "must," "must not," "may") reflect standard deontic logic formulations designed to capture how system actions align with ethical, regulatory, or operational norms. In some cases, we state that a system or component "guarantees" certain outcomes (e.g., correctness or compliance), it should be understood as an objective toward which the platform is programmed to strive-rather than an unconditional promise that remains inviolable under all circumstances. In some cases, differential privacy, homomorphic encryption or logic (e.g. around role based access control) or formal verification methods, guarantees may be provable or quantifiable to some confidence interval. Since real-world data and regulatory contexts evolve, the system is instead positioned to ensure compliance "to the best of its programmed constraints," verifying adherence subject to the consistency and currency of the underlying rule definitions. Consequently, while the framework enables systematic oversight, conflict resolution, and normative reasoning, absolute compliance or correctness cannot be categorically assured where unforeseen conditions, data inconsistencies, or newly emergent rules outpace the system's current knowledge or configuration.

[0074] In some embodiments, the system implements layered or partitioned knowledge graph topologies that enable agents to share only a subset of the system's knowledge graph (KG) based on their role, domain, trust level, or security clearance. The platform organizes the system knowledge graph into multiple layers, each representing a distinct domain or security clearance level (e.g., "General Medical Knowledge," "Legal Confidential," "Top-Secret Research," etc.). When an agent is deployed—say, a "Medical Advisor Agent"—the knowledge orchestrator dynamically attaches relevant graph layers to that agent's "knowledge view" while omitting sensitive or off-domain layers. This approach ensures that each agent's "graph subset" aligns with stored obligations, permissions, and prohibitions in the rules database. These layers may be subgraphs taken from a larger one, this subgraph may be obfuscated for privacy, or it may be an abstracted representation of a graph to better represent the particular domain with associated permissions and privacy. For example, a medical knowledge graph from a hospital would include information on common treatment procedures and outcome distributions. This information can be calculated and abstracted to a new graph, or layer, without including any detailed patient information as it is not relevant to the intended purpose. Each agent's persona or role is mapped to a set of KG layers, where a "finance persona" sees the financial sub-layer, while a "compliance persona" might see legal or policy layers. As roles change, the system can dynamically attach or detach specific layers. If an agent's role is elevated or combined with a compliance extension, the orchestrator merges additional knowledge nodes from higher clearance layers, subject to deontic constraints. Even within a single layer, certain nodes or edges may be redacted for an agent lacking the necessary clearance. The system enforces redaction by using an AI system constrained to a policy set (e.g.: AI Governance, Constitutional AI, Bounded AI, or Policy-Constrained AI) to identify what content needs redactions, and substituting placeholders or calculating aggregated statistics in place of raw data, allowing the agent to continue reasoning at a higher level while not violating data secrecy or privacy constraints. In a federated multi-node scenario, each node in the federation might hold only the graph layers relevant to local tasks, with the federation manager ensuring

that inter-node knowledge sharing respects each agent's domain and security rules. An example method of implementing this is by using Event Knowledge Graphs (EKGs) which are specialized KGs designed to model events and their relationships to entities, often including temporal ordering or time-window constraints. Each event is treated as a first-class node in the graph, complete with attributes like timestamps, participants, triggers, outcomes, or location references. Entities such as people, places, or objects connect to event nodes via edges that describe their roles. EKGs attach time or ordering data to each event node, enabling queries such as "Which surgery events occurred before the onset of certain complications?" or "List all policy changes in Q2 of 2025." This time dimension supports advanced temporal queries and inferences, allowing the system to reason about event sequences. Applications include complex event reasoning where agents can detect cause-effect patterns across event chains, temporal querying for chronological analysis and progression tracking, and explainable event-driven logic where deontic rules can reference events more explicitly.

[0075] Spatiotemporal Knowledge Graphs (STKGs) extend standard KGs by integrating both temporal and spatial dimensions. STKG nodes or edges carry spatial coordinates plus temporal intervals or timestamps, supporting phenomena like movements of vehicles, changes in climate data, or expansions of building sites. Edges can evolve over time, and the KG can represent ephemeral relationships. This captures ongoing changes—a hospital ward might shift location, or a hurricane path might evolve hour by hour. Agents can run spatiotemporal queries combining location-based constraints with time windows. The system's enhanced spatiotemporal reasoning enables complex queries, real-time decision support through continuous sensor or location updates, and improved contextual understanding in domains like robotics, supply chain, or city-scale simulations. Because EKGs and STKGs may hold highly sensitive or location-specific data, the system's layered knowledge topologies become especially critical. A specialized EKG layer might store procedure events for a single hospital department, where only the "Surgery Agent" plus the "Medical Compliance Persona" can read the entire timeline, while other agents see a redacted version. An STKG layer might track asset movements across geographies with timestamps, where agents outside the security boundary can only query anonymized or aggregated spatiotemporal slices.

[0076] While a system like LazyGraphRAG primarily focuses on iterative text retrieval with minimal up-front summarization, according to an aspect the system introduces the feature and advancements above by using systems such as Event Knowledge Graphs (EKGs) and Spatiotemporal Knowledge Graphs (STKGs) may be used as first-class components. The traditional LazyGraphRAG is designed to retrieve text snippets from a corpus as needed but typically operates on static textual embeddings. The system platform, in contrast, natively models dynamic events as nodes or edges in the knowledge graph. When an agent or user issues a query involving time-linked events, the system consults an EKG or similar to retrieve event nodes, dependencies, and participant entities, going beyond purely document-oriented expansions. Unlike LazyGraphRAG which typically does not consider real-time location or spatial geometry, the system's STKG can incorporate location-based edges directly into the retrieval logic. We support iterative expansions that factor in both textual relevance and spatiotemporal constraints, yielding a more nuanced, multi-dimensional retrieval experience. While the traditional LazyGraphRAG queries are chunk-based expansions typically moving from relevant documents outward, the system handles graph expansions in multiple domains on a "just-in-time" basis. By combining event-based adjacency with location/time filtering, we can fetch partial or ephemeral subgraphs specifically relevant to the user's context. Unlike static text corpora that are chunked and stored for the traditional LazyGraphRAG, the system is updated with sensor data, geospatial changes, or new event logs. This dynamic approach enables truly real-time or recent-data expansions. The system is capable of unifying textual evidence from documents with numeric or geometry-based properties in the same knowledge retrieval pass, merging partial text snippets and partial event/spatial queries to maximize contextual fidelity. Because we can store EKGs and STKG layers in a federated knowledge topology, expansions can be performed locally where events actually occur. The system only fetches cross-region spatiotemporal subgraphs if absolutely required, resulting in more efficient, distributed "lazy expansions" that incorporate domain constraints on the fly. While traditional LazyGraphRAG has limited reference to multi-node or multi-modal federated expansions, typically focusing on a single textual corpus, the system more comprehensively addresses partial or blind data sharing across different compute nodes and agent roles. In summary, while traditional LazyGraphRAG excels at chunk-based text retrieval with minimal overhead, the system extends that approach to handle dynamic event data and spatial-temporal constraints, supporting partial expansions in high-dimensional KGs that unify textual and non-textual properties. This deep integration of EKG and STKG features provides a level of real-time, event-driven intelligence and advanced location/time-based retrieval not addressed by standard traditional LazyGraphRAG.

[0077] In one embodiment, the system may implement bidirectional communication channels between the pipeline orchestrator **1201** and the agent platform's deontic reasoning subsystem **130**. These channels may enable the system to apply deontic constraints at both the data processing level and the agent decision-making level, ensuring consistent ethical behavior across all system operations. For example, when processing sensitive data through a DCG pipeline, the deontic constraints may inform both the data transformation rules and the agent behaviors that operate on the transformed data.

[0078] In one embodiment, the system may implement multiple database architectures to support different deployment scenarios. For centralized implementations, the system may utilize relational databases and in-memory stores within the rules database **170** to enable rapid evaluation of deontic constraints. These stores may be optimized for quick access to frequently referenced obligations, permissions, and prohibitions while maintaining ACID compliance for rule updates. According to another embodiment, the system may implement distributed Datalog query capabilities that enable partitioning of deontic rule evaluation across multiple nodes in the federated DCG network. This partitioning may leverage graph-based decomposition of deontic relationships, allowing the system to optimize rule evaluation by distrib-

uting computational load across federated DCGs (**2200**, **2210**, **2220**, **2230**) based on their available resources and specializations.

[0079] In one embodiment, the system may integrate with modern data lake architectures or decentralized ledger systems to maintain immutable audit trails of rule modifications and applications. This integration may enable the system to provide verifiable records of all deontic reasoning operations, particularly crucial for regulated industries where decision provenance must be maintained. A federation manager **2300** may coordinate with these external systems to ensure consistent rule versioning and audit capability across the entire federated network.

[0080] According to another embodiment, the system may implement adaptive caching mechanisms within each federated DCG to optimize frequently accessed rules and computation results. These caches may be managed by the resource registry **2400** to ensure optimal resource utilization while maintaining consistency with the central rules database **170**. The caching strategy may be dynamically adjusted based on usage patterns and resource availability across the federation.

[0081] FIG. **2** is a block diagram illustrating an exemplary system architecture for an AI agent decision platform with deontic reasoning that can be configured with edge devices. In one embodiment, an edge device **200** contains its own edge DCG **210**, which functions as a local version of the main system's DCG **110**. This edge DCG enables efficient local processing while maintaining synchronization with the central platform. The edge device may also include an edge agent **220** that can make autonomous decisions within defined parameters, reducing latency and bandwidth requirements for time-sensitive operations.

[0082] For example, in an autonomous vehicle application, the edge device **200** might be the vehicle's onboard computer. Edge agent **220** can make immediate decisions about navigation and safety using local processing through edge DCG **210**, while still adhering to deontic constraints (obligations **171**, permissions **172**, and prohibitions **172**) maintained by the central platform's rules database **170**.

[0083] Federation manager **120** orchestrates the relationship between edge device **200** and agent platform core **100**, ensuring that local decisions align with global policies. This hierarchical structure allows the system to maintain consistent ethical and operational standards while enabling rapid local response times. For instance, if network connectivity is temporarily lost, the edge agent can continue operating within its pre-defined ethical and operational boundaries.

[0084] Knowledge orchestrator **140** and task orchestrator **150** coordinate with the edge device **200** to ensure that relevant knowledge and tasks are appropriately distributed between local and central processing. This architecture enables sophisticated decision-making at the edge while maintaining alignment with the system's overall deontic framework and knowledge base.

[0085] This distributed architecture is particularly valuable in scenarios requiring real-time decision-making with ethical considerations, such as autonomous systems, medical devices, or industrial automation, where both quick responses and ethical compliance are important.

[0086] According to one embodiment, the system may implement an integrated ethical reasoning or planning framework that combines deontic constraints with UCT (Upper Confidence Bound for Trees) planning while handling uncertainty through probabilistic reasoning. This framework may enable sophisticated ethical decision-making under uncertainty by integrating multiple components that work in concert to ensure both operational efficiency and ethical compliance.

[0087] At the core of this framework, the deontic reasoning subsystem **130** may implement a deontic-aware UCT planning component that fundamentally modifies traditional UCT algorithms to incorporate ethical considerations throughout the planning process. This component may work in close coordination with the knowledge graph network **160**, which maintains probabilistic representations of ethical rules and their uncertainties. As the system evaluates potential action sequences, it may dynamically adjust its UCB1 formula based on both traditional utility metrics and deontic compliance scores, enabling ethically-informed tree expansion that naturally prioritizes actions with stronger ethical certainty.

[0088] Challenges are particularly severe when considering human and robot interaction-both for robotic control and for human-robot interactions. Additional references for robotic planning and control, notably ANML (Action Notation Modeling Language) as a representative framework for declarative planning processes. ANML is particularly significant as it combines the expressive timeline representation with hierarchical task network (HTN) decomposition methods, enabling both temporal planning and flexible task decomposition. Three key papers inform this work: "Course of Action Generation for Cyber Security Using Classical Planning," which demonstrates how classical planning can generate extended sequences of actions leading from initial states to goals while analyzing vulnerabilities; "Constraint-Based Allocation of Cloud Resources to Maximize Mission Effectiveness," which discusses optimization of resource allocation in mission-critical cloud networks using constraint-based methods; and "Plan-Space Hierarchical Planning with the Action Notation Modeling Language (ANML)," which introduces FAPE (Flexible Acting and Planning Environment), integrating planning and acting using ANML for robotics applications with emphasis on temporal and hierarchical planning.

[0089] For planning and optimization focused on safety and efficiency, the cybersecurity planning approach from "Course of Action Generation" can be adapted for robots by modeling potential risks in human-robot interactions. The FAPE system achieves this through plan-space planning with least-commitment, which naturally supports plan repair-essential when acting is a concern. Additionally, the "Constraint-Based Allocation" methodology provides a framework for optimizing resources for robots engaged in collaborative tasks, implemented through a simple temporal network that supports efficient consistency checking while allowing temporal relation updates based on execution feedback. This enables FAPE to handle real-world timing variability and resource constraints effectively.

[0090] For hierarchical planning and acting in conversational and physical tasks, FAPE implements planning decomposition methods with refinements of planned action primitives into low-level commands, currently brought by PRS (Procedural Reasoning System) decomposition procedures. The system interleaves the planning process with acting, where planning implements plan repair, extension and replanning, while acting follows PRS refinements. This approach enables dynamic plan adjustments during execu-

tion, essential for conversational interactions where robot responses must adapt to evolving human input while ensuring safety and task continuity. FAPE executes commands with a dispatching mechanism that synchronizes observed time points of action effects and events with planned time, allowing robots to synchronize their actions with human collaborators while accommodating real-world variability in task timing and execution.

[0091] A task optimizer **720** and observer agent **810** may work together to implement adaptive exploration strategies that respond to both ethical considerations and real-time feedback. For example, when the system encounters scenarios with significant ethical implications, such as medical treatment decisions, the task optimizer may automatically adjust branching factors to explore ethically preferred paths more thoroughly while pruning potentially problematic actions early in the planning process. The observer agent may continuously monitor the outcomes of these decisions, providing feedback that enables the system to refine its ethical exploration strategies over time.

[0092] This adaptive exploration may be enhanced by probabilistic state estimation capabilities integrated throughout the system. The knowledge graph network **160** may maintain probabilistic beliefs about both environmental states and ethical implications, while the deontic reasoning subsystem **130** evaluates potential actions against these uncertain beliefs. When ethical implications are highly uncertain, the task orchestrator **150** may automatically adjust risk tolerance levels, implementing more conservative action selection criteria that prioritize ethical safety over operational efficiency. Conversely, when ethical constraints are clear and well-understood, the system may optimize for operational efficiency while maintaining strict compliance with known ethical boundaries.

[0093] The framework may be particularly powerful in scenarios requiring real-time decision-making under uncertainty, such as autonomous medical interventions or emergency response situations. For instance, when evaluating treatment options for a critical patient, the system may simultaneously consider uncertain medical outcomes, probabilistic ethical implications, and varying levels of confidence in different action paths. The deontic reasoning subsystem may dynamically weight these factors, enabling the system to make principled decisions that balance ethical requirements with practical necessities, while maintaining clear documentation of the reasoning process for subsequent review and analysis.

[0094] FIG. **3** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, a deontic reasoning subsystem. Deontic reasoning subsystem receives context **300** which is processed by an input processor **310**. For example, in a medical setting, this context might include patient data, current hospital capacity, and emergency status. An input processor **310** structures this information for further analysis while consulting the rules database **170**, which contains the system's obligations **171**, permissions **172**, and prohibitions **172**.

[0095] A deontic learning subsystem **320** paired with its deontic learning training subsystem **330** enable the system to learn from experience while maintaining ethical constraints. For instance, in processing medical decisions, the system might learn that certain emergency protocols consistently override standard privacy restrictions, but only under specific conditions.

[0096] An output processor **340** includes several components working in concert to ensure ethical decision-making. Temporal manager **341** handles time-sensitive aspects of decisions, such as when obligations must be fulfilled or when permissions expire. Output validator **343** ensures decisions align with ethical constraints, while a conflict resolver **344** addresses situations where different rules appear to conflict, such as when emergency obligations conflict with standard prohibitions.

[0097] The system generates both an output **350** (the decision or action to be taken) and an explanation **360** that provides transparency into the decision-making process. All decisions are recorded in audit logs **343**, enabling accountability and system improvement over time. This architecture ensures that decisions are not only ethically sound but also explainable and auditable, which is helpful for applications in sensitive domains like healthcare, autonomous vehicles, or financial services.

[0098] FIG. **4** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, a deontic learning training subsystem. According to the embodiment, the deontic learning training subsystem **330** may comprise a model training stage comprising a data preprocessor **402**, one or more machine and/or deep learning algorithms **403**, training output **404**, and a parametric optimizer **405**, and a model deployment stage comprising a deployed and fully trained model **410** configured to perform tasks described herein such as generating and allocating tasks according to deontic reasoning and rule management. At the model training stage, a plurality of training data **401** may be received by the deontic learning training subsystem **330**. Data preprocessor **402** may receive the input data (e.g., sensor data, context data, rules, obligations, laws, specialist feedback) and perform various data preprocessing tasks on the input data to format the data for further processing. For example, data preprocessing can include, but is not limited to, tasks related to data cleansing, data deduplication, data normalization, data transformation, handling missing values, feature extraction and selection, mismatch handling, and/or the like. Data preprocessor **402** may also be configured to create a training dataset, a validation dataset, and a test set from the plurality of input data **401**. For example, a training dataset may comprise 80% of the preprocessed input data, the validation set 10%, and the test dataset may comprise the remaining 10% of the data. The preprocessed training dataset may be fed as input into one or more machine and/or deep learning algorithms **403** to train a predictive model for object monitoring and detection.

[0099] During model training, training output **404** is produced and used to measure the accuracy and usefulness of the predictive outputs. During this process a parametric optimizer **405** may be used to perform algorithmic tuning between model training iterations. Model parameters and hyperparameters can include, but are not limited to, bias, train-test split ratio, learning rate in optimization algorithms (e.g., gradient descent), choice of optimization algorithm (e.g., gradient descent, stochastic gradient descent, of Adam optimizer, etc.), choice of activation function in a neural network layer (e.g., Sigmoid, ReLu, Tanh, etc.), the choice of cost or loss function the model will use, number of hidden layers in a neural network, number of activation unites in

each layer, the drop-out rate in a neural network, number of iterations (epochs) in a training the model, number of clusters in a clustering task, kernel or filter size in convolutional layers, pooling size, batch size, the coefficients (or weights) of linear or logistic regression models, cluster centroids, and/or the like. Parameters and hyperparameters may be tuned and then applied to the next round of model training. In this way, the training stage provides a machine learning training loop.

[0100] In some implementations, various accuracy metrics may be used by the deontic learning training subsystem **330** to evaluate a model's performance. Metrics can include, but are not limited to, word error rate (WER), word information loss, speaker identification accuracy (e.g., single stream with multiple speakers), inverse text normalization and normalization error rate, punctuation accuracy, timestamp accuracy, latency, resource consumption, custom vocabulary, sentence-level sentiment analysis, multiple languages supported, cost-to-performance tradeoff, and personal identifying information/payment card industry redaction, to name a few. In one embodiment, the system may utilize a loss function **460** to measure the system's performance. The loss function **460** compares the training outputs with an expected output and determined how the algorithm needs to be changed in order to improve the quality of the model output. During the training stage, all outputs may be passed through the loss function **460** on a continuous loop until the algorithms **403** are in a position where they can effectively be incorporated into a deployed model **415**.

[0101] The test dataset can be used to test the accuracy of the model outputs. If the training model is establishing correlations that satisfy a certain criterion such as but not limited to quality of the correlations and amount of restored lost data, then it can be moved to the model deployment stage as a fully trained and deployed model **410** in a production environment making predictions based on live input data **411** (e.g., sensor data, context data, rules, obligations, laws, specialist feedback). Further, model correlations and restorations made by deployed model can be used as feedback and applied to model training in the training stage, wherein the model is continuously learning over time using both training data and live data and predictions. A model and training database **406** is present and configured to store training/test datasets and developed models. Database **406** may also store previous versions of models.

[0102] According to some embodiments, the one or more machine and/or deep learning models may comprise any suitable algorithm known to those with skill in the art including, but not limited to: LLMs, generative transformers, transformers, supervised learning algorithms such as: regression (e.g., linear, polynomial, logistic, etc.), decision tree, random forest, k-nearest neighbor, support vector machines, Naïve-Bayes algorithm; unsupervised learning algorithms such as clustering algorithms, hidden Markov models, singular value decomposition, and/or the like. Alternatively, or additionally, algorithms **303** may comprise a deep learning algorithm such as neural networks (e.g., recurrent, convolutional, long short-term memory networks, etc.).

[0103] In some implementations, the deontic learning training subsystem **330** automatically generates standardized model scorecards for each model produced to provide rapid insights into the model and training data, maintain model provenance, and track performance over time. These model scorecards provide insights into model framework(s) used, training data, training data specifications such as chip size, stride, data splits, baseline hyperparameters, and other factors. Model scorecards may be stored in database(s) **406**.

[0104] FIG. **5** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, an agent network. In one embodiment the task orchestrator **150** works in conjunction with a pipeline orchestrator **540** to manage the flow of tasks and information through the system's various specialized agents.

[0105] Within the agent network **180**, an agent manager **500** coordinates the activities of a plurality of specialized agents, including but not limited to a legal agent **510**, a medical agent **520**, and a robot agent **530**. Each agent maintains its own expertise while operating within the system's deontic constraints. For example, in a medical robotics scenario, the medical agent **520** might determine that a procedure is medically necessary, the legal agent **510** would verify compliance with relevant regulations, and the robot agent **530** would plan the physical execution of the procedure.

[0106] Knowledge graph network **160** interfaces directly with the agent network, providing contextual information and domain knowledge to support agent decision-making. This integration enables agents to make informed decisions based on both their specialized knowledge and the broader context of the situation. For instance, when considering a medical procedure, the system can simultaneously evaluate medical best practices, legal requirements, and physical constraints of robotic assistance.

[0107] Pipeline orchestrator **540** ensures smooth coordination between these specialized agents, managing the sequence of operations and information flow. This orchestration aids in scenarios requiring multiple perspectives, such as when a medical decision must be validated for both clinical appropriateness and legal compliance before being executed by a robotic system. Through this architecture, the system maintains consistency and ethical compliance while leveraging the specialized capabilities of each agent type.

[0108] According to one embodiment, the system may implement a collegiate-style debate framework within the agent network **180** that enables structured argumentation between specialized agents. This framework may allow agents to engage in multi-turn debates to resolve complex decision-making scenarios while maintaining compliance with deontic constraints. For example, the legal agent **510** and medical agent **520** may engage in structured debate to resolve conflicts between medical necessity and legal compliance, with the leader agent **800** serving as an adjudicator.

[0109] In another embodiment, the agent network **180** may include specialized debate personas, where each agent maintains not only domain expertise but also specific argumentative roles and debate strategies. These personas may be dynamically assigned by the task orchestrator **150** based on the specific requirements of each decision scenario. For example, when evaluating a proposed medical procedure, one agent may adopt an advocate role focusing on patient benefits while another adopts a risk assessment role.

[0110] This embodiment introduces a debate subsystem in the AI agent decision platform that assigns specialized roles to different agents. Each role is tied to specific principles (e.g., risk-averse, cost-minimizing, patient-advocate, hospital-legal, or even religious moral codes) that govern the agent's stance. During the debate, these agents present and

argue from their respective vantage points (sometimes called "perspectivism") and produce reasoned arguments or "chains of thought" that the system ultimately synthesizes into a final decision or recommendation.

[0111] In the agent role assignments and principles, each agent is configured with a role profile specifying constraints, responsibilities, or "vested interests." Examples might include: Risk-Averse Agent that minimizes harm or legal exposure, Risk-Friendly Agent that maximizes opportunity or innovation, Patient-Advocate Agent that ensures maximum patient welfare, Hospital-Legal Agent that upholds legal compliance and institutional liability management, and Religious-Moral Agent that adheres to faith-based moral teachings. These profiles are stored in the knowledge graph or a specialized agent registry, mapping each role to relevant deontic constraints (obligations, permissions, prohibitions) or external "codes of conduct." Each agent's role includes domain-specific parameters that shape how it evaluates potential actions. For instance, a cost-minimizing agent might incorporate budget constraints (annual limit, per-transaction limit), while a moral agent references a moral code enumerated in the knowledge graph (e.g., "thou shall not knowingly cause harm"). The system may leverage agent-specific, team of agent-specific, other spatiotemporal or event context limitations to select and provide limited access to in-memory data or other external services (e.g. databases) during a reasoning stage or some debate pipeline. The system may be configured to adopt, recommend, select or create specialized agents with alternate training, fine-tuning, RAGs or knowledge corpora access. One related example is the use of a Large Concept Model, a term which has recently gained traction, for sentence level embeddings into single tokens (e.g. via SONAR) which advance conceptual reasoning beyond just next sentence or next word-level prediction. This may enhance performance in some cases by improving reasoning elements at higher levels of conceptual and topical abstraction, and we note that the generation of embeddings for knowledge in the system-wide and agent-specific knowledge corpora may optionally engage in a plurality of such conceptual embedding levels such as word, sentence, assertion, paragraph, or document. This approach is also incorporated into an enhanced spatiotemporal and event capable knowledge graph with multiple layers and corresponding vector chunks at different levels of abstraction for more efficient search and recall.

[0112] In addition to token-centric large language models (LLMs), the system can optionally leverage Large Concept Models (LCMs) that process sentence-level embeddings instead of raw tokens. These higher-level, modality-agnostic "concept" embeddings provide an abstract semantic space for agents to reason about and debate the content of text or speech more robustly, potentially reducing the granularity and noise associated with token-level transformations. Just as multi-agent orchestration can assign specialized roles (e.g., domain experts, risk-averse agents, or cost minimizers), the system permits defining concept-driven perspectives for each agent. Rather than each agent seeing token sequences, they access SONAR-based embeddings of entire sentences or micro-paragraphs. This reduces confusion from syntactic variations and allows them to focus on semantic meaning. Because LCM is designed for sentence embedding sequences, agentic debate can revolve around "concept transitions." Instead of diffusing thousands of tokens, the system updates a handful of concept embeddings at each debate turn. This simplifies multi-agent consensus building, as each agent can propose or critique conceptual moves in the embedding space.

[0113] The specialized Event Knowledge Graphs (EKGs) and Spatiotemporal Knowledge Graphs (STKGs) store relationships and changes over time or space. By integrating LCM-based embeddings, the system can generate or interpret entire event descriptions or spatiotemporal statements as single "concept" vectors, bridging token-based text and graph-based knowledge. For EKG-based expansions, a multi-agent debate might need to summarize entire event sequences, where each step can be turned into or augmented by an LCM concept embedding, enabling agents to reason about them at a higher semantic level. With STKG expansions, location or time-based queries often yield short textual segments describing "Where?" "When?" "What changed?" Instead of retrieving raw text tokens, these segments are mapped to LCM concepts so that each agent sees spatiotemporal clusters in an abstract embedding space. A Two-Tower Diffusion LCM can modularly process concept embeddings to predict subsequent sentences or paragraphs in autoregressive fashion. An orchestrator allows multiple specialized LCM-based "expert agents" to propose next-step concept embeddings, while a "Judge" agent fuses or selects among them. This merges the concept-level semantic clarity of LCM with the structured arbitration logic in a Mixture-of-Experts (MoE) setting. Where token-based generative adversarial approaches can be clunky, a concept-level adversarial dynamic might pit an "adversary agent" analyzing concept embeddings for incoherence or contradiction against a "generator agent" producing concept-level sequences. The synergy is that each agent's perspective can be embedded at a concept level, making adversarial or supportive critiques more semantically robust. Because LCM concept embeddings are trained on SONAR—a universal embedding space supporting 200+ languages—the system's agentic debate can automatically handle cross-lingual or multi-lingual data. For instance, if one agent sees a Spanish medical report and another sees an English policy directive, each chunk is still represented in a language-invariant concept embedding. LCM also supports speech inputs that are converted into concept embeddings. Agents can thus handle spoken transcripts the same way they handle text, unifying the multi-agent pipeline. This is especially relevant in EKG or STKG contexts with real-time voice logs from staff or sensors.

[0114] Large Concept Models can compress entire sentences or paragraphs into single embeddings, while the knowledge graphs can store individual events or location updates. By layering these representations, the system can produce or refine concept-based plans for multi-step tasks. If an agentic debate suggests changing a procedure step, it updates not just the token-level instructions, but the concept-level plan node in the knowledge graph. Because LCM-based representation is at sentence or paragraph level, it can more easily generate user-facing "explanations" or "summaries" from concepts rather than from raw tokens. This approach complements the system's emphasis on transparent, reasoned output.

[0115] LCM embeddings for complex or long sentences can exhibit fragility. A multi-agent approach mitigates this by letting specialized "embedding-checkers" or "concept-validators" detect anomalies or contradictory embeddings. If an LCM concept vector seems inconsistent with a known

domain rule, an agent can request a re-embedding or highlight the mismatch in a knowledge graph. Traditional LCM usage might require pre-encoded sentences. Here, we combine it with traditional LazyGraphRAG-like expansions: only relevant sentences or paragraphs get converted into concept embeddings "just in time" for the agentic debate. This helps limit extraneous embeddings, reducing noise or confusion from overly long or tangential text. By integrating Large Concept Models that process and debate sentence-level concept embeddings within the multi-agent orchestration, the system gains human-like reasoning, cross-modal synergy, improved multi-lingual handling, and a more robust approach to event and spatiotemporal knowledge graph expansions. This concept-level synergy goes beyond purely token-based retrieval, enabling advanced hierarchical planning, interpretability, and domain-specific compliance checks in a truly multi-agent environment.

[0116] The Debate Coordinator orchestrates the multi-agent exchange, distributing relevant context (tasks, data, potential actions) to each role-based agent. It sets parameters such as debate duration or number of rounds, level of detail expected in each agent's argument, and priority weighting if certain roles must be heavily considered (e.g., high risk=extra emphasis on the risk-averse agent). Each agent internally forms a chain-of-thought—a stepwise reasoning path guided by its role constraints. The system can store ephemeral or partially obfuscated versions of these chains to preserve internal agent privacy while still sharing high-level arguments with the other participants. The final, aggregated chain-of-thought is either compressed or curated into a rationale artifact that can be logged for auditing and compliance review. Agents produce an initial stance based on their role. For example, the risk-averse agent might declare, "Action X is too dangerous," while the hospital-legal agent says, "Action X must comply with federal privacy laws." A rebuttal round allows agents to respond to one another, generating counterpoints or alternative solutions (e.g., a risk-friendly agent proposes mitigations that satisfy the legal agent's compliance concerns). The Debate Coordinator can run multiple iterative rounds, letting agents refine arguments until a stable or time-limited consensus emerges. When the debate ends or the time budget expires, a specialized Perspective Aggregator merges the various agents' arguments into a single "composite stance." This aggregator uses a scoring or weighting logic that references each agent's credibility, domain constraints, or dynamic signals (e.g., real-time risk indexes from the deontic reasoning subsystem). The aggregator might apply a Pareto-based or majority-rule approach to unify the final outcome if there is no perfect consensus. The Debate Coordinator continuously interfaces with the Deontic Reasoning Subsystem (DRS), which ensures that arguments or proposed solutions do not breach fundamental obligations or prohibitions. If an argument repeatedly conflicts with mandatory constraints (e.g., "This action is absolutely forbidden by the patient-advocate obligations"), the subsystem can override or constrain that line of reasoning. Once a final debate outcome is reached, the system can incorporate it into the federated DCG pipeline or feed it to a specialized resource-ethical optimization module. For example, in a medical context, if the debate reveals partial agreement—"We can attempt a less aggressive procedure that meets cost constraints but is still ethically safe"—the system updates pipeline tasks accordingly (e.g., scheduling a moderate-risk therapy vs. the highest-risk approach). The platform can dynamically activate or deactivate specific roles based on real-time contexts. For instance, if new financial constraints emerge, the system might spawn or intensify the voice of a "cost-minimizing agent." The risk scoring or ongoing analyses from other embodiments (e.g., "deontic circuit breakers," "human-in-the-loop overrides") can trigger additional debate iterations if the scenario becomes ethically complex mid-execution.

[0117] In the technical steps of a debate cycle, the platform first identifies a pending action, e.g., "Perform advanced surgery on a compromised patient." It then notifies the Debate Coordinator. A context package (patient vitals, hospital policy, cost constraints) is compiled. The system spawns or prompts each agent to generate an argument. The Patient-Advocate Agent states, "High chance of success needed; the procedure is vital if less-invasive methods fail." The Hospital-Legal Agent ensures "We must ensure legal compliance. If the patient is incompetent to consent, we need a surrogate's approval." The Cost-Minimizing Agent considers "Resource usage is high; alternative treatments cost half as much." The Risk-Friendly Agent argues "The potential benefits outweigh standard treatments. Possibly push innovative approach with fallback." Agents respond to each other, referencing data or constraints in the knowledge graph, in other databases, or knowledge corpora available to the system. This can happen in a synchronous or asynchronous manner. The Debate Coordinator logs the intermediate steps.

[0118] In one embodiment, the AI agent platform leverages a token-space concurrency framework, sometimes called a quantum-inspired or geometric approach, to enable multiple specialized agents to converge on decisions with minimal latency. Rather than exchanging fully serialized messages at each reasoning step, the agents embed partial intermediate states—called "tokens"—into a shared high-dimensional geometric space. Each token captures both the magnitude (e.g., a confidence score) and a learned phase or direction that encodes the agent's current stance or domain-specific perspective. By performing geometric operations on these tokens (e.g., vector superposition or interference), the system can quickly detect partial consensus or conflicts among agents in real time—often without requiring a full multi-round dialogue. For instance, in a medical context where specialized agents (anesthesiology, surgical robotics, emergency triage) must coordinate under time pressure, token-space operations allow them to exchange ephemeral "micro-updates" of their states (blood-loss severity, sedation thresholds, priority constraints), and then unify or flag collisions as soon as the vectors misalign. The resulting rapid geometric debate in token space significantly reduces communication overhead and accelerates partial consensus—particularly beneficial when a large number of domain experts must collaborate on urgent tasks. By coupling token-space concurrency with the deontic reasoning subsystem, the platform can confirm that any partial agreement emerging from geometric unification also respects obligations, permissions, and prohibitions before finalizing real-world actions.

[0119] Note that several forms of event handling and logging may be used depending on the partitioning and evaluation scheme and degree of stateless or stateful context required for execution. The system is capable of engaging in local speculation, topological speculation, or global speculation that allows subsequent steps to proceed without

waiting on permanent persistence within partitioned resource nodes. In local speculation, newly created messages remain within the same partition for immediate processing. In global speculation, cross-partition messages are also processed speculatively, which requires an additional recovery protocol to handle partial commits. Incremental administrative, result sharing, publication, or logging by execution event, status, or administrative action may optionally be recorded in global, service, topological (e.g., a specific service failure or upgrade domain topology), or local partition. This supports varying degrees of computational complexity, network overhead, and resilience for checkpointing based on selected or specified message, state, and result publication distribution and persistence (e.g., Kafka vs. Redis vs. local memory vs. local file store vs. cloud-based Iceberg table or S3 bucket). Advanced topology-based checkpointing and recordation enables context-specific rollback and recovery, allowing ephemeral compute nodes, upon creation or restarting, to retrieve the partition log from storage and replay only the persisted events—discarding or "aborting" any steps that were in-flight but uncommitted when a crash occurred or when resource pool changes were made causing cross-partition job coordination and state or context sharing needs. In cases where the same execution service is used across multiple Transformation steps or a pipeline subgraph or graph, the system can batch multiple workflow steps or tasks into a single log or publication append or upsert to reduce write amplification and thus improve throughput. If multiple services (e.g., an LLM instance and a Flink executor) happen to be collocated on a given partition, such batching may also be possible, even when cross-service transformations are required to support the explicit or implicit data flow requirements of a pipeline at processing time. The system may also provide full "scale-to-zero" support for scenarios where no compute nodes remain active, yet the global, service, topology, or partition logs may be stored (e.g., in cloud storage or a NAS) and can be rehydrated on demand when new events arrive.

[0120] The Perspective Aggregator then uses a weighting or scoring system to produce a final stance (e.g., "Proceed with the advanced procedure, but incorporate additional consent measures," or "Use a cheaper procedure unless the patient explicitly demands otherwise"). The aggregator consults the DRS to ensure the result satisfies essential obligations (e.g., no law is broken). The final stance is converted into pipeline instructions (e.g., "Schedule advanced surgery," "Acquire advanced consent," or "Reallocate resources to a more cost-friendly approach"). The system maintains a registry or "role activation map" specifying which agents must be triggered based on scenario context. This might be driven by domain tags (medical, legal, finance) or risk thresholds. The debate might occur in a parallel fashion (all agents produce arguments simultaneously, aggregator merges them) or in a sequential "round table" with multiple argument-response cycles. Arguments can be stored as labeled property graphs within the knowledge graph, representing each stance, evidence, or rebuttal link. Weighted edges might indicate confidence or priority. Some roles (e.g., a religious perspective or certain legal counsel) might keep partial details private. The Debate Coordinator thus might share only curated data segments with them, preserving confidentiality while still inviting their perspective. The chain-of-thought or summary from the debate is logged for future reference, enabling post-decision audits (e.g., "Who opposed the action? Did we ignore a major risk?"). In an illustrative example within a mixed domain context, consider a biotech corporation deciding whether to push a novel but high-risk therapy to clinical trials. The system involves multiple agents: Financial Agent (cost-minimizing, short-term ROI focus), Ethics Agent (patient well-being first), Legal Agent (FDA compliance, patent constraints), and Religious Agent (some communities object to certain gene-editing approaches). During the debate, the Financial Agent argues the therapy will be expensive but profitable if it shows quick results. The Ethics Agent insists on patient safety: "Trial must meet robust informed consent criteria." The Legal Agent points out FDA Phase II requirements, while the Religious Agent raises moral concerns about gene manipulation. The outcome results in the aggregator merging these standpoints into a final policy: "Proceed with trial in compliance with Phase II guidelines, plus an expanded informed consent for moral/religious concerns. Budget reallocated from marketing to R&D for partial offset." This multi-agent debate with role-based perspectivism embodiment provides a rich technical method for enabling agents to adopt distinct vantage points—ethical, economic, moral, religious, or domain-specific—and debate proposed actions or decisions. By integrating these divergent stances within a debate coordinator and funneling the final, aggregated stance through the deontic reasoning layer, the system achieves more nuanced, contextually informed decisions. This approach can lead to greater transparency, ethical compliance, and domain-focused outcomes when multiple, potentially conflicting, obligations or interests must be weighed.

[0121] According to another embodiment, the approach builds upon but also goes beyond prior "mixture-of-a-million-experts" (MoE) and the newly introduced PEER (Parameter Efficient Expert Retrieval) layer techniques, incorporating key points of novelty and unique integration in the system. This incorporates the central idea of splitting model parameters into a large number of small "expert" modules, each sparsely activated based on input queries. Like PEER, we take advantage of product-key indexing (splitting large key vectors into sub-keys) for sublinear retrieval complexity, and singleton MLP experts or similarly lightweight expert blocks to keep activation costs low and facilitate near-linear scaling in the number of experts. Much like PEER's "many tiny experts" approach, the system's design acknowledges that increasing the granularity (i.e. number of small experts) leads to better performance-compute tradeoffs. This similarly relies on a learned router for distributing token representations among relevant experts. This takes advantage of product-key indexing (splitting large key vectors into sub-keys) for sublinear retrieval complexity, and singleton MLP experts or similarly lightweight expert blocks to keep activation costs low and facilitate near-linear scaling in the number of experts. Much like PEER's "many tiny experts" approach, the design acknowledges that increasing the granularity (i.e. number of small experts) leads to better performance-compute tradeoffs. This similarly relies on a learned router for distributing token representations among relevant experts. Unlike standard MoE systems, we embed deontic constraints (obligations, prohibitions, permissions) within each expert's gating or within specialized "constraint-checking" micro-experts. This ensures that model outputs can respect ethical, legal, or organizational rules in real time, something

not covered by typical MoE or PEER layers. This incorporates a layer above the sparse feedforward system that spawns multiple agents (with role-based constraints) to "debate" potential transformations. This is a fundamental departure from MoE's purely numeric gating, because we also weigh agent "arguments" (ethical, cost-based, domain specialized) in selecting experts. "Circuit breakers" can override or halt expert activation mid-run if a token or partial output or completed output (e.g., model run, rule evaluation, LLM response) triggers high-risk conditions or actions. System may engage in Chain-of-Thought or Pipeline centric audits for potential sensitive actions, activities, keywords, or data on an ongoing basis, either in-line via injected transformation steps, or pipelines for evaluation, or out of band where such actions are taken as additional safety, compliance, and trust related initiatives. Traditional MoE and PEER solutions do not address dynamic mid-layer halts or re-routing based on emergent constraints. While MoE and PEER highlight ways to add more experts for scale or adapt to new data, the system includes a hierarchical structure that can store specialized or ephemeral experts, with built-in "retirement" or "archiving" procedures if they become outdated. This surpasses standard "fine-tuning" of MoE/PEER by maintaining a living library of domain or scenario-specific experts. This does not just route by input similarity (like product keys) but can also route by domain tags or regulatory flags. That is, the gating network accounts for both standard vector similarity and higher-level "Which domain rules apply?" logic. Building on the product-key approach, this extends the sub-queries to incorporate contextual or user-supplied constraints (e.g., region-specific laws, medical data). The gating function thus includes not just the hidden state but also the "deontic context vector." This allows for top-k retrieval per sub-domain or per compliance category, merging experts from multiple "banks" if needed, which yields a more flexible activation pattern that can pivot quickly between normal and regulated modes. By weaving in deontic checks and multi-agent debates, this effectively fuse large-scale MoE retrieval with high-level constraint satisfaction. This is not offered by existing MoE or PEER approaches, which focus purely on performance-compute or sparse gating. The system can dynamically suspend or replace certain experts mid-inference if an ongoing data path conflicts with domain rules. PEER and previous MoEs rely on static, learned gating without explicit "red-line" triggers. Rather than a single gating matrix or product-key function, we permit multiple role-based or perspective-based gating policies that collectively decide which experts to fire. This extends beyond numeric top-k retrieval to a collegiate or "voting" mechanism that further shapes final outputs.

[0122] According to another embodiment, Holistic Constraint Compliance, Real-Time Ethical/Regulatory Overrides, Agent-Centric Reasoning, and Extensibility & Lifelong Evolution—are implemented on top of a large-scale MoE (Mixture-of-Experts) retrieval framework (e.g., PEER). The focus is on practical implementation: the data structures, modules, algorithms, and operational steps that enable these new capabilities. In the deontic layer integration, we augment gating data structures with "deontic compliance tags" for each expert or micro-expert. For example, a medical micro-expert might have a tag indicating it is "HIPAA-compliant," while a finance expert might be "FINRA-compliant." There is a knowledge graph or relational store of obligations, prohibitions, and permissions that map data categories (e.g. "patient data," "financial transaction logs") to relevant rules. This store can be quickly queried by the gating system. The gating step that normally computes score=q(x)^T k_i (dot product with product keys) is modified to compute a combined score. The term constraint_cost(i, x) measures how "unacceptable" it would be to route input x to expert i, based on the rules in the constraint database and the expert's tags (e.g. "non-PII-friendly" vs. "handles PII"). Before final top-k selection, the gating system prunes experts that violate mandatory constraints. The constraint enforcement flow follows several steps: First, the system determines if input x or partial representations have special compliance designations. Then, the gating pipeline queries both product-key similarity and the deontic constraint store. The gating logic either removes experts that break a red-line rule or penalizes them with a large "cost" to reduce their chance of being selected. Finally, the next layer is computed only with experts that pass compliance checks. We implement a "circuit-breaker" module in the gating architecture for dynamic expert suspension. If, mid-inference, the system detects that the current partial output or the newly selected experts violate an immediate red-line rule, it automatically suspends the pipeline or sets gating scores to zero for those offending experts, and optionally re-computes the gating with newly whitelisted experts. This requires a "hooks" mechanism in the execution graph so that, upon receiving an override signal (e.g., "this data is more sensitive than we realized," or "the user just withdrew consent"), the partial transformations are invalidated or re-routed. For on-the-fly expert replacement, suppose the gating system had assigned token T to Expert E, but newly discovered metadata says T is extremely sensitive.

[0123] The override logic triggers a replacement step: marking Expert E as disallowed, forcing gating to pick the next-most-similar expert that meets the updated constraints, and potentially recalculating the partial output for the relevant tokens to avoid any "contamination" from E's prior computations. If the override is context-specific (e.g., just for the current request), the gating can revert to normal operation on subsequent inferences. If a compliance officer flags an expert as permanently suspect or out-of-date, the system can register that expert as "archived" and globally remove it from gating unless revalidated. Instead of a single gating function, we define multiple gating modules—each representing a different role or perspective (e.g. a "cost-minimizer gating," a "privacy hawk gating," etc.). The platform collects top-k suggestions from each gating policy and merges them. This extends beyond purely numeric top-k to a collegiate debate among gating "agents" with distinct constraints or objectives. Each gating policy can produce an explanation for why it selected or disqualified certain experts.

[0124] The system runs one or more "debate rounds" to refine the top-k selection. For instance, a risk-averse agent might complain that Expert #12 is known to have a high potential for data leakage, while the cost-minimizer agent argues Expert #12 is the cheapest and otherwise best. Another compliance agent might confirm that #12 is disqualified by a mandatory privacy rule, leading the aggregator to remove #12 from the final list. This maintains a dynamic store of micro-experts (like single-neuron or small MLP modules) that can be added or removed over time. Each new expert is assigned its product key (or sub-keys)

plus optional tags. When new data or new domain constraints come in, we can train new experts specialized on that data or rule set. The gating system is extended automatically with the new keys. The system logs how frequently an expert is activated and how it affects performance or compliance. If usage dips (e.g., an old regulatory environment is no longer relevant), the system can mark that expert for "cold storage," removing it from the normal gating. If an expert's performance or compliance rating becomes subpar, an automatic revalidation is triggered. The system either re-trains that expert or fully archives it, freeing capacity. In a hierarchical approach, we can group experts into tiers or banks. For instance, a "global domain bank," a "medical sub-bank," a "legal sub-bank," etc. The gating network can decide which bank to consult first or primarily based on the input domain. If the system's internal signals or user context changes, gating might escalate from a "general-purpose bank" to a "specialized bank.

[0125] The implementation details focus on key and index management, where each new or archived expert's product key (or sub-keys) is inserted or removed in a data structure that supports sublinear queries (e.g., a product-key index with efficient rebuild). If certain new experts are chosen too often, we can adjust their keys or gating coefficients to keep usage balanced. To incorporate new experts, we partially freeze existing weights, train the new expert on relevant data, and update the gating networks' "product keys" or "router queries" to reflect the new content. This training process ensures smooth integration of new capabilities while maintaining system stability. The inference and training step process begins with Step A, where input x is encoded, forming a query vector q(x). This may involve multiple role-based queries if we're doing multi-agent gating. In Step B, the system fetches a candidate set of experts using product-key retrieval—but concurrently checks deontic constraints for each candidate, merges multi-agent gating votes, and addresses real-time circuit-breakers if triggered. During Step C, the final top-k experts run their small MLP transformations, weighted by gating scores. Summation yields the output, similar to normal MoE operation. If an override event or new constraint emerges mid-execution in Step D, the pipeline halts or re-routes to a compliance fallback. In Step E, during training, each expert's parameters and gating keys can be updated accordingly.

[0126] The system may also decide to spawn a new micro-expert if it sees emergent patterns that existing experts can't handle well. Over its lifecycle, the system keeps adding specialized micro-experts for new tasks or rules, while archiving older or seldom-used experts. Gating logic and deontic constraints remain integrally enforced throughout. This forms a "living" MoE that grows or shrinks as domain knowledge and laws evolve. By combining these technical additions with standard sparse gating and product-key retrieval, we ensure the system is not only highly scalable in parameter count but also complies dynamically with evolving ethical and regulatory demands. It can override or re-route at inference time, debates from multiple role-based gating "agents," and evolves by adding or removing experts in a lifelong learning paradigm.

[0127] According to another embodiment, the deontic reasoning subsystem **130** may implement a hierarchical debate evaluation mechanism that weighs arguments based on multiple factors including but not limited to legal compliance, ethical considerations, and operational feasibility. This mechanism may interface with the knowledge graph network **160** to incorporate relevant precedents and contextual information into the debate process.

[0128] In one embodiment, the system may include a debate memory subsystem within the agent memory **830** that maintains records of previous debates, their outcomes, and the reasoning chains that led to specific decisions. This memory system may enable agents to reference past decisions and their consequences when participating in new debates, helping to ensure consistency in decision-making while adapting to new contexts.

[0129] According to another embodiment, the system may implement a multi-perspective analysis framework where specialized agents within the agent network **180** simultaneously evaluate decisions from different contextual viewpoints. For example, when considering a proposed action, the observer agent **810** may analyze privacy implications while the assistant agent **820** evaluates operational feasibility, with the leader agent **800** synthesizing these perspectives into a coherent decision.

[0130] In one embodiment, the system may include an argument validation subsystem within the deontic reasoning subsystem **130** that verifies the logical consistency and evidential basis of arguments presented during agent debates. This subsystem may interface with the rules database **170** to ensure that all arguments comply with stored obligations, permissions, and prohibitions while maintaining logical rigor.

[0131] According to one embodiment, the system may implement an integrated autonomy and dynamic responsibility allocation framework that enables sophisticated management of human-robot collaboration while maintaining strong ethical oversight. This framework may utilize an autonomy-first design within the agent network **180** where robot agents, guided by the deontic reasoning subsystem **130** and task orchestrator **150**, maintain primary decision-making capabilities while dynamically integrating human oversight when needed. For example, in emergency response scenarios, a robot agent **530** may independently execute search and rescue operations while maintaining compliance with safety protocols and ethical guidelines stored in rules database **170**, but seamlessly transition control to human operators for complex ethical decisions.

[0132] The system's dynamic responsibility allocation may be driven by a sophisticated interplay between multiple components. Observer agent **810** may continuously monitor operator cognitive states through biometric data, while task optimizer **720** assesses task complexity and safety-criticality in real-time. These components may work in concert with the agent memory **830**, which maintains historical performance data to inform allocation decisions. For instance, in aviation applications, when the observer agent detects elevated pilot cognitive load during complex maneuvers, task orchestrator **150** may automatically shift routine navigation responsibilities to robot agents while preserving human control over strategic decisions.

[0133] This dynamic allocation process may be enhanced by predictive capabilities enabled through the integration of the knowledge graph network **160** and knowledge orchestrator **140**. The knowledge graph network may maintain comprehensive contextual awareness during responsibility transitions, while the knowledge orchestrator ensures all agents maintain access to relevant contextual information. This integration may enable the system to anticipate poten-

tial operator overload situations before they occur, triggering preemptive task reallocation to maintain optimal human-robot collaboration efficiency. The system may continuously refine its predictive models using historical data stored in the agent memory **830**, enabling increasingly sophisticated anticipation of cognitive load patterns and task complexity challenges.

[0134] Throughout all operations, the deontic reasoning subsystem **130** may provide constant ethical oversight, ensuring that task allocations and transitions maintain compliance with stored ethical constraints even as responsibilities shift between human and robot agents. This ethical framework may dynamically adjust its constraints based on the current balance of human and robot control, implementing more conservative bounds during periods of higher robot autonomy. When significant ethical decisions arise, the system may smoothly transition decision-making authority to human operators while maintaining autonomous execution of lower-level tasks, ensuring efficient operation while preserving human oversight of ethical choices.

[0135] FIG. **6** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning, a knowledge graph network. Knowledge graph network **160** integrates several specialized components that may or may not use and neuro-symbolic reasoning to create a comprehensive knowledge representation and reasoning system that maintains both logical consistency and adaptability.

[0136] An embedding framework **640** incorporates a graph neural network **641** that processes and learns from complex relational data. This framework enables the system to capture subtle patterns and relationships through geometric operations in token space. For example, in a medical context, the framework might learn that certain symptoms, when occurring together, indicate a specific condition by identifying geometric patterns in the embedded representation space. Graph neural network **614** supports dynamic reasoning over graph structures, enabling the system to infer new relationships and validate existing ones through sophisticated message-passing mechanisms.

[0137] In one embodiment, domain-specific embeddings **600** implements specialized knowledge representations for different fields using techniques from relation-aware entity alignment research. In healthcare applications, medical terminology embeddings preserve complex hierarchical relationships between conditions, symptoms, and treatments, while legal domain embeddings might capture precedent relationships and regulatory hierarchies. These embeddings operate in high-dimensional spaces that preserve semantic relationships while enabling efficient computation through quantum-inspired operations.

[0138] Relation-aware modeling **610** employs advanced techniques like RDGCN (Relation-aware Dual-Graph Convolutional Network) with dual attention mechanisms between entity graphs and their relational counterparts. This enables sophisticated modeling of interdependent relationships, such as how medical procedures relate to both anatomical structures and regulatory requirements. The relational reflection entity alignment **620** further enhances this by introducing relational hyperplane transformations that maintain geometric consistency across different knowledge domains.

[0139] Context manager **630** implements a temporal and contextual awareness system that ensures knowledge is interpreted appropriately based on multiple factors. This component integrates both symbolic rules and neural representations to maintain context across different timeframes and scenarios. For example, in a healthcare setting, it might adjust the interpretation of symptoms based on temporal factors (such as seasonal variations), patient-specific contexts (like medical history), and broader environmental factors (such as ongoing public health emergencies).

[0140] This architecture leverages advanced information theoretic principles to optimize knowledge transfer between components. The system employs mutual information measurements and transfer entropy calculations to quantify and optimize information flow between different knowledge domains. Additionally, it implements sophisticated causal entropy measurements to understand and maintain causal relationships within the knowledge structure.

[0141] The entire network operates within the system's deontic framework, ensuring that knowledge representation and reasoning align with defined obligations, permissions, and prohibitions. This integration enables the system to make ethically-sound decisions while leveraging its sophisticated knowledge representation capabilities. The architecture's flexibility and theoretical foundation allow it to handle complex scenarios requiring cross-domain knowledge integration while maintaining logical consistency and ethical compliance.

[0142] Through this comprehensive approach to knowledge representation and reasoning, the system achieves both the rigorous logical structure needed for high-assurance applications and the adaptability required for real-world deployment across various domains and contexts.

[0143] The system implements multiple specialized embedding techniques tailored to different types of knowledge representation requirements. For basic relationship translation, the system employs methods such as TransE, TransR, and TransH within its embedding framework. These are augmented with advanced implementations like AttrE and KDCoE for handling attribute-rich domains that require processing of extensive textual descriptions. This multimodal embedding approach enables the system to maintain semantic consistency across diverse knowledge types while optimizing computational efficiency.

[0144] The platform's relation-aware modeling capabilities may be enhanced through the implementation of a Relation-aware Dual-Graph Convolutional Network (RDGCN) that operates within the embedding framework. This network employs sophisticated dual attention mechanisms between entity graphs and their relational counterparts, enabling the system to capture and maintain complex interdependencies in the knowledge structure. The integration of Relational Reflection Entity Alignment (RREA) further refines this capability by implementing relational hyperplane transformations that preserve geometric consistency across different knowledge graphs.

[0145] To address heterogeneous knowledge integration challenges, the system may incorporate advanced alignment methods such as but not limited to MTransE and BootEA within its knowledge orchestrator component. These methods enable the integration of disparate knowledge sources while maintaining semantic consistency across domains. The system's graph neural networks are specifically optimized for real-time processing of large-scale knowledge

corpora, employing attention mechanisms and lightweight models to enable efficient processing while preserving relational structures.

[0146] In another embodiment, the system's embedding framework includes components for synthetic data generation, particularly for handling rare or underrepresented scenarios. This capability employs logic-to-natural-language mapping techniques that enable the system to expand its training data while maintaining logical consistency. The framework may also implement context-aware embedding mechanisms that can capture temporal, geographical, and modality-specific variations in the knowledge representation, enabling more nuanced and accurate reasoning across diverse application domains.

[0147] FIG. **7** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning wherein an agent can predict and optimize actions based on user feedback and contextual information. A task orchestrator **150** serves as the central coordination hub, incorporating a task optimizer **720** that continuously refines execution strategies based on both predicted and actual outcomes across multiple interaction scenarios.

[0148] Within this framework, a robot agent **530** incorporates an effect predictor **710** that leverages advanced modeling techniques to anticipate the outcomes of potential actions before execution. This predictive capability enables the system to evaluate multiple approaches in parallel, considering both immediate outcomes and longer-term implications. For example, in a surgical setting, the effect predictor might simultaneously evaluate different incision locations, tool selections, and approach angles, simulating how each choice might affect patient recovery time, risk levels, and procedure success rates. In a manufacturing context, it might model how different assembly sequences could impact product quality, production time, and resource utilization.

[0149] The human agent **700** component represents a possible interface in the system, tracking both performed actions **701** and collecting detailed feedback **701** on the robot's performance. This bidirectional interaction creates a learning loop where the robot's predictions are continuously refined based on real-world outcomes and expert human knowledge. When a surgeon demonstrates a novel technique or a manufacturing expert suggests a more efficient assembly method, the system can incorporate these insights into its prediction models and optimization strategies. The feedback mechanism also captures subtle aspects of human expertise that might not be immediately obvious from performance data alone, such as situation-specific adaptations or expert intuition about edge cases.

[0150] Task optimizer **720** serves as the system's learning center, integrating multiple data streams—including the robot's predictions, actual performance metrics, human feedback, and historical outcomes—to continuously enhance task execution strategies. This optimization process employs sophisticated machine learning techniques to identify patterns and relationships that might not be apparent through traditional programming approaches. For instance, it might discover that certain surgical techniques are more effective under specific patient conditions, or that particular assembly sequences work better with certain material variations. The optimizer maintains a balance between exploiting known successful strategies and exploring potential improvements, all while operating within defined safety and ethical boundaries.

[0151] This architecture enables nuanced human-robot collaboration that goes beyond simple task execution, creating a learning system that combines the precision and consistency of robotics with the adaptability and expertise of human operators. The continuous feedback loop ensures that the system becomes increasingly sophisticated over time, while the human oversight component maintains appropriate safety and ethical guardrails throughout the learning process.

[0152] FIG. **8** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning and agents organized in a hierarchy that store task and action information. In one embodiment, the system may utilize specialized agent roles and advanced memory systems to facilitate dynamic knowledge sharing while maintaining ethical constraints and operational efficiency.

[0153] In the embodiment, task orchestrator **150** and its task optimizer **720** coordinate with multiple specialized agents, each serving distinct roles in the system's decision-making process. The leader agent **800** functions as a primary coordinator, implementing dynamic responsibility allocation mechanisms that adjust based on real-time cognitive load assessments and task priorities. For instance, in a medical emergency scenario, the leader agent might shift primary decision-making authority between different specialist agents based on the evolving situation while maintaining compliance with deontic constraints.

[0154] An observer agent **810** implements monitoring capabilities based on advanced information theoretic principles. It tracks both explicit actions and implicit patterns in agent behavior, calculating mutual information and transfer entropy metrics to optimize information flow between agents. This agent is particularly useful in maintaining the system's observer-aware processing capabilities, ensuring that different perspectives and knowledge states are properly maintained and integrated.

[0155] The assistant agent **820** provides support functions and carries out delegated tasks, working in concert with both the human agent **700** and other system agents. It employs advanced neural network architectures for context-aware task execution while maintaining alignment with the system's ethical frameworks. The human agent **700** interface captures both performed actions **701** and feedback **701**, creating a rich interaction channel that enables the system to learn from human expertise while maintaining appropriate autonomy levels.

[0156] An agent memory **830** implements a knowledge retention and retrieval system. This memory component utilizes systems like knowledge graphs or token space techniques to maintain and organize experiential knowledge, enabling efficient cross-domain learning and knowledge transfer. The memory system not only stores past experiences but also maintains temporal and contextual relationships, allowing agents to learn from historical interactions while adapting to new scenarios.

[0157] The entire network operates within a federated learning framework that enables agents to learn from each other through structured debates and case studies, similar to collegiate-level academic discourse. This approach allows for sophisticated peer-to-peer knowledge integration while

maintaining privacy and security through differential privacy mechanisms. The system's dynamic quality assessment capabilities ensure that knowledge transfer remains effective and relevant across different domains and contexts, while the built-in validation frameworks maintain logical consistency and ethical compliance throughout the learning process.

[0158] According to one embodiment, the system may implement an integrated biometric monitoring and contextual understanding framework that combines multiple components to enable sophisticated human-robot collaboration. This framework may center on an enhanced observer agent **810** that processes multiple biometric signals including electroencephalogram (EEG) data, heart rate variability (HRV), galvanic skin response (GSR), eye tracking, and motion sensor data. The observer agent may interface directly with knowledge graph network **160** to contextualize these biometric readings against environmental data captured through multiple sensors including visual, LiDAR, thermal, and audio inputs. This integrated approach may enable the system to maintain comprehensive awareness of both operator state and operational context while dynamically adjusting task allocation between human and robot agents.

[0159] Observer agent **810** may work in concert with task orchestrator **150** to implement task allocation strategies based on the processed biometric and contextual data. When the observer agent detects elevated cognitive load through a combination of EEG signatures, increased heart rate variability, and altered eye tracking patterns, it may signal the task orchestrator to initiate a dynamic reallocation of responsibilities. For example, in a search-and-rescue scenario, if the human operator's cognitive load exceeds predetermined thresholds while managing multiple rescue operations, robot agent **530** may automatically assume control of navigation and environmental mapping tasks while leaving high-level victim prioritization decisions to the human operator.

[0160] To support this dynamic task allocation, knowledge orchestrator **140** may maintain an evolving understanding of the operational environment through scene graphs that represent spatial relationships, dynamic object tracking data, and risk maps. These representations may be continuously updated based on both sensor data and feedback from executed actions. The knowledge orchestrator may also implement retrieval-augmented generation (RAG) capabilities that enable it to enhance current decision-making by incorporating relevant historical experiences and domain expertise from knowledge graph network **160**. For instance, when encountering a complex rescue scenario, the system may retrieve and analyze similar past situations to inform its current task allocation and execution strategies.

[0161] Deontic reasoning subsystem **130** may work alongside these components to ensure that all task allocations and executions remain compliant with ethical constraints while adapting to changing conditions. When observer agent **810** indicates high operator stress levels, the deontic reasoning subsystem may adjust its ethical evaluation thresholds to become more conservative, ensuring safer operation during periods of reduced human oversight. This adaptive ethical framework may be particularly crucial in scenarios where reduced operator attention could lead to increased safety risks.

[0162] The system may further implement sophisticated feedback mechanisms that adapt based on both operator state and environmental conditions. Task orchestrator **150** may select from multiple feedback modalities including visual, auditory, haptic, and direct stimulation, with the specific choice guided by observer agent's **810** assessment of operator cognitive state and environmental factors. For example, in high-noise environments with elevated operator stress levels, the system may prioritize haptic feedback for alerts while reserving visual feedback for less urgent communications.

[0163] These integrated components may operate within a unified token-space communication framework that enables efficient geometric operations between different specialist representations. This framework may allow rapid convergence of information across the system's components while preserving semantic relationships. Knowledge orchestrator **140** may leverage this token-space framework to maintain consistency between symbolic knowledge representations and neural network-based processing, enabling seamless integration of rule-based reasoning with learned behaviors.

[0164] FIG. **9** is a block diagram illustrating an exemplary component of a system for an AI agent decision platform with deontic reasoning and an integrated LLM network capable of managing resources. In one embodiment, agent platform core **100** incorporates an LLM network **900** that interfaces directly with the deontic reasoning subsystem **130**. This integration enables the system to leverage the pattern recognition and natural language understanding capabilities of LLMs while ensuring all outputs comply with defined obligations, permissions, and prohibitions. The LLM network **900** implements specialized models for different aspects of reasoning, including but not limited to task decomposition, ethical reasoning, and context integration, each operating within the system's deontic constraints.

[0165] A resource management framework, comprising the resource manager **910** and resource planner **920** provide resource and ethics tradeoff management, considering both computational efficiency and ethical implications when allocating system resources. For example, in a medical emergency scenario, the resource planner might prioritize diagnostic processes while ensuring sufficient resources remain available for maintaining ethical guardrails and safety protocols.

[0166] The system processes inputs from multiple sources, including but not limited to user **190** interactions, contextual information **191**, and sensor data **192**, through the DCG **110** architecture. The federation manager **120** coordinates these inputs while the knowledge orchestrator **140** maintains semantic consistency across the knowledge graph network **160**. This multi-modal input processing enables the system to maintain comprehensive situational awareness while adapting its resource allocation and decision-making strategies accordingly.

[0167] An action selector **150** implements decision-making algorithms that combine LLM-generated recommendations with deontic constraints and resource availability considerations. This component may employ quantum-inspired token space operations to evaluate potential actions efficiently while maintaining ethical compliance. Task orchestrator **150** then coordinates with agent network **180** to execute selected actions, ensuring that all operations remain within the system's ethical and operational boundaries.

[0168] This architecture demonstrates how advanced language models can be integrated into a deontic reasoning framework while maintaining strict ethical guidelines and efficient resource utilization. The system's ability to balance

computational resources, ethical considerations, and operational requirements enables sophisticated decision-making across diverse application domains while ensuring consistent alignment with defined moral and operational constraints.

[0169] In one embodiment, the system may include a multi-agent responsibility arbitration mechanism that dynamically manages task allocation between human and non-human agents. This mechanism may operate within the agent network **180**, utilizing the task orchestrator **150** and task optimizer **720** to continuously evaluate and adjust agent responsibilities based on real-time capabilities, resource availability, and operational constraints. The arbitration system may enable negotiation-based task redistribution, where agents can propose and accept task reallocations while maintaining compliance with stored deontic constraints.

[0170] In another embodiment, the system may implement causal dependency mapping capabilities that enhance the knowledge graph network **160** with explicit encoding of cause-effect relationships between human and machine agent actions. This enhancement may enable the platform to predict and optimize downstream effects of agent actions, particularly in collaborative scenarios. The observer agent **810** may leverage these causal maps to monitor and adjust task execution based on predicted impacts across the agent network.

[0171] According to another embodiment, the system may include a trust calibration subsystem operating within the deontic reasoning subsystem **130**, implementing feedback loops that dynamically adjust system behavior based on human trust levels. This subsystem may work in conjunction with the experience curation engine to modify explanation detail levels and confidence thresholds based on observed user interactions and explicit feedback. The trust calibration mechanism may maintain compliance with deontic constraints while adapting to individual user needs and preferences.

[0172] In one embodiment, the system may incorporate personalized norm adaptation through specialized knowledge graphs within the knowledge graph network **160**. These graphs may capture individual user preferences and routines while maintaining alignment with overarching deontic constraints stored in the rules database **170**. The adaptation mechanism may enable the system to learn and apply user-specific norms while ensuring compliance with fundamental obligations and prohibitions.

[0173] According to another embodiment, the system may include an interactive scenario simulation component that enhances the platform's planning capabilities by enabling collaborative pre-execution testing of complex tasks. This component may interface with the deontic reasoning subsystem **130** to validate proposed actions against stored constraints while allowing human agents to participate in scenario refinement through the human agent interface **700**. The simulation component may generate detailed analytics about potential risks, inefficiencies, and conflicts, enabling iterative improvement of task plans before execution.

[0174] In another embodiment, the system may implement a layered ethical prioritization framework within the deontic reasoning subsystem **130** that dynamically weighs ethical considerations against operational objectives. This framework may enable sophisticated ethical decision-making by incorporating situation-specific factors while maintaining compliance with fundamental deontic constraints. The prioritization system may include dynamic re-evaluation triggers that adjust ethical weightings based on changing mission conditions or emerging constraints.

[0175] In one embodiment, the system may include a context-aware conversational memory system that enhances the platform's interaction capabilities by maintaining detailed interaction histories within the agent memory **830**. This system may enable agents to track and reference past interactions, preferences, and context-specific details across multiple sessions. The memory system may interface with the knowledge orchestrator **140** to ensure that historical context informs ongoing agent decisions and interactions while maintaining compliance with privacy-related deontic constraints.

[0176] FIG. **22** is a block diagram illustrating an exemplary system architecture for a federated distributed graph-based computing platform. The system comprises a centralized DCG **2240** that coordinates with a plurality of federated DCGs **2200**, **2210**, **2220**, and **2230**, each representing a semi-independent computational entity.

[0177] The interaction between federated units in this system represents one of several possible architectural patterns for coordinating distributed computing tasks. The federated architecture supports multiple implementation approaches, with centralized DCG **2240** representing just one possible configuration. In a peer-to-peer federation pattern, DCGs can operate in a fully decentralized manner, discovering and coordinating with each other through gossip protocols, where each DCG advertises its capabilities and available resources to peers, and workloads are distributed through direct DCG-to-DCG communication without central coordination. For bot-to-bot federation scenarios, each DCG can act as an interface to specific user requests or tasks, with DCGs discovering peer capabilities through gossip protocols and matching tasks to capabilities through autonomous selection. When implemented as a centralized federation, as shown with DCG **2240**, it may maintain a high-level view of resources and processes similar to syndication patterns in enterprise architecture, though with limited visibility into internal DCG operations. For instance, in this pattern, task distribution may be facilitated by the centralized DCG **2240**, but the fundamental capabilities for autonomous operation remain distributed across the federation, allowing each DCG to maintain independent control over its resources and processing decisions. In one embodiment, centralized DCG **2240** oversees the distribution of workloads across the federated system, maintaining a high-level view of available resources and ongoing processes. In some embodiment, centralized DCG **2240** may not have full visibility or control over the internal operations of each federated DCG. Each DCG system involved in the federated DCG platform may be represented by the system **300** as depicted in FIG. **3**.

[0178] Each federated DCG (**2200**, **2210**, **2220**, **2230**) operates as a semi-autonomous unit. These federated DCGs have their own internal structure, similar to the DCG depicted in FIG. **3**. In one embodiment, each federated DCG communicates through pipelines that extend across multiple systems, facilitating a flexible and distributed workflow. The pipeline orchestrator P.O. **1201** serves as a conduit for task delegation from the DCG **2240** to the federated DCGs. Each federated DCG (**2200**, **2210**, **2220**, **2230**) operates as a fully autonomous unit with complete capability to function independently within the federation. These federated DCGs have

their own internal structure, similar to the DCG depicted in FIG. **3**, and can operate without requiring central coordination. The federated DCGs communicate through pipelines that extend across multiple systems, enabling flexible and distributed workflows through various architectural patterns. In one implementation, DCGs can directly advertise and coordinate tasks with other DCGs in the federation without central mediation, where the pipeline orchestrator P.O. **1201** in each DCG manages task distribution and execution locally while coordinating with peer DCGs through federation protocols. These pipelines may span any number of federated systems, with a plurality of pipeline managers (P.M. A **1211***a*, P.M. B **1211***b*, etc.) overseeing different segments or aspects of the workflow based on whether the federation is operating in peer-to-peer, hierarchical, or hybrid patterns. Federated DCGs interact with corresponding local service clusters **1220***a-d* and associated Service Actors **1221***a-d* to execute tasks represented by services **1222***a-d*, allowing for efficient local processing while maintaining flexible connections to the broader federated network through whichever federation pattern best suits the current needs. While a centralized orchestration through DCG **2240** may be implemented in some scenarios, it represents just one possible configuration rather than a requirement of the federation architecture. These pipelines may span any number of federated systems, with a plurality of pipeline managers (P.M. A **1211***a*, P.M. B **1211***b*, etc.) overseeing different segments or aspects of the workflow. Federated DCGs interact with corresponding local service clusters **1220***a-d* and associated Service Actors **1221***a-d* to execute tasks represented by services **1222***a-d*, allowing for efficient local processing while maintaining a connection to the broader federated network.

[0179] Centralized DCG **2240** may delegate resources and projects to federated DCGs via the pipeline orchestrator P.O. **1201**, which then distributes tasks along the pipeline structure. This hierarchical arrangement allows for dynamic resource allocation and task distribution across the federation. Pipelines can be extended or reconfigured to include any number of federated systems, adapting to the complexity and scale of the computational tasks at hand.

[0180] Federated DCGs **2200**, **2210**, **2220**, and **2230** may take various forms, representing a diverse array of computing environments. They may exist as cloud-based instances, leveraging the scalability and resources of cloud computing platforms. Edge computing devices can also serve as federated DCGs, bringing computation closer to data sources and reducing latency for time-sensitive operations. Mobile devices, such as smartphones or tablets, can act as federated DCGs, contributing to the network's processing power and providing unique data inputs. Other forms may include on-premises servers, IoT devices, or even specialized hardware like GPUs or TPUs. This heterogenicity allows the federated DCG platform to adapt to various computational needs and take advantage of diverse computing resources, creating a robust and versatile distributed computing environment.

[0181] In this federated system, workloads can be distributed across different federated DCGs based on a plurality factors such as but not limited to resource availability, data locality, privacy requirements, or specialized capabilities of each DCG. Centralized DCG **2240** may assign entire pipelines or portions of workflows to specific federated DCGs, which then manage the execution internally. Communication between centralized DCG **2240** and federated DCGs, as well as among federated DCGs themselves, may occur through the pipeline network which is being overseen by the plurality of pipeline managers and the pipeline orchestrator P.O. **1201**.

[0182] The interaction between federated units, the centralized unit, and other federated units in this system may be partially governed by privacy specifications, security requirements, and the specific needs of each federated unit. The interaction between federated DCGs in this system is governed by self-enforced privacy specifications, security requirements, and the specific operational needs of each federated unit. Each DCG autonomously manages its privacy and security constraints while participating in the federation. For example, a DCG processing healthcare data can maintain internal mapping tables for data anonymization, transform sensitive data using temporary IDs before sharing, and control data visibility without requiring other DCGs to be aware of the underlying privacy measures. In one embodiment, DCGs advertise their operational requirements to the federation, such as geographic processing restrictions (e.g., EU-only data processing), security clearance requirements, and regulatory compliance certifications. When assigning or accepting tasks, each DCG independently evaluates and enforces its privacy and security controls based on its declared capabilities. For instance, a DCG might autonomously determine whether to process sensitive healthcare data based on its certifications and security measures, without requiring central coordination. While a centralized DCG **2240** may exist in some implementations to facilitate coordination, the fundamental privacy and security controls remain distributed across the federated DCGs, enabling flexible and secure collaboration through self-managed privacy controls and peer-based task distribution. DCG **2240** may manage the overall workflow distribution while respecting privacy and security constraints. In one embodiment, DCG **2240** may be centralized and maintain a high-level view of the system but may have limited insight into the internal operations of each federated DCG. When assigning tasks or pipelines, DCG **2240** may consider the privacy specifications associated with the data and the security clearance of each federated DCG. For instance, it might direct sensitive healthcare data only to federated DCGs with appropriate certifications or security measures in place.

[0183] Federated DCGs (**2200**, **2210**, **2220**, **2230**) may interact with the DCG **2240** and each other based on predefined rules and current needs. A federated DCG might request additional resources or specific datasets from DCG **2240**, which would then evaluate the request against security protocols before granting access. In cases where direct data sharing between federated DCGs is necessary, DCG **2240** may facilitate this exchange, acting as an intermediary to ensure compliance with privacy regulations. The level of information sharing between federated DCGs can vary. Some units might operate in isolation due to strict privacy requirements, communicating only with DCG **2240**. Others might form collaborative clusters, sharing partial results or resources as needed. For example, federated DCG **2200** might share aggregated, anonymized results with federated DCG **2210** for a joint analysis, while keeping raw data confidential.

[0184] DCG **2240** may implement a granular access control system, restricting information flow to specific federated

DCGs based on the nature of the data and the task at hand. It may employ techniques like differential privacy or secure multi-party computation to enable collaborative computations without exposing sensitive information. In scenarios requiring higher security, DCG **2240** may create temporary, isolated environments where select federated DCGs can work on sensitive tasks without risking data leakage to the broader system. This federated approach allows for a balance between collaboration and privacy, enabling complex, distributed computations while maintaining strict control over sensitive information. The system's flexibility allows it to adapt to varying privacy and security requirements across different domains and use cases, making it suitable for a wide range of applications in heterogeneous computing environments.

[0185] In another embodiment, a federated DCG may enable an advanced data analytics platform to support non-experts in machine-aided decision-making and automation processes. Users of this system may bring custom datasets which need to be automatically ingested by the system, represented appropriately in nonvolatile storage, and made available for system-generated analytics to respond to with questions the user(s) want to have answered or decisions requiring recommendations or automation. In this case the DCG orchestration service would create representations of DCG processes that have nodes that each operate on the data to perform various structured extraction tasks, to include schematization, normalization and semantification activities, to develop an understanding of the data content via classification, embedding, chunking, and knowledge base construction and vector representation persistence and structured and unstructured data view generation and persistence, and may also smooth, normalize or reject data as required to meet specified user intent. Users may optionally be asked to provide feedback, e.g. via layperson content and subsequent interpretation by LLM re: the generated tasks or DCG pipelines generated, or in expert or power user modes access or view or modify actual declarative formulations of pipelines or transformation tasks. Based on the outcome of the individual transformation steps and various subgraph pipeline execution and analysis additional data may be added over time or can be accessed from either a centralized data repository, or enriched via ongoing collection from one or more live sources. Data made available to the system can then be tagged and decomposed or separated into multiple sets for training, testing, and validation via pipelines or individual transformation stages. A set of models must then be selected, trained, and evaluated before being presented to the user, which may optionally leverage data and algorithm marketplace functionality. This step of model selection, training, and evaluation can be run many times to identify the optimal combination of input dataset(s), selected fields, dimensionality reduction techniques, model hyper parameters, embeddings, chunking strategies, or blends between use of raw, structured, unstructured, vector and knowledge corpora representations of data for pipelines or individual transformation nodes. The ongoing search and optimization process engaged in by the system may also accept feedback from a user and take new criteria into account such as but not limited to changes in budget that might impact acceptable costs or changes in timeline that may render select techniques or processes infeasible. This may mean system must recommend or select a new group of models, adjusting how training data was selected, or how the model outputs are evaluated or otherwise adjust DCG pipelines or transformation node declarations according to modified objective functions which enable comparative ranking (e.g. via score, model or user feedback or combination) of candidate transformation pipelines with resource and data awareness. The user doesn't need to know the details of how models are selected and trained, but can evaluate the outputs for themselves and view ongoing resource consumption, associated costs and forward forecasts to better understand likely future system states and resource consumption profiles. Based on outputs and costs, they can ask additional questions of the data and have the system adjust pipelines, transformations or parameters (e.g. model fidelity, number of simulation runs, time stepping, etc. . . .) as required in real time for all sorts of models including but not limited to numerical methods, discrete event simulation, machine learning models or generative AI algorithms.

[0186] In one embodiment, the AI agent decision platform integrates a resource-ethical optimization module that continuously evaluates both computational resource metrics (e.g., CPU load, GPU memory utilization, latency constraints) and ethical or compliance metrics derived from the system's deontic logic framework. This approach ensures that task allocation and scheduling decisions are not driven solely by technical efficiency but also by adherence to obligations, permissions, and prohibitions encoded in the knowledge graphs. Each node in the federated system (e.g., cloud instances, edge devices, or specialized hardware) provides real-time telemetry, reporting CPU usage, GPU utilization, memory availability, and network bandwidth. This telemetry feeds into a resource registry, continuously updated to reflect the federation's current load distribution. Simultaneously, the deontic reasoning subsystem supplies the resource-ethical optimization module with compliance-relevant signals—such as the level of data sensitivity (e.g., personal health information), regulatory constraints per geographic region, and severity of potential violations (e.g., "strict prohibition," "high-risk obligation"). The platform's scheduling or orchestration process employs a multi-objective cost function that blends standard performance metrics (e.g., throughput, latency, resource cost) with ethical/compliance scores. For instance, each node or data pipeline may be assigned a "compliance risk value" if it handles sensitive data, while also including a "performance efficiency value" for raw technical throughput.

[0187] The optimization engine may adopt an approach akin to Pareto optimization—or any suitable constrained optimization algorithm—that seeks solutions minimizing total "cost" while ensuring no active deontic rule is violated. For example, if a node is physically located in a jurisdiction with strict privacy obligations, the system might only allocate tasks involving personal data to nodes that meet or exceed that jurisdiction's compliance threshold. When new tasks arrive—such as large-scale modeling jobs or medical data analytics—the system queries the resource-ethical optimization module to find the best node or group of nodes. "Best" here includes not only capacity for faster runtime but also alignment with relevant deontic constraints (e.g., "must not process data outside region X," "must ensure real-time access logs," "must prioritize tasks with urgent life-safety implications"). If the system detects changing circumstances—such as a node's resource spike or new legal restrictions—the module recalculates allocations and can dynamically reassign tasks. For instance, a node that was

efficient but becomes overburdened or out-of-compliance can trigger automatic fallback to a second-choice node with slightly lower performance but higher compliance adherence. Administrators or domain experts can inspect a combined metrics dashboard that plots performance metrics (throughput, latency, cost) against compliance/ethical standings (deviation from obligations, severity of potential data leakage). The platform can generate alerts if performance optimizations begin to push boundaries of compliance risk beyond acceptable thresholds. Over time, the module refines its weighting factors by tracking outcomes—e.g., near misses, actual violations, or user satisfaction data—ensuring continuous learning.

[0188] The deontic reasoning subsystem updates constraints if new obligations arise, while the optimization engine adjusts the weight distribution in the cost function to remain balanced between ethical compliance and computational efficiency. By using a multi-objective optimization strategy that explicitly weighs compliance and ethical criteria alongside computational performance, this embodiment ensures that the AI agent decision platform respects both real-world constraints (e.g., laws, regulations, data sensitivities) and technical demands. The system can thus make intelligent, context-aware allocations—such as routing life-critical healthcare data only to nodes with the highest security clearances—even when it might reduce pure computational efficiency. Through this resource-ethical optimization module, this goes beyond conventional load balancing into a holistic approach that merges ethical compliance with operational excellence.

[0189] According to another embodiment, a federated DCG may enable advanced malware analysis by accepting one or more malware samples. Coordinated by the DCG, system may engage in running a suite of preliminary analysis tools designed to extract notable or useful features of any particular sample, then using this information to select datasets and pretrained models developed from previously observed samples. The DCG can have a node to select a new model or models to be used on the input sample(s), and using the selected context data and models may train this new model. The output of this new model can be evaluated and trigger adjustments to the input dataset or pretrained models, or it may adjust the hyperparameters of the new model being trained. The DCG may also employ a series of simulations where the malware sample is detonated safely and observed. The data collected may be used in the training of the same or a second new model to better understand attributes of the sample such as its behavior, execution path, targets (e.g.: what operating systems, services, networks is it designed to attack), obfuscation techniques, author signatures, or malware family group signatures.

[0190] According to an embodiment, a DCG may federate and otherwise interact with one or more other DCG orchestrated distributed computing systems to split model workloads and other tasks across multiple DCG instances according to predefined criteria such as resource utilization, data access restrictions and privacy, compute or transport or storage costs et cetera. It is not necessary for federated DCGs to each contain the entire context of workload and resources available across all federated instances and instead may communicate, through a gossip protocol for example or other common network protocols, to collectively assign resources and parts of the model workload across the entire federation. In this way it is possible for a local private DCG instance to use resources from a cloud based DCG, owned by a third party for example, while only disclosing the parts of the local context (e.g. resources available, DCG state, task and model objective, data classification), as needed. For example, with the rise of edge computing for AI tasks a federated DCG could offload all or parts computationally intensive tasks from a mobile device to cloud compute clusters to more efficiently use and extend battery life for personal, wearable or other edge devices. According to another embodiment, workloads may be split across the federated DCG based on data classification. For example, only process Personally identifiable information (PII) or Protected Health Information (PHI) on private compute resources, but offload other parts of the workload, with less sensitive data, to public compute resources (e.g. those meeting certain security and transparency requirements).

[0191] In an embodiment, the federated distributed computational graph (DCG) system enables a sophisticated approach to distributed computing, where computational graphs are encoded and communicated across devices alongside other essential data. This data may include application-specific information, machine learning models, datasets, or model weightings. The system's design allows for the seamless integration of diverse computational resources.

[0192] The federated DCG facilitates system-wide execution with a unique capability for decentralized and partially blind execution across various tiers and tessellations of computing resources. This architecture renders partially observable, collaborative, yet decentralized and distributed computing possible for complex processing and task flows. The system employs a multi-faceted approach to resource allocation and task distribution, utilizing rules, scores, weightings, market/bid mechanisms, or optimization and planning-based selection processes. These selection methods can be applied at local, regional, or global levels within the system, where "global" refers to the entirety of the interconnected federated DCG network, regardless of the physical location or orbital position of its components.

[0193] This approach to federated computing allows for unprecedented flexibility and scalability. It can adapt to the unique challenges posed by diverse computing environments, from traditional terrestrial networks to the high-latency, intermittent connections characteristic of space-based systems. The ability to operate with partial blindness and decentralized execution is particularly valuable in scenarios where complete information sharing is impossible or undesirable due to security concerns, bandwidth limitations, or the physical constraints of long-distance space communications.

[0194] FIG. **23** is a block diagram illustrating an exemplary system architecture for a federated distributed graph-based computing platform that includes a federation manager. In one embodiment, a federation manager **2300** serves as an intermediary between the DCG **2240** and the federated DCGs (**2200**, **2210**, **2220**, **2230**), providing a more sophisticated mechanism for orchestrating the federated system. It assumes some of the coordination responsibilities previously handled by the centralized DCG, allowing for more nuanced management of resources, tasks, and data flows across the federation. In this structure, DCG **2240** communicates high-level directives and overall system goals to the federation manager **2300**. Federation manager **2300** may then translate these directives into specific actions and assignments for each federated DCG, taking into account

their individual capabilities, current workloads, and privacy requirements. Additionally, federation manager **2300** may also operate in the reverse direction, aggregating and relaying information from federated DCGs back to DCG **2240**. This bi-directional communication allows federation manager **2300** to provide real-time updates on task progress, resource utilization, and any issues or anomalies encountered within the federated network. By consolidating and filtering this information, federation manager **2300** enables centralized DCG **2240** to maintain an up-to-date overview of the entire system's state without being overwhelmed by low-level details. This two-way flow of information facilitates adaptive decision-making at the centralized level while preserving the autonomy and efficiency of individual federated DCGs, ensuring a balanced and responsive federated computing environment

[0195] In an embodiment, federation manager **2300** may be connected to a plurality of pipeline managers **1211***a* and **1211***b*, which are in turn connected to a pipeline orchestrator **1201**. This connection allows for the smooth flow of information between each of the various hierarchies, or tessellations, within the system. Federation manager **2300** may also oversee the distribution and execution of tasks **2310**, **2320**, **2330**, **2340** across the federated DCGs. It can break down complex workflows into subtasks, assigning them to appropriate federated DCGs based on their specializations, available resources, and security clearances. This granular task management allows for more efficient utilization of the federated system's resources while maintaining strict control over sensitive operations.

[0196] Federation manager **2300** may allocate tasks and transmit information in accordance with privacy and security protocols. It may act as a gatekeeper, controlling the flow of information between federated DCGs and ensuring that data sharing complies with predefined privacy policies. For instance, it could facilitate secure multi-party computations, allowing federated DCGs to collaborate on tasks without directly sharing sensitive data. Federation manager **2300** may also enable more dynamic and adaptive resource allocation. It can monitor the performance and status of each federated DCG in real-time, reallocating tasks or resources as needed to optimize overall system performance. This flexibility allows the system to respond more effectively to changing workloads or unforeseen challenges.

[0197] By centralizing federation management functions, this architecture provides a clearer separation of concerns between global coordination (handled by centralized DCG **2240**) and local execution (managed by individual federated DCGs). This separation enhances the system's scalability and makes it easier to integrate new federated DCGs or modify existing ones without disrupting the entire federation.

[0198] In one embodiment, the federated DCG system can be applied to various real-world scenarios. In healthcare, multiple hospitals and research institutions can collaborate on improving diagnostic models for rare diseases while maintaining patient data confidentiality. Each node (hospital or clinic) processes patient data locally, sharing only aggregated model updates or anonymized features, allowing for the creation of a global diagnostic model without compromising individual patient privacy. In financial fraud detection, competing banks can participate in a collaborative initiative without directly sharing sensitive customer transaction data. The system enables banks to maintain local observability of their transactions while contributing to a shared fraud detection model using techniques like homomorphic encryption or secure multi-party computation. For smart city initiatives, the system allows various entities (e.g., transportation authorities, environmental monitors, energy providers) to collaborate while respecting data privacy. Each entity processes its sensor data locally, with the system orchestrating cross-domain collaboration by enabling cross-institution model learning without full observability of the underlying data.

[0199] In one embodiment, the federated DCG system is designed to support partial observability and even blind execution across various tiers and tessellations of computing resources. This architecture enables partially observable, collaborative, yet decentralized and distributed computing for complex processing and task flows. The system can generate custom compute graphs for each federated DCG, specifically constructed to limit information flow. A federated DCG might receive a compute graph representing only a fraction of the overall computation, with placeholders or encrypted sections for parts it should not access directly. This allows for complex, collaborative computations where different parts of the system have varying levels of visibility into the overall task. For instance, a federated DCG in a highly secure environment might perform computations without full knowledge of how its output will be used, while another might aggregate results without access to the raw data they're derived from.

[0200] In one embodiment, the federated DCG system is designed to seamlessly integrate diverse computational resources, ranging from edge devices to cloud systems. It can adapt to the unique challenges posed by these varied environments, from traditional terrestrial networks to high-latency, intermittent connections characteristic of space-based systems. The system's ability to operate with partial blindness and decentralized execution is particularly valuable in scenarios where complete information sharing is impossible or undesirable due to security concerns, bandwidth limitations, or physical constraints of long-distance communications. This flexibility allows the system to efficiently manage workloads across a spectrum of computing resources, from mobile devices and IoT sensors to edge computing nodes and cloud data centers.

[0201] In one embodiment, the system employs a multi-faceted approach to resource allocation and task distribution, utilizing rules, scores, weightings, market/bid mechanisms, or optimization and planning-based selection processes. These selection methods can be applied at local, regional, or global levels within the system. This approach allows the federated DCG to dynamically adjust to varying privacy and security requirements across different domains and use cases. For example, the system can implement tiered observability, where allied entities may have different levels of data-sharing access depending on treaties or bilateral agreements. This enables dynamic privacy management, allowing the system to adapt to changing regulatory landscapes or shifts in data sharing policies among collaborating entities.

[0202] FIG. **24** is a block diagram illustrating an exemplary component of a federated distributed graph-based computing platform that includes a federation manager, the federation manager. In one embodiment, a resource registry **2400** maintains a dynamic inventory of available resources across all federated DCGs. This may be accomplished by periodically polling each federated DCG for updates on their

computational capacity, storage availability, and current workload. This information is stored in a structured database, allowing for quick querying and analysis. The registry may use a gossip protocol to efficiently propagate updates across the federation, ensuring that resource information remains current even in large-scale deployments.

[0203] A task analyzer **2410** examines incoming tasks from the centralized DCG **2240** or from federated DCGs, breaking them down into subtasks and determining their requirements. It achieves this by parsing task descriptions, which may be encoded in a domain-specific language, and creating a directed acyclic graph (DAG) representing the task's structure and dependencies. The analyzer may also provide estimates regarding resource requirements for each subtask based on historical data and predefined heuristics.

[0204] A matching engine **2420** aligns tasks with appropriate federated DCGs by cross-referencing task requirements from task analyzer **2410** with available resources that have been documented by resource registry **2400**. In one embodiment, matching engine may employ algorithms such as constraint satisfaction solvers or machine learning models, to optimize task distribution. The engine **2420** considers factors such as but not limited to data locality, processing power requirements, and privacy constraints when making matching decisions. It may use a scoring system to rank potential matches, selecting the highest-scoring options for task assignment.

[0205] A communication interface **2430** facilitates secure and efficient information exchange between federation manager **2300**, centralized DCG **2240**, and federated DCGs. It implements various communication protocols (e.g., gRPC, MQTT) to accommodate different network conditions and security requirements. The interface may encrypt data transfers and may employ techniques like zero-knowledge proofs for sensitive communications, allowing entities to verify information without revealing underlying data.

[0206] A privacy and security module **2440** enforces data protection policies across the federation. It achieves this by maintaining a set of rules and permissions for each federated DCG and task. When a task is assigned, this module checks the security clearance of the target federated DCG against the task's requirements. It may implement differential privacy techniques, adding controlled noise to data or results to prevent the extraction of individual information. For collaborative tasks, it could set up secure multi-party computation protocols, enabling federated DCGs to jointly compute results without sharing raw data.

[0207] In a decentralized, blind or double blind embodiments, DCG **2240** encodes high-level computational tasks into graphs that can be distributed across the federation. However, unlike traditional distributed systems, these graphs are designed to be partitioned and obscured, allowing for partial or even blind execution. Federation manager **2300** receives computational graphs from DCG **2240**, and breaks down the graphs into subtasks which are designed to be executable with limited context. Matching engine **2420** then allocates these subtasks to federated DCGs **2200**, **2210**, **2220**, **2230** based not just on their capabilities, but also on their clearance levels and need-to-know basis.

[0208] For each federated DCG, the system may generate a custom compute graph. These graphs are not merely simplified versions of the original, but are specifically constructed to limit information flow. A federated DCG might receive a compute graph that represents only a fraction of the overall computation, with placeholders or encrypted sections representing parts of the computation it should not have direct access to. Communication interface **2430** securely transmits these tailored compute graphs to the federated DCGs through the pipeline structure **1201**. This transmission process itself can incorporate encryption and access control mechanisms to maintain the partial blindness of the execution.

[0209] Within each federated DCG, the activity actors **1212***a-d* perform computations based on their received graph, potentially without full knowledge of the overall task they're contributing to. This blind or partially blind execution may be managed by the local pipeline orchestrator **1201**, which ensures that each component only accesses the information it's cleared for. The system's ability to operate with partial observability comes into play as computations progress. Federated DCGs report results back through the pipeline structure, but these results may be encrypted or obfuscated to maintain partial blindness. This architecture allows for complex, collaborative computations where different parts of the system have varying levels of visibility into the overall task. For instance, a federated DCG in a highly secure environment might perform computations without full knowledge of how its output will be used, while another federated DCG might aggregate results without access to the raw data they're derived from.

[0210] By enabling this decentralized, partially blind execution, the federated DCG system can tackle complex computational tasks that span entire networks, while maintaining strict control over information flow and resource utilization. This approach is particularly valuable for scenarios involving sensitive data, limited communication bandwidth, or the need for compartmentalized computing across vast distances in space.

[0211] In one embodiment, the system implements dynamic task allocation based on real-time conditions and changing requirements. As computations progress, each federated DCG reports back through the pipeline structure, providing feedback on task progress, resource utilization, and any issues encountered. The federation manager aggregates this information, providing a high-level overview of the system's state. Based on this real-time feedback, the system can dynamically adjust compute graphs and task allocations. It might modify compute graphs in real-time, reassign tasks to different federated nodes, or adjust resource allocations in response to changing workloads or unforeseen challenges. This adaptive process ensures efficient utilization of resources across the entire federated system, from terrestrial networks to space-based computing nodes, allowing the system to respond effectively to changing conditions and requirements in real-time while maintaining security and efficiency.

[0212] FIG. **25** is a block diagram illustrating an exemplary system architecture for a federated distributed graph-based computing platform that includes a federation manager where different compute graphs are forward to various federated distributed computation graph systems. In one embodiment, DCG **2240** generates a plurality of compute graphs **2500**, **2510**, **2520**, **2530** tailored to each federated DCG's requirements and specifications. This approach allows for fine-grained control over information access and task execution across the federation. DCG **4940** analyzes the overall task requirements and the characteristics of each federated DCG **2200**, **2210**, **2220**, **2230**, considering factors

such as but not limited to processing capabilities, data access permissions, security clearance levels, and specialized functions. Based on this analysis, it constructs custom compute graphs for each Federated DCG through a multi-step process that involves creating a master compute graph, applying transformations based on each DCG's specifications, and potentially replacing sensitive operations with privacy-preserving alternatives.

[0213] Federation manager **2300** may provide the DCG **2240** with up-to-date information about each federated DCG's current status, capabilities, and access rights by leveraging the pipeline infrastructure. This information is used to dynamically adjust the compute graphs as conditions change. When distributing tasks **2310**, **2320**, **2330**, **2340**, centralized DCG **2240** sends the corresponding compute graph along with the task, serving as a blueprint for how the federated DCG should execute the task, specifying data access, operations, and handling of intermediate results.

[0214] Compute graphs may also be used to facilitate secure collaboration between federated DCGs, potentially including special nodes that define how intermediate results should be shared or combined without revealing sensitive information. As federated DCGs execute their tasks according to their assigned compute graphs, they report progress back to federation manager **2300**. Federation manager may then update DCG **2240**, which may decide to modify the compute graphs in real-time if necessary, such as when new data requires additional processing steps or if a security policy changes mid-execution.

[0215] This dynamic, graph-based approach allows the system to maintain strict control over information flow and task execution while still leveraging the full capabilities of the federated architecture. It provides a flexible framework for handling complex, distributed tasks with varying security and privacy requirements across heterogeneous computing environments, enabling the system to adapt to changing conditions and requirements in real-time while maintaining security and efficiency for both complete and intermediate results sharing as well as entire chain-of-thought sharing between different expert/persona models.

[0216] With federated Distributed Computational Graphs, each node in the federation can operate both autonomously and cooperatively through compute graphs. The system orchestrates tasks (and sub-tasks) across various nodes, each of which may have different security, regulatory, or performance constraints. The physical topology represents the actual hardware layout-clusters of servers, edge devices, sensor arrays. The logical topology represents how these nodes are interconnected logically, e.g., which nodes have secure VPN tunnels, which have higher-latency WAN connections, etc. The data-flow graph depicts which nodes produce or consume data in pipelines, along with transformations or partial results that flow among them. A specialized annotation layer, the deontic overlay, encodes the rules, constraints, or obligations/prohibitions relevant to each node or each stage in the pipeline (e.g., "Node X must not process personal data," "Sub-task Y requires a professional overseer agent," etc.). By layering these topologies (physical, logical, data flow) and adding a deontic overlay, we can produce a comprehensive "graph of graphs" that the federation manager and DCG orchestrator can consult in real time to maintain compliance, security, and efficient resource usage. In some embodiments, the federation manager may not possess full visibility into the detailed computations or intermediate states occurring within each federated node—especially when privacy-preserving transformations, data anonymization, or partially blind execution arc enforced. Instead, the federation manager primarily orchestrates the high-level resource allocation, ensures that tasks are routed to nodes equipped with the requisite security clearances or specialized capabilities, and enforces relevant deontic constraints by referencing a global rules database or knowledge graph. At a granular level, each local node may execute its assigned subtasks without transmitting raw data or revealing sensitive intermediate artifacts back to the federation manager, thereby maintaining strict privacy requirements. Consequently, the federation manager retains optionality to act as a "coordinator" role rather than a fully informed "controller," balancing system-wide oversight of task scheduling and policy compliance without intruding on confidential or domain-specific details at each node for both implicit and explicitly defined computational graphs regardless of how many federation managers may participate in collective data flow management across a compound or composite process.

[0217] In addition to standard transformation nodes, the system may add special nodes dedicated to controlling or transforming sensitive outputs. If a task processes personal or proprietary data, a "masking node" can sanitize or anonymize the partial outputs before they move downstream. The deontic overlay encodes the requirement: "Data from sub-task A must not reveal personal info to Node B unless Node B is certified." Before sending partial results across an untrusted link, a node can encrypt or compress them in a zero-knowledge manner. The DCG can also define "secure aggregation" nodes that combine partial results from multiple sources without revealing any single party's raw data. If a "persona" or "expert agent" needs to share chain-of-thought with another agent, the system can insert a node that "merges" or "filters" the reasoning steps according to deontic constraints. This is crucial in contexts with multiple roles (e.g., doctor-lawyer-engineer collaboration) where some reasoning steps might remain private while others can be safely disclosed. As tasks proceed, each node in the federated DCG continuously reports progress or partial results back to the federation manager (FM).

[0218] The FM tracks which partial results are being used, where they're shared, and whether any new constraints have appeared (e.g., updated security policies). If a new constraint emerges—say a privacy policy changes—the FM can instruct the DCG orchestrator to inject new masking or encryption nodes mid-execution, ensuring compliance going forward. When the FM decides to alter an existing pipeline, it can pause relevant tasks or sub-tasks, modify the compute graph nodes (e.g., add an encryption node, reroute outputs to a different data store), and resume tasks with updated constraints or transformations. This ensures tasks can adapt on the fly without needing to tear down the entire pipeline. In the physical topology, nodes represent machines, devices, or entire data centers, while edges represent physical interconnects (fiber links, local networks, etc.). The federation must keep track of real-world constraints: bandwidth, latency, physical location (e.g., to comply with data residency laws). In the logical topology, nodes can represent "logical units of computation" rather than hardware—like a microservice that performs encryption, an AI model that performs classification, etc. Edges reflect the permission or capability to call one service from another (like an internal microservice call behind a firewall). The compute graph

used by the DCG is effectively a data-flow graph: each transformation node receives input streams, applies transformations, and outputs downstream. Special nodes for partial results can direct outputs to ephemeral storage or to aggregator services. The deontic overlay adds various constraints or "attributes" on each node or edge, including regulatory constraints ("Node must comply with HIPAA," "Edge requires encryption"), organizational constraints ("This pipeline is restricted to Team A's eyes only"), and obligations & prohibitions (e.g., "must store logs for at least 7 days" "Must not share chain-of-thought with unapproved external nodes").

[0219] Consider a practical example: a multi-organization collaboration on a medical AI system where different institutions share partial models or chain-of-thought but must keep patient data private. The physical topology consists of three data centers in different regions, where the pipeline must consider which region is allowed to handle PII or which region is cost-optimal for GPU usage. The logical topology comprises a secure overlay network for each partner's microservices, with some microservices only accessible via zero-trust gateways. The data-flow includes multiple sub-tasks: (a) read anonymized data from Hospital A, (b) combine with partial chain-of-thought from a remote aggregator, (c) produce refined model parameters. The deontic overlay enforces constraints such as "Hospital A's data must never be stored outside Region X" and "Chain-of-thought can only be shared with nodes that have 'medical staff' clearance." The federation manager sees that the aggregator node is a "trusted persona," so partial chain-of-thought is approved. However, the aggregator might need to pass the results to a second node—the overlay enforces a rule: "Stop or mask the chain-of-thought before it hits Node B unless Node B has 'clearance level 2' or higher." Mid-execution, a new regulation might arrive restricting certain data movements across state lines. The federation manager instructs the compute graph to insert an encryption node (or partial re-route) so that only aggregated results, not raw data, are shipped to a node in a different state. This approach provides fine-grained control over collaboration by encoding security and privacy constraints in the deontic overlay, ensuring no unapproved chain-of-thought or partial result is leaked. It enables dynamic compliance where changes in security posture or regulation can be integrated instantly, with the federated DCG reconfiguring the data-flow in real time. The system enables efficient chain-of-thought sharing where agents with the right clearances see the full chain-of-thought while others might receive redacted transformations or only final outputs. It provides scalability and robustness, allowing the system to run large, distributed computations across heterogeneous nodes while maintaining explicit control and monitoring from the federation manager. Combining the six example graph topologies as elements—physical, logical, control flow, process-flow, data-flow, and deontic—into the federated DCG resource aware orchestration model ensures end-to-end compliance, security, and adaptivity. This approach goes beyond mere static provisioning by enabling real-time insertion of special nodes, dynamic re-routing, and selective chain-of-thought sharing in alignment with each organization's requirements.

[0220] ALTO primarily focuses on streaming partial outputs from large language model (LLM) stages to subsequent pipeline stages (instead of waiting for a full generation), and aggregation-aware routing and distributed scheduling to ensure partial outputs from the same request flow to the same instance (when needed), while balancing load across multiple replicas. This is a strong approach to optimize throughput and reduce latency for "compound AI pipelines." However, ALTO mostly deals with single-organization pipeline orchestration of LLM-based tasks, ignoring deeper security, compliance, or spatio-temporal constraints that might arise in real-world multi-organization or multi-agent scenarios. The system similarly streams partial outputs (akin to ALTO), but also introduces federated DCG with multiple, semi-autonomous DCGs that share tasks across organizational or geographic boundaries. The implementation allows for deontic overlays for real-time constraints on data usage, chain-of-thought sharing, spatio-temporal regulations, and agent-specific policies. This enables dynamic graph modification with the ability to insert specialized nodes or entire subgraphs mid-execution if constraints or data patterns change. The system supports multi-agent collaboration where different agents—some with restricted vantage points or different compliance rules—cooperate across pipeline stages while preserving privacy or economic constraints.

[0221] A scenario demonstrating the enhanced capabilities involves distributed federated DCG pipelines with real-time security constraints. Consider a pipeline that includes partial LLM outputs from Node A (healthcare domain) which must be masked or anonymized before sending to Node B (a finance partner). While ALTO's streaming would let Node B get partial tokens as soon as they're emitted, a federated DCG can insert an on-the-fly redaction node if a new policy disallows personal data from crossing an organizational boundary. The pipeline is updated mid-run, so partial tokens that might contain PII are sanitized or withheld based on deontic rules. ALTO does not natively handle mid-execution policy injection or the dynamic insertion of secure nodes to enforce partial chain-of-thought constraints. The Federation Manager herein coordinates multi-party tasks, ensuring each DCG node respects local regulations or role-based constraints. While ALTO typically uses a single centralized runtime for scheduling partial outputs among stage instances, the federation manager functions as an ALTO-like router plus a deontic logic engine. For instance, if partial output tokens suddenly reference regulated content (e.g., a patient's prescription data), the manager can re-route or forcibly mask these tokens. This real-time deontic enforcement surpasses ALTO's basic "aggregation-aware routing," because we also integrate privacy or ethical rules that forbid certain data from traveling beyond certain nodes, or that require cryptographic transformations mid-stream. While ALTO streams tokens from one model stage to the next with aggregation ensuring continuity, the system supports partial or "filtered" Chain-of-Thought (CoT) handoffs in multi-agent or multi-step LLM scenarios. This includes full CoT to an internal trusted agent, redacted CoT for external or less-trusted collaborators, and no CoT if the policy states "agent must not see reasoning steps, only final summary." In many real-time tasks (disaster response, location-based services, medical interventions), the spatio-temporal dimension drastically changes which partial results are valid or sharable. While ALTO primarily focuses on pipeline throughput, ignoring geospatial or time-based constraints, the system might store each partial chunk of text with a time stamp and location dimension. A rule might say "After T+15 minutes, all partial states must be purged," or "If the agent is physically outside Region X, don't forward certain tokens."

Consider a complex "chatbot verification+location-based compliance" pipeline as an illustrative example. Stage 1 (LLM Chat) streams user question tokens. Stage 2 (Claim Extraction+Deontic Rule Check) processes claims where some may reveal sensitive medical info that must be masked for certain sub-stages. Stage 3 (Search Query Generation) generates streamed queries where each partial search query might embed regulated terms that cannot cross a national border. Stage 4 (Search+Re-rank) operates similar to ALTO's BM25 or colBERT stage, but includes a "geo-check node" that discards or transforms partial queries referencing restricted data.

[0222] This implementation surpasses ALTO because while we do all the partial streaming and concurrency that ALTO does, gaining throughput and low-latency benefits, this also enables a federated manager to detect if the user is in a region that does not permit certain cross-border data transmissions or sharing—modifying the pipeline mid-execution to route search queries through a local node or anonymize them for remote nodes in addition to or in lieu of canonical federated model and data set exchange or learning or similar (e.g. gossip-based, vertically or horizontally federated, or cross-silo federated).

[0223] In some embodiments, the system may leverage an optional approach similar to DroidSpeak—a technique that reuses partial layer outputs (e.g., KV-caches) across multiple fine-tuned Large Language Models (LLMs) derived from a common foundation model—to enhance efficiency in multi-agent or multi-model workflows. When combined with streaming-based orchestration (e.g., -like intermediate result streaming), the invention can dynamically route partial outputs from one or more specialized LLMs to subsequent nodes or sub-pipelines in the federated environment, all while enforcing deontic constraints (e.g., policy checks on how partial chain-of-thought or KV-caches can be shared). Context-sharing across fine-tuned LLMs: in multi-agent pipelines, multiple fine-tuned LLMs (e.g., "Baseline agent," "Debugging agent," "Validation agent," etc.) often consume overlapping or identical contexts (e.g., shared conversation histories, code snippet corpora, or knowledge bases). Recomputing embeddings and key-value (KV) caches for each LLM on the same input can waste both compute and memory. To address this, some embodiments optionally implement a mechanism akin to DroidSpeak. One LLM's partial layer outputs (particularly the lower-level KV caches or embeddings that are minimally impacted by domain-specific fine-tuning) are shared with a second LLM in the same foundation family. The second LLM selectively recomputes only the more "critical" layers that diverge under fine-tuning—thereby reducing the full prefill overhead while preserving high accuracy. In parallel with partial KV-cache reuse, the invention supports real-time streaming of partial results—such as partial token outputs, partial summaries, or incremental embeddings. Instead of waiting for a full generation to complete, the system forwards partial tokens (or partial claims) to subsequent pipeline nodes. Dynamic resource coordination: with the federation manager's coordination, these partial streams can be routed to the next stage of computation (e.g., a specialized "Validation agent" or "Robotics planner agent"). If a circuit breaker triggers due to a deontic violation, the system can immediately halt or mask subsequent partial tokens or KV-caches. Policy checks for shared caches: Each time an LLM attempts to reuse KV caches from a sibling or baseline model, the system consults the deontic reasoning subsystem to confirm it is permissible to share context embeddings at that granularity. For instance, certain personal data or code segments might be restricted to higher-clearance models, preventing naive KV reuse. Obligations and permissions: if an obligation states that "Agent A must not process data from Domain B unless flagged by Expert," the system dynamically withholds partial layer outputs or triggers a "DroidSpeak Recompute Path" for the receiving model. This ensures compliance with domain-level constraints even when reusing intermediate states. The optional DroidSpeak embodiment identifies "critical layers" that are more sensitive to fine-tuning changes; only those layers are recomputed, while the rest of the KV caches can be reused from the baseline model's output. The invention may also combine small-scale summarization with lazy expansions, so only partial subgraphs or chunked expansions are reloaded, further reducing overhead. In other scenarios, an LLM can revert to full prefill if the partial reuse is disallowed by a new or emergent policy constraint. Since partial tokens arrive continuously (as in-like systems), the invention can detect policy violations or high risk-scores mid-generation. Upon detection, the pipeline injects a circuit-breaker node, halting further partial token flows. If the chain-of-thought or KV-cache in question is flagged, the system may revert to recomputing from an earlier "safe checkpoint," ignoring the invalid partial layer outputs or imposing anonymization measures. This ensures real-time compliance while leveraging the benefits of partial caching. Latency and throughput gains: By skipping full context re-processing, the system can reduce the prefill latency for each specialized agent by up to 2-3×(depending on how many layers are reused). In high-throughput or multi-tenant environments, this translates to significantly improved system concurrency. Memory footprint: fewer duplicate caches are stored across nodes, thus cutting memory overhead. The invention optionally includes caching compression or ephemeral offloading to further optimize memory usage while meeting deontic constraints (for instance, private data might require ephemeral in-memory storage with short time-to-live). Common foundation model: DroidSpeak-based KV-cache sharing is most effective when the specialized LLMs share a single underlying foundation. However, the system may also support partial cross-model alignment for certain near-related architectures, subject to performance disclaimers and policy constraints. Selective activation: administrators or the federation manager can disable or limit these KV reuse strategies if a new policy arises (e.g., new privacy regulations). In this scenario, the system reverts to a more standard "each LLM does a full prefill" approach to ensure compliance. By coupling DroidSpeak-inspired KV-cache sharing with intermediate result streaming in a federated multi-agent environment, the invention provides both computational efficiency (through partial recomputes) and policy-aware real-time control (through on-the-fly circuit breakers and deontic checks). This flexibility allows enterprises to scale multi-model workflows without incurring exponential overhead, preserving the higher accuracy of specialized LLMs and preventing unauthorized disclosure of sensitive partial embeddings or chain-of-thought data.

[0224] According to a preferred embodiment, the system may leverage an optional approach similar to DroidSpeak—a technique that reuses partial layer outputs (e.g., KV-caches) across multiple fine-tuned Large Language

Models (LLMs) derived from a common foundation model—to enhance efficiency in multi-agent or multi-model workflows. When combined with streaming-based orchestration, the invention can dynamically route partial outputs from one or more specialized LLMs to subsequent nodes or sub-pipelines in the federated environment, while enforcing deontic constraints (e.g., policy checks on how partial chain-of-thought or KV-caches can be shared). In multi-agent pipelines, multiple fine-tuned LLMs (e.g., "Baseline Agent," "Debugging Agent," "Validation Agent") often consume overlapping or identical contexts (e.g., shared conversation histories, code snippet corpora, or knowledge bases). Recomputing embeddings and key-value (KV) caches for each LLM on the same input can waste both compute and memory. To address this, some embodiments optionally implement a mechanism akin to DroidSpeak. One LLM's partial layer outputs (particularly the lower-level KV caches or embeddings that are minimally impacted by domain-specific fine-tuning) are shared with a second LLM in the same foundation family. The second LLM selectively recomputes only the more "critical" layers that diverge under fine-tuning, thereby reducing the full prefill overhead while preserving high accuracy.

[0225] In parallel with partial KV-cache reuse, the invention supports real-time streaming of partial results—such as partial token outputs, partial summaries, or incremental embeddings. Instead of waiting for a full generation to complete, the system forwards partial tokens (or partial claims) to subsequent pipeline nodes. Through the federation manager's coordination, these partial streams can be routed to the next stage of computation (e.g., a specialized "Validation Agent" or "Robotics Planner Agent"). If a circuit breaker triggers due to a deontic violation, the system can immediately halt or mask subsequent partial tokens or KV-caches.

[0226] Each time an LLM attempts to reuse KV caches from a sibling or baseline model, the system consults the deontic reasoning subsystem to confirm it is permissible to share context embeddings at that granularity. For instance, certain personal data or code segments might be restricted to higher-clearance models, preventing naive KV reuse. If an obligation states that "Agent A must not process data from Domain B unless flagged by Expert," the system dynamically withholds partial layer outputs or triggers a "DroidSpeak Recompute Path" for the receiving model. This ensures compliance with domain-level constraints even when reusing intermediate states.

[0227] The optional DroidSpeak embodiment identifies "critical layers" that are more sensitive to fine-tuning changes; only those layers are recomputed, while the rest of the KV caches can be reused from the baseline model's output. The invention may also combine small-scale summarization with lazy expansions, so only partial subgraphs or chunked expansions are reloaded, further reducing overhead. In other scenarios, an LLM can revert to full prefill if the partial reuse is disallowed by a new or emergent policy constraint. Since partial tokens arrive continuously, this embodiment can detect policy violations or high-risk scores mid-generation. Upon detection, the pipeline injects a circuit-breaker node, halting further partial token flows. If the chain-of-thought or KV-cache in question is flagged, the system may revert to recomputing from an earlier "safe checkpoint," ignoring the invalid partial layer outputs or imposing anonymization measures. This ensures real-time compliance while leveraging the benefits of partial caching.

[0228] By skipping full context re-processing, the system can reduce the prefill latency for each specialized agent by up to 2-3× (depending on how many layers are reused). In high-throughput or multi-tenant environments, this translates to significantly improved system concurrency. Fewer duplicate caches are stored across nodes, thus cutting memory overhead. The embodiment optionally includes caching compression or ephemeral offloading to further optimize memory usage while meeting deontic constraints (for instance, private data might require ephemeral in-memory storage with short time-to-live).

[0229] DroidSpeak-based KV-cache sharing is most effective when the specialized LLMs share a single underlying foundation. However, the system may also support partial cross-model alignment for certain near-related architectures, subject to performance disclaimers and policy constraints. Administrators or the federation manager can disable or limit these KV reuse strategies if a new policy arises (e.g., new privacy regulations). In this scenario, the system reverts to a more standard "each LLM does a full prefill" approach to ensure compliance.

[0230] By coupling DroidSpeak-inspired KV-cache sharing with intermediate result streaming in a federated multi-agent environment, the embodiment provides both computational efficiency (through partial recomputes) and policy-aware real-time control (through on-the-fly circuit breakers and deontic checks). This flexibility allows enterprises to scale multi-model workflows without incurring exponential overhead, preserving the higher accuracy of specialized LLMs and preventing unauthorized disclosure of sensitive partial embeddings or chain-of-thought data.

[0231] In summary, while ALTO is a pioneering system for partial-output streaming within a single pipeline, this goes further in multi-domain federation by orchestrating partial-output streaming across multiple autonomous DCGs with potentially conflicting or dynamic policies. The implementation for deontic overlays for real-time constraints, enforcing obligations, prohibitions, or permissions in mid-stream. This addresses compliance or ethical rules not just for final outputs, but also for ephemeral intermediate states. The hierarchical and role-based chain-of-thought allows some pipeline stages to see full CoT while others see only summarized or redacted partial tokens. The system ensures correct partial aggregation for valid agents, while restricting or masking partial data for unapproved agents. It is incorporated with spatio-temporal and economic dimensions by integrating location-based or time-based rules into the pipeline, thus gating partial token flows based on dynamic conditions (time limits, distance constraints, cost thresholds). Through dynamic graph modification, the pipeline can be updated during execution if new constraints appear or if the data changes. This might include injecting encryption or masking nodes, or splitting partial outputs among multiple new sub-pipelines, something ALTO does not fully address. By merging ALTO-like partial streaming and load balancing with advanced federated DCG capabilities—real-time deontic overlays, secure chain-of-thought transformations, multi-agent role-based rules, and spatio-temporal constraints—this is a truly flexible system for orchestrating partial results in complex, multi-party AI pipelines. This approach retains ALTO's performance benefits (low latency, high throughput from streaming partial outputs) but extends it with crucial

compliance, security, and context-awareness features that ALTO alone does not support—particularly in federated or multi-domain contexts where dynamic rules or spatio-temporal overlays are central to each pipeline stage's intermediate results.

[0232] FIG. **15** is a block diagram illustrating an exemplary system architecture for a distributed generative artificial intelligence reasoning and action platform **1520**, according to an embodiment. According to the embodiment, platform **1520** is configured as a cloud-based computing platform comprising various system or sub-system components configured to provide functionality directed to the execution of neuro-symbolic generative AI reasoning and action. Exemplary platform systems can include a distributed computational graph (DCG) computing system **1521**, a curation computing system **1522**, a marketplace computing system **1523**, and a context computing system **1524**. In some embodiments, systems **1521-1524** may each be implemented as standalone software applications or as a services/microservices architecture which can be deployed (via platform **1520**) to perform a specific task or functionality. In such an arrangement, services can communicate with each other over an appropriate network using lightweight protocols such as HTTP, gRPC, or message queues. This allows for asynchronous and decoupled communication between services. Services may be scaled independently based on demand, which allows for better resource utilization and improved performance. Services may be deployed using containerization technologies such as Docker and orchestrated using container orchestration platforms like Kubernetes. This allows for easier deployment and management of services.

[0233] The distributed generative AI reasoning and action platform **1520** can enable a more flexible approach to incorporating machine learning (ML) models into the future of the Internet and software applications; all facilitated by a DCG architecture capable of dynamically selecting, creating, and incorporating trained models with external data sources and marketplaces for data and algorithms.

[0234] According to the embodiment, DCG computing system **1521** provides orchestration of complex, user-defined workflows built upon a declarative framework which can allow an enterprise user **1510** to construct such workflows using modular components which can be arranged to suit the use case of the enterprise user. As a simple example, an enterprise user **1510** can create a workflow such that platform **1520** can extract, transform, and load enterprise-specific data to be used as contextual data for creating and training a ML or AI model. The DCG functionality can be extended such that an enterprise user can create a complex workflow directed to the creation, deployment, and ongoing refinement of a trained model (e.g., LLM). For example, in some embodiments, an enterprise user **1510** can select an algorithm from which to create the trained model, and what type of data and from what source they wish to use as training data. DCG computing system **1521** can take this information and automatically create the workflow, with all the requisite data pipelines, to enable the retrieval of the appropriate data from the appropriate data sources, the processing/preprocessing of the obtained data to be used as inputs into the selected algorithm(s), the training loop to iteratively train the selected algorithms including model validation and testing steps, deploying the trained model, and finally continuously refining the model over time to improve performance.

[0235] A context computing system **1524** is present and configured to receive, retrieve, or otherwise obtain a plurality of context data from various sources including, but not limited to, enterprise users **1510**, marketplaces **1530***a-n*, third-party sources **1550**, and other data sources **1540***a-n*. Context computing system **1524** may be configured to store obtained contextual data in a data store. For example, context data obtained from various enterprise endpoints **1510***a-n* of a first enterprise may be stored separately from the context data obtained from the endpoints of a second enterprise. In some embodiments, context data may be aggregated from multiple enterprises within the same industry and stored as a single corpus of contextual data. In such embodiments, contextual data may be transformed prior to processing and storage so as to protect any potential private information or enterprise-specific secret knowledge that the enterprise does not wish to share.

[0236] A curation computing system **1522** is present and configured to provide curated (or not) responses from a trained model (e.g., LLM) to received user queries. A curated response may indicate that it has been filtered, such as to remove personal identifying information or to remove extraneous information from the response, or it may indicate that the response has been augmented with additional context or information relevant to the user. In some embodiments, multiple trained models (e.g., LLMs) may each produce a response to a given prompt, which may include additional contextual data/elements, and a curation step may include selecting a single response of the multiple responses to send to a user, or the curation may involve curating the multiple responses into a single response. The curation of a response may be based on rules or policies that can set an individual user level, an enterprise level, or at a department level for enterprises with multiple departments (e.g., sales, marketing, research, product development, etc.).

[0237] According to the embodiment, an enterprise user **1510** may refer to a business organization or company. An enterprise may wish to incorporate a trained ML model into their business processes. An enterprise may comprise a plurality of enterprise endpoints **1510***a-n* which can include, but are not limited to, mobile devices, workstations, laptops, personal computers, servers, switches, routers, industrial equipment, gateways, smart wearables, Internet-of-Things (IoT) devices, sensors, and/or the like. An enterprise may engage with platform **1520** to create a trained model to integrate with its business processes via one or more enterprise endpoints. To facilitate the creation of purpose-built, trained models, enterprise user **1510** can provide a plurality of enterprise knowledge **1511** which can be leveraged to build enterprise specific (or even specific to certain departments within the enterprise) ML/AI models. Enterprise knowledge **1511** may refer to documents or other information important for the operation and success of an enterprise. Data from internal systems and databases, such as customer relationship management (CRM) systems, enterprise resource planning (ERP) systems, rules and policies databases, and transactional databases, can provide information about the operational context of an enterprise. For example, product knowledge, market knowledge, industry trends, regulatory knowledge, business processes, customer knowledge, technology knowledge, financial knowledge, organi-

zation knowledge, and risk management knowledge may be included in enterprise knowledge base **1511**.

[0238] According to the embodiment, platform **1520** is configured to retrieve, receive, or otherwise obtain a plurality of data from various sources. A plurality of marketplaces **1530***a-n* may be present and configured to provide centralized repositories for data, algorithms, and expert judgment, which can be purchased, sold, or traded on an open marketplace. External data sourced from various marketplaces **1530***a-n* can be used as a training data source for creating trained models for a particular use case. A marketplace computing system **1523** is present and configured to develop and integrate various marketplaces **1530***a-n*. Marketplace computing system **1523** can provide functionality directed to the registration of experts or entities. An expert may be someone who has a deep understanding and knowledge of a specific industry, including its trends, challenges, technologies, regulations, and best practices. Industry experts often have many years of experience working in the industry and have developed a reputation for their expertise and insights. Examples of experts can include, but are not limited to, consultants, analysts, researchers, academics, or professionals working in the industry. In some embodiments, experts and/or entities can register with platform **1520** so that they may become verified experts/entities. In such an embodiment, an expert/entity profile may be created which can provide information about expert judgment, scored data and algorithms, and comparisons/statistics about the expert's/entity's scores and judgment with respect to other expert/entities. Marketplace computing system **1523** may further provide functionality directed to the management of the various marketplaces and the data/algorithms provided therein.

[0239] According to some embodiments, platform **1520** can communicate with and obtain data from various third-party services **1550**. For example, third-party services can include LLM services such as APIs and LLM hosting platforms, which platform **1520** can interface with to obtain algorithms or models to use as starting points for training a neuro-symbolic generative AI reasoning and action model to be deployed at the enterprise or individual level. As another example, social media platforms can provide data about trends, events, and public sentiment, which can be useful for understanding the social context of a situation. Exemplary data sources **1540***a-n* can include, but are not limited to, sensors, web data, environmental data, and survey and interviews.

[0240] FIG. **16** is a block diagram illustrating an exemplary aspect of a distributed generative AI reasoning and action platform incorporating various additional contextual data. According to the aspect, a plurality of contextual data from various data sources may be integrated into platform **1520**. A simple exemplary directed computational graph **1600** is illustrated within the cloud and utilizing the plurality of contextual data to create and train a model. Various marketplaces **1530***a-n* are shown which can provide contextual data to platform **1520** including an expert judgment marketplace **1660** and a model and retrieval augmented generation (RAG) marketplace **1620**. According to the aspect, DCG **1600** orchestrates model (and model weight) selection **1604**, including multi-model usage in series or parallel (i.e., feed output of one model into another, or compare and choose outputs across multiple models), based on multiple data sources (both trained and external), input from crowdsourced expert judgment, training or tuning data set corpora, and RAG libraries.

[0241] Expert judgment will become increasingly important in the world of proprietary or otherwise blackbox ML or AI models where hallucinations and training data quality may produce misleading or otherwise incorrect results. The expert judgment marketplace **1660** provides a way for experts **1630** to weigh-in on the correctness of data whether that is training data or model output, and can be facilitated by a browser extension **1640**, for example, to score things like data sources during their daily "trip around web". This trip report scoring **1650** concept allows experts to score data sources. In an implementation, a browser extension **1640** is developed with an accuracy score input where the user can rank a news article they are reading as they consume it. Expert judgment marketplace **1660** allows for consumers to pick and rank "experts" based on how well their judgment helps or hinders their overall consumption of model output. For example, experts that routinely highly rank data sources, like news sites, that are known to spread false information should likewise be less trusted over time compared to their peers, and any models trained on that data similarly less trusted. Ultimately a database **1670** of data sources and schemas scored by algorithms or experts could be used as input into the DCG **1600** for more accurate and real-time inference based on ongoing rating of preferred data set and data format combinations (e.g. the same data might be purchased in unstructured, structured, schematized, normalized, or semantified formats) which may introduce different types of bias or impacts on performance, results, or processing costs.

[0242] Accordingly, a RAG marketplace **1620** may be implemented to further refine model output. RAG input information may be included as additional context which can be supplied to a GenAI model in addition to a prompt (engineered, or otherwise). Marketplace **1620** may be global or local to a given device or system since they might cache resources locally for on demand purchase or execution. This is especially important where companies may want to sell access to their proprietary dataset through the form of input to a RAG. For example, a medical research company may have valuable information they could sell to other institutions in the form of the output of their dataset fed to a RAG to augment related research without specifically providing access to the raw training data. Retrieval-augmented generation is a framework that combines elements of retrieval-based and generative models to improve the performance of natural language processing tasks. In RAG, a retriever component is used to select relevant information from a large corpus, and a generator component is used to produce a final output based on both the retrieved information and the input query. RAG marketplace **1620** may be scored by experts for accuracy and effectiveness across domains. The owner of these datasets may also further protect raw data access while also increasing retrieval accuracy by developing a set of models trained for each AI model that can allow retrieved data to be projected into a latent space capable of being fed into a specific AI model. This approach may leverage techniques such as autoencoders, Variational Autoencoders (VAEs), or adversarial training to create lower-dimensional representations that capture essential features while obscuring raw data. These latent representations can be tailored to specific AI tasks, providing just enough information for the model to perform effectively without

exposing unnecessary details. This latent representation of data would prevent the user from reversing it back to raw data, while also being designed to efficiently inform the selected AI model. Furthermore, by applying dimensionality reduction techniques like t-SNE or UMAP, and incorporating differential privacy methods, in some cases the system can offer formal privacy guarantees while maintaining data utility. This strategy allows for a balance between protecting sensitive information and enabling high-performance AI applications, as each latent space can be optimized for its intended use case while minimizing the risk of data reconstruction.

[0243] According to the aspect, a user experience curation engine **1610** is needed that is able to curate output whether that is in the form of filtering out sensitive data or simply customizing results in a way the user prefers (which may be based on user-/entity-defined rules or policies). A user can submit a query to experience curation engine **1610** which can send the query to the DCG trained model to obtain a response. Experience curation **1610** may then process the received response to curate it (or not) to meet the preferences of the user.

[0244] As illustrated, DCG **1600** shows a simple example of a directed computational graph which can be used to create a complex workflow to create and train an MI/AI model (e.g., variations of or standard transformer architecture). A shown, the DCG comprises multiple sources of information for training the selected models(s) including multiple data sources **1601***a-n* which may or may not be scored by experts, expert judgment **1602**, and one or more RAGs **1603** which may be obtained from RAG marketplace **1620** or may be obtained directly from enterprise knowledge. DCG may have access to stored models or variants thereof. In the illustration, LLAMA (Learned Layer-wise Attention Metric for Transformers), PALM (Permuted Adaptive Lateral Modulation), and HYENA (Hyperbolic Encoder for Efficient Attention) are shown as possible examples of the types of models which can be selected by the DCG to create and train a GenAI model. Furthermore, the "model parameters" and mathematical techniques or assumptions used in each model may be cataloged and included in a model-specific template which may be stored in cloud-based storage on platform **1520**. In some embodiments, platform **1520** may store a hierarchical representation of transformer models (e.g., as a graph), which may represent a lineage of the evolution of transformer models. In an implementation, model selection or exploration involves selections based on the evolutionary tree of one or more model types and use said tree (e.g., graph) for selections in heuristic search for best algorithm/data combinations, licensing costs/explorations, etc. It should be appreciated that certain aspects of the invention may be tailored based on what kind of mathematical approach underpins a specific model.

[0245] In operation, DCG **1600** obtains the various contextual data from the connected data sources, creates training, validation, and test datasets from the obtained data, and uses the various datasets to train, validate, and test the model as it undergoes a model training loop that iteratively trains the model to generate responses based on the plurality of contextual data.

[0246] The multi-layered Knowledge Graph (KG) implements several node types including Entity Nodes, which represent real-world objects (e.g., users, devices, medical records) or abstract concepts (e.g., data types, tasks), and Deontic Nodes, which represent individual constraints "ObligationNode," "PermissionNode," "ProhibitionNode." Each node stores metadata such as scope, priority, or assigned domain (e.g., medical, financial). Edge labels in the Knowledge Graph include "AppliesTo" which links a deontic node to an entity or data type node, "Overrides or ConflictsWith" which encodes hierarchical or precedence relationships between constraints, and "Temporal Validity" which tracks time windows or conditions under which a constraint is active (e.g., "valid from January 2025 to December 2025"). Each node or edge can include a version identifier and a timestamp, with old versions remaining in the KG for audit purposes but deactivated, while new versions become active upon insertion. The Rules Database or "Deontic Store" implements relational-like tables including a "Constraints" table with columns for constraint_id, constraint_type (obligation/permission/prohibition), description, scope, priority, effective_date, expiration_date, etc., and a "Constraint_Overrides" table to store conflict resolution data detailing which constraints override which, with justification and update tracking. The system maintains an index or specialized B-tree on (scope, priority, effective_date) to quickly look up relevant constraints in real time, and another index for (constraint_type, domain_tag) to group constraints by domain. The Deontic "Schema" or Ontology includes constraint categories like "Privacy," "Safety," "Legal," "Ethical," each of which might be a sub-ontology specifying standard keys or relationships. The Deontic Reasoning Subsystem (DRS) includes an inference engine that compiles each new or updated constraint into an internal logic representation or specialized "constraint-check" function. This inference engine runs whenever tasks or data transitions occur—e.g., mid-task if an agent requests a new action. The system can register callbacks or "listeners" on key events (e.g., "agent X tries to access data Y,") "machine node tries to run transformation Z"). When triggered, these events cause the DRS to fetch relevant constraints from the knowledge graph or rules DB. Each multi-step task or pipeline phase can define "compliance checkpoints"—the system halts or pauses the task at these points and invokes the DRS to confirm no constraints are being violated. Each agent's workflow is represented as a state machine, where transitions between states only occur if the DRS "green-lights" them. If a constraint fails, the state machine goes to a "blocked" or "escalation required" state. For conflict resolution, if two constraints clash (e.g., "Data must be disclosed in emergencies" vs. "Data must never be disclosed without consent"), the DRS references an Overrides or Precedence relationship. If the system cannot automatically decide which constraint to follow (equal priority?), it triggers a "human-in-the-loop override" or "multi-agent debate," requiring explicit resolution. Once resolved, the DRS logs the override or new precedence rule back into the knowledge graph or rules DB, so future tasks see that resolution without re-litigating the same conflict. The constraint lifecycle management includes states such as Draft/Pending (a new constraint might first appear in "draft" mode, visible to administrators but not enforced), Active (once approved or once the effective_date is reached), and Retired/Archived (after the expiration date or if an updated version replaces it). For hot swapping rules in a distributed system, new constraint versions can be "migrated" into the knowledge graph or rules DB using an atomic transaction.

Agents see the new constraint as soon as it commits. Agents that cache constraints must check if the constraints have changed mid-task. If so, they must re-validate. In heavily regulated domains (e.g., finance, healthcare), new rules or clarifications appear often.

[0247] The system implements a "continuous integration pipeline" that automatically ingests external regulatory updates, merges them into the knowledge graph, and triggers an internal test suite to ensure no contradictory rules break the system. A typical runtime enforcement flow for on-the-fly access checks involves multiple steps: First, an AI agent requests to read a piece of personal data. The system calls the DRS, passing (agent_id, data_id, action=read, context=medical). The DRS queries the rules DB for constraints relevant to (medical data, read operations, agent's role). If a prohibition is found (e.g., "HIPAA: must not access personal data unless authorized"), the system checks if the agent has the required "permission node." If there's a mismatch, the DRS denies the request and the agent receives a "forbidden" response. Otherwise, the DRS logs the compliance rationale and returns an "OK." In cases where conflicts are detected mid-process, consider a situation where a pipeline is halfway through analyzing user data for a recommendation when a new regulation takes effect stating "All data older than 5 years is restricted." The knowledge graph updates, adding a new ProhibitionNode with effective_date=now( ). When the pipeline hits a compliance checkpoint and sees that some data it uses is 7 years old, it must either discard or anonymize that old data. Each agent (human or machine) is assigned a "compliance level" or "role." The DRS references a "Role-to-Constraint" mapping. For instance, doctors might have certain obligations or permissions that nurses don't. If an agent's role changes or if that agent obtains new certifications, the system updates the agent's record. Next time the DRS checks constraints, the agent's expanded permissions are recognized. For performance optimization in high-throughput systems, caching certain frequent lookups can speed up real-time enforcement. For example, "Is user #123 allowed to do X with data Y?" might be a frequent question. The system uses short-lifetime caches with invalidation triggers if constraints change. In large-scale deployments, constraints are partitioned by domain or region. The DRS can do a local shard lookup to reduce overhead. Multiple subtasks might run concurrent checks. By hooking into the pipeline orchestrator, we can evaluate each subtask's constraints in parallel, only blocking tasks that conflict. Every time a constraint is enforced, the system logs timestamp, constraint_id, agent_id, action_attempted, result (allowed/denied), and rationale. This log is stored for compliance or later analysis. The system provides an explanation mechanism that can detail why a certain constraint triggered a denial or requirement, such as "this action is disallowed because it tries to modify patient data without consent under HIPAA rule #12." The system can run in "test mode" or "simulation mode" where updated rules are tested on recorded workloads to see if tasks break or yield undesired rejections.

[0248] FIG. **17** is a diagram illustrating incorporating symbolic reasoning in support of LLM-based generative AI, according to an aspect of a neuro-symbolic generative AI reasoning and action platform. According to the aspect, platform **1520** can incorporate symbolic reasoning and in-context learning to create and train off the shelf models (e.g., an LLM foundational model or narrow model) through clever prompting and conditioning on private data or very situation specific "contextual" data. Platform **1520** can obtain contextual data **1701** and preprocess the data for storage. Contextual data **1701** may refer to data obtained from marketplaces **1530***a-n*, third-party services **1550**, and enterprise knowledge **1511**, as well as other types of contextual data that may be obtained from other sources. DCG **1730** is responsible for orchestrating the entire process and can create data pipelines **1710** as needed to facilitate the ingestion of contextual data **1701**. Contextual data can include text documents, PDFs, and even structure formats like CSV (comma-separated values) or SQL tables or other common generic data formats like OWL or RDF or domain specific content such as the Financial Industry Business Ontology (FIBO) or Open Graph of Information Technology (OGIT). This stage involves storing private data (e.g., context data) to be retrieved later.

[0249] Typically, the context data **1701** is broken into chunks, passed through and embedding model **315**, then stored in a specialized database called a vector database **1720**. Embedding models are a class of models used in many tasks such as natural language processing (NLP) to convert words, phrases, or documents into numerical representations (embeddings) that capture similarity which often correlates semantic meaning. Exemplary embedding models can include, but are not limited to, text-embedding-ada-002 model (i.e., OpenAI API), bidirectional encoder representations form transformers, Word2Vec, FastText, transformer-based models, and/or the like. The vector database **1715** is responsible for efficiently storing, comparing, and retrieving a large plurality of embeddings (i.e., vectors). Vector database **1715** may be any suitable vector database system known to those with skill in the art including, but not limited to, open source systems like Pinecone, Weaviate, Vespa, and Qdrant. According to the embodiment, embedding model **1715** may also receive a user query from experience curation **1740** and vectorize it where it may be stored in vector database **1720**. This provides another useful datapoint to provide deeper context when comparing received queries against stored query embeddings.

[0250] In one embodiment, the AI agent decision platform is configured with a domain-specific ontology that encodes both standard operating procedures (SOPs) and regulatory texts relevant to the target application domain—e.g., medical, legal, or financial. This ontology is integrated into the platform's knowledge graph network, enabling a systematic approach to updating and enforcing obligations, permissions, and prohibitions as new regulations and guidelines emerge.

[0251] A specialized ontology builder component analyzes domain sources, such as statutory codes, clinical guidelines, and organizational SOPs, then maps each regulatory clause or best practice to corresponding deontic predicates in the knowledge graph. For example, in a healthcare setting, regulatory clauses on patient confidentiality become explicit prohibitions (e.g., "must not disclose identifiable patient data to unauthorized agents"), while mandatory infection control policies become obligations (e.g., "must perform sterilization procedures before every surgery"). Each concept within the domain ontology (e.g., "Patient Privacy," "Prescription Drug Guidelines," "Data Sharing Agreement") is tagged with semantic labels that reflect not only hierarchical and relational information (e.g.,

parent-child, cause-effect, domain-specific classification) but also the deontic status of each relevant rule.

[0252] The knowledge graph thus contains edges labeled with "required," "allowed," or "forbidden," linking specific procedures or tasks to the relevant norms and regulations. This labeling is synchronized with the knowledge orchestrator, ensuring that any domain-specific update instantly propagates through the rest of the system. The platform includes an ontology update manager that monitors regulatory bulletins or organizational policy announcements. When a new policy text arrives—such as an amendment to a medical code or a novel legal statute—the ontology update manager parses the text, extracts the relevant sections, and dynamically adjusts the ontology structure (e.g., inserting new nodes, deprecating old regulations). For instance, if new privacy protocols mandate anonymization thresholds, the manager creates or updates a rule node labeled as "new privacy restriction," automatically re-linking any procedures that involve patient-data sharing to this updated prohibition or condition in the knowledge graph. The deontic reasoning subsystem consults this enriched ontology whenever an agent (human or machine) proposes an action. If the proposed action conflicts with a prohibition or lacks compliance with an obligation indicated in the updated ontology, the subsystem flags the violation, triggering a conflict resolution process or requiring escalation to a human agent for override decisions. This ensures live detection of regulatory non-compliance, even if the rule was only recently added or modified in the ontology. During execution of tasks, agents continuously reference the domain-specific ontology for guidance on permissible operations. If an agent is uncertain about a new rule or experiences a conflict, it can retrieve the relevant sections of the ontology (e.g., the text excerpt mapping to a specific code article) and provide a human-readable explanation—e.g., "This procedure must not proceed without explicit patient consent as per newly introduced privacy regulation Code Section 5.2." Explainability is thus directly tied to the ontology's labeling of deontic constraints and is automatically updated to reflect the latest regulatory changes. By storing and updating domain-specific ontological elements in real time within the knowledge graph, the system ensures that all agent decisions remain aligned with evolving regulatory requirements.

[0253] A user may submit a query **1703** to an experience curation engine **1740** which starts the prompt construction and retrieval process. The query is sent to DCG **1730** which can send the query to various components such as prompt engineering **1725** and embedding model **1715**. Embedding model **1715** receives the query and vectorizes it and stores it in vector database **1720**. The vector database **1720** can send contextual data (via vectors) to DCG **1730** and to various APIs/plugins **1735**. Prompt engineering **1725** can receive prompts **1702** from developers to train the model on. These can include some sample outputs such as in few-shot prompting. The addition of prompts via prompt engineering **1725** is designed to ground model responses in some source of truth and provide external context the model wasn't trained on. Other examples of prompt engineering that may be implemented in various embodiments include, but are not limited to, chain-of-thought, self-consistency, generated knowledge, tree of thoughts, directional stimulus, and/or the like.

[0254] During a prompt execution process, experience curation **1740** can send a user query to DCG **1730** which can orchestrate the retrieval of context and a response. Using its declarative roots, DCG **1730** can abstract away many of the details of prompt chaining; interfacing with external APIs **1735** (including determining when an API call is needed); retrieving contextual data from vector databases **1730**; and maintaining memory across multiple LLM calls. The DCG output may be a prompt, or series of prompts, to submit to a language model via LLM services **1760** (which may be potentially prompt tuned). In turn, the LLM processes the prompts, contextual data, and user query to generate a contextually aware response which can be sent to experience curation **1740** where the response may be curated, or not, and returned to the user as output **1704**.

[0255] FIG. **18** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph **1800**, according to one aspect. According to the aspect, a DCG **1800** may comprise a pipeline orchestrator **1801** that may be used to perform a variety of data transformation functions on data within a processing pipeline, and may be used with a messaging system **1810** that enables communication with any number of various services and protocols, relaying messages and translating them as needed into protocol-specific API system calls for interoperability with external systems (rather than requiring a particular protocol or service to be integrated into a DCG **1800**).

[0256] Pipeline orchestrator **1801** may spawn a plurality of child pipeline clusters **1802***a-b*, which may be used as dedicated workers for streamlining parallel processing. In some arrangements, an entire data processing pipeline may be passed to a child cluster **1802***a* for handling, rather than individual processing tasks, enabling each child cluster **1802***a-b* to handle an entire data pipeline in a dedicated fashion to maintain isolated processing of different pipelines using different cluster nodes **1802***a-b*. Pipeline orchestrator **1801** may provide a software API for starting, stopping, submitting, or saving pipelines. When a pipeline is started, pipeline orchestrator **1801** may send the pipeline information to an available worker node **1802***a-b*, for example using AKKA™ clustering. For each pipeline initialized by pipeline orchestrator **1801**, a reporting object with status information may be maintained. Streaming activities may report the last time an event was processed, and the number of events processed. Batch activities may report status messages as they occur. Pipeline orchestrator **1801** may perform batch caching using, for example, an IGFS™ caching filesystem. This allows activities **1812***a-d* within a pipeline **1802***a-b* to pass data contexts to one another, with any necessary parameter configurations.

[0257] A pipeline manager **1811***a-b* may be spawned for every new running pipeline, and may be used to send activity, status, lifecycle, and event count information to the pipeline orchestrator **1801**. Within a particular pipeline, a plurality of activity actors **1812***a-d* may be created by a pipeline manager **1811***a-b* to handle individual tasks, and provide output to data services **1822***a-d*. Data models used in a given pipeline may be determined by the specific pipeline and activities, as directed by a pipeline manager **1811***a-b*. Each pipeline manager **1811***a-b* controls and directs the operation of any activity actors **1812***a-d* spawned by it. A pipeline process may need to coordinate streaming data between tasks. For this, a pipeline manager **1811***a-b* may spawn service connectors to dynamically create TCP connections between activity instances **1812***a-d*. Data con-

texts may be maintained for each individual activity **1812***a-d*, and may be cached for provision to other activities **1812***a-d* as needed. A data context defines how an activity accesses information, and an activity **1812***a-d* may process data or simply forward it to a next step. Forwarding data between pipeline steps may route data through a streaming context or batch context.

[0258] A client service cluster **1830** may operate a plurality of service actors **1821***a-d* to serve the requests of activity actors **1812***a-d*, ideally maintaining enough service actors **1821***a-d* to support each activity per the service type. These may also be arranged within service clusters **1820***a-d*, in a manner similar to the logical organization of activity actors **1812***a-d* within clusters **1802***a-b* in a data pipeline. A logging service **1830** may be used to log and sample DCG requests and messages during operation while notification service **1840** may be used to receive alerts and other notifications during operation (for example to alert on errors, which may then be diagnosed by reviewing records from logging service **1830**), and by being connected externally to messaging system **1810**, logging and notification services can be added, removed, or modified during operation without impacting DCG **1800**. A plurality of DCG protocols **1850***a-b* may be used to provide structured messaging between a DCG **1800** and messaging system **1810**, or to enable messaging system **1810** to distribute DCG messages across service clusters **1820***a-d* as shown. A service protocol **1860** may be used to define service interactions so that a DCG **1800** may be modified without impacting service implementations. In this manner it can be appreciated that the overall structure of a system using an actor driven DCG **1800** operates in a modular fashion, enabling modification and substitution of various components without impacting other operations or requiring additional reconfiguration.

[0259] FIG. **19** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph **1800**, according to one aspect. According to the aspect, a variant messaging arrangement may utilize messaging system **1810** as a messaging broker using a streaming protocol **1910**, transmitting and receiving messages immediately using messaging system **1810** as a message broker to bridge communication between service actors **1821***a-b* as needed. Alternately, individual services **1822***a-b* may communicate directly in a batch context **1920**, using a data context service **1930** as a broker to batch-process and relay messages between services **1822***a-b*.

[0260] FIG. **20** is a diagram of an exemplary architecture for a system for rapid predictive analysis of very large data sets using an actor-driven distributed computational graph **1800**, according to one aspect. According to the aspect, a variant messaging arrangement may utilize a service connector **2010** as a central message broker between a plurality of service actors **1821***a-b*, bridging messages in a streaming context **1910** while a data context service **1930** continues to provide direct peer-to-peer messaging between individual services **1822***a-b* in a batch context **1920**.

[0261] It should be appreciated that various combinations and arrangements of the system variants described above may be possible, for example using one particular messaging arrangement for one data pipeline directed by a pipeline manager **1811***a-b*, while another pipeline may utilize a different messaging arrangement (or may not utilize messaging at all). In this manner, a single DCG **1800** and pipeline orchestrator **1801** may operate individual pipelines in the manner that is most suited to their particular needs, with dynamic arrangements being made possible through design modularity as described above in FIG. **18**.

[0262] FIG. **21** is a block diagram of an architecture for a transformation pipeline within a system for predictive analysis of very large data sets using distributed computational graph computing system **2100**. According to the aspect, streaming input from a data filter software module, **2105** serves as input to the first transformation node **2110** of the transformation pipeline. Each transformation node's function **2110**, **2120**, **2130**, **2140**, **2150** is performed on input data stream and transformed output message **2115**, **2125**, **2135**, **2145**, **2155**, **2165** is sent to the next step. In this aspect, transformation node **2** **2120** has a second input stream **2160**. The specific source of this input is inconsequential to the operation of the invention and could be another transformation pipeline software module, a data store, human interaction, physical sensors, monitoring equipment for other electronic systems or a stream from the internet as from a crowdsourcing campaign, just to name a few possibilities **2160**. For example, a first input stream may comprise enterprise knowledge and a second input stream may comprise RAG data from a RAG marketplace. Functional integration of a second input stream into one transformation node requires the two input stream events be serialized. The illustrated system can perform this serialization using a decomposable transformation software module. While transformation nodes are described according to various aspects as uniform shape, such uniformity is used for presentation simplicity and clarity and does not reflect necessary operational similarity between transformations within the pipeline. It should be appreciated that one knowledgeable in the field will realize that certain transformations in a pipeline may be entirely self-contained; certain transformations may involve direct human interaction, such as selection via dial or dials, positioning of switch or switches, or parameters set on control display, all of which may change during analysis; other transformations may require external aggregation or correlation services or may rely on remote procedure calls to synchronous or asynchronous analysis engines as might occur in simulations among a plurality of other possibilities. For example, engines may be singletons (composed of a single activity or transformation). Furthermore, leveraging the architecture in this way allows for versioning and functional decomposition (i.e. embedding entire saved workflows as single nodes in other workflows). Further according to the aspect, individual transformation nodes in one pipeline may represent function of another transformation pipeline. It should be appreciated that the node length of transformation pipelines depicted in no way confines the transformation pipelines employed by the invention to an arbitrary maximum length **2110**, **2120**, **2130**, **2140**, **2150**, as, being distributed, the number of transformations would be limited by the resources made available to each implementation of the invention. It should be further appreciated that there need be no limits on transform pipeline length. Output of the last transformation node and by extension, the transform pipeline, **2150** may be sent back to a messaging software module for pre-decided action.

Detailed Description of Exemplary Aspects

[0263] FIG. **10** is a flow diagram illustrating an exemplary method for an AI agent decision platform with deontic

reasoning that can be configured with edge devices. In a first step **1000**, the system receives tasks at a network of specialized agents, where each agent maintains domain-specific knowledge and operates under deontic constraints such as but not limited to obligations, permissions, and prohibitions stored in knowledge graphs. As detailed in the disclosure, these agents employ sophisticated domain-specific embeddings and relation-aware modeling to maintain their specialized knowledge.

[0264] In a step **1010**, the system forwards tasks to a centralized distributed graph-based system, utilizing the DCG architecture described in the disclosure. This process may leverage quantum-inspired token operations to efficiently distribute and track task information across the network. In various embodiments, the term "quantum-inspired token operations" is not intended to imply the use of physical quantum computing hardware or quantum entanglement. Rather, these operations refer to a geometric or wave-interference-inspired mechanism for combining and evaluating vector embeddings within a high-dimensional token space, drawing conceptual parallels from quantum superposition without requiring actual quantum gates or qubits. For example, an agent's partial "states" (e.g., constraints, risk indicators, or subtask results) may be treated like waveforms whose amplitudes and phases can constructively or destructively interfere, thus providing a rapid, token-level means of detecting consensus or conflict among multiple agents. Although the system architecture also permits optional integration with genuine quantum computing resources—where quantum hardware might perform specialized optimizations or advanced search routines—this hybrid capability is neither a requirement nor the default assumption. Instead, "quantum-inspired token operations" broadly covers purely classical, geometry-based methods that borrow wave-like principles to enhance how information is merged or compared at scale. For example, an agent's partial "states" (e.g., constraints, risk indicators, or subtask results) may be treated like waveforms whose amplitudes and phases can constructively or destructively interfere, thus providing a rapid, token-level means of detecting consensus or conflict among multiple agents. This geometric interpretation allows efficient parallel evaluation of multiple agent perspectives by encoding them as vectors in a high-dimensional space where similarity and conflicts can be detected through mathematical operations analogous to wave interference patterns.

[0265] In a step **1020**, the system analyzes tasks using the deontic reasoning subsystem to evaluate compliance with stored constraints. As described in the disclosure, this analysis employs neuro-symbolic reasoning techniques to combine neural network capabilities with formal logical verification.

[0266] In a step **1030**, the system generates compute graphs representing subtasks using the sophisticated graph neural network capabilities detailed in the disclosure. These graphs capture both operational requirements and ethical constraints in a mathematically rigorous format.

[0267] In a step **1040**, the system decomposes compliant tasks into subtasks based on agent expertise and constraints. This decomposition process employs the collegiate-style knowledge exchange framework described in the disclosure, enabling intelligent task distribution while maintaining ethical boundaries.

[0268] In a step **1050**, the system generates compute graphs for subtasks with their associated deontic constraints. As detailed in the disclosure, these graphs incorporate both operational logic and ethical requirements using advanced information theoretic principles.

[0269] In a step **1060**, the system distributes compute graphs to appropriate agents based on expertise and permissions. This distribution leverages the sophisticated resource management and load balancing capabilities described in the disclosure, ensuring optimal task allocation while maintaining ethical compliance.

[0270] In a step **1070**, the system executes subtasks while maintaining compliance with stored deontic constraints. This execution process employs the observer-aware processing capabilities and dynamic feedback mechanisms detailed in the disclosure, ensuring continuous ethical compliance throughout task execution.

[0271] FIG. **11** is a flow diagram illustrating an exemplary method for updating knowledge graphs based on incoming sensor and contextual information. In a first step **1100**, the system generates knowledge graphs by processing sensor data and contextual information using sophisticated domain-specific embeddings and relation-aware modeling techniques. For example, in a medical context, this might involve processing patient vital signs, medical history, and current hospital conditions into a structured knowledge representation that preserves complex relationships between symptoms, diagnoses, and treatments.

[0272] In a step **1110**, the system incorporates deontic rules including obligations, permissions, and prohibitions into the knowledge graph. This integration leverages the disclosed relation-aware modeling techniques and quantum-inspired token operations to maintain logical consistency while representing complex ethical constraints. For instance, medical privacy regulations would be encoded alongside treatment protocols, ensuring that all subsequent decisions respect both operational and ethical requirements.

[0273] In a step **1120**, the system trains an LLM using the combined sensor data, contextual information, and deontic rules to identify and fill gaps in the knowledge graphs. As disclosed, this process employs sophisticated information theoretic principles to measure knowledge transfer effectiveness and optimize learning across domains. The training process specifically leverages the collegiate-style knowledge exchange framework, enabling structured debate between different expert agents to identify and address knowledge gaps.

[0274] In a step **1130**, the system generates actions based on the updated knowledge graphs. This process utilizes the disclosed neuro-symbolic reasoning framework, combining neural network capabilities with symbolic logic to ensure actions are both effective and ethically sound. The action generation process employs the system's advanced observer-aware processing capabilities to maintain appropriate perspective and context.

[0275] In a step **1140**, the system executes actions by sending them to appropriate tailored agents. As detailed in the disclosure, this involves sophisticated resource-ethical tradeoff management and dynamic responsibility allocation based on real-time cognitive load assessments and task priorities.

[0276] In a step **1150**, the system uses LLMs to generate human-readable explanations for executed actions and gather user feedback. This step leverages the disclosed

explainable AI capabilities, ensuring transparency while maintaining the system's sophisticated reasoning capabilities. The explanation generation process specifically considers the observer frame and temporal context to provide appropriate and meaningful explanations.

[0277] In a step **1160**, the system updates both the knowledge graphs and LLM based on user feedback, implementing the continuous learning mechanisms described in the disclosure. This update process employs causal entropy measurements and mutual information transfer components to optimize knowledge integration while maintaining system coherence and ethical compliance.

[0278] FIG. **12** is a flow diagram illustrating an exemplary method for integrating deontic constraints into UCT planning. In a first step **1200**, the system initializes a UCT tree with deontic constraints, incorporating the quantum-inspired token space operations disclosed in the system. This initialization includes mapping obligations, permissions, and prohibitions into the tree structure using advanced geometric transformations in token space.

[0279] In a step **1210**, the system selects parameters based on ethical severity, utilizing the disclosed information theoretic principles for measuring impact. For example, in a medical context, parameters might be adjusted based on the potential harm of violations, with life-critical decisions receiving higher ethical severity weights.

[0280] In a step **1220**, the system generates ethics and compliance scores by comparing potential actions against deontic constraints. As described in the disclosure, this process employs sophisticated neuro-symbolic reasoning to evaluate actions across multiple ethical dimensions, using both neural network pattern recognition and symbolic logic validation.

[0281] In a step **1230**, the system aggregates and normalizes ethics and compliance scores across all applicable rules. The disclosure details how this aggregation uses advanced information theoretic metrics and causal entropy measurements to ensure consistent evaluation across different types of constraints and contexts.

[0282] In a step **1240**, the system calculates risk-adjusted values for each action using the sophisticated risk assessment frameworks detailed in the disclosure. This includes consideration of both immediate risks and potential longer-term implications, weighted by the system's confidence in its predictions.

[0283] In a step **1250**, the system adjusts each score based on risk adjustment, implementing the dynamic risk-awareness mechanisms described in the disclosure. This adjustment process considers both ethical severity and operational uncertainty, using quantum-inspired operations to maintain computational efficiency.

[0284] In a step **1260**, the system executes actions by sending them to tailored agents, leveraging the sophisticated agent network and resource management capabilities detailed in the disclosure. The execution process maintains awareness of both ethical constraints and operational requirements throughout implementation.

[0285] FIG. **13** is a flow diagram illustrating an exemplary method an AI agent decision platform with deontic reasoning with task optimization and monitoring. In a first step **1300**, the system monitors and balances task load between agents using the advanced cognitive load estimation techniques detailed in the disclosure. This includes tracking both explicit metrics (like processing load and response times) and implicit indicators (such as stress levels for human agents) through sophisticated biometric and performance monitoring.

[0286] In a step **1310**, the system incorporates cost functions for both human and machine agents into load balancing calculations. As described in the disclosure, these cost functions consider multiple factors including cognitive load, resource utilization, and task-specific expertise levels. For example, in a medical setting, the cost function might consider a surgeon's fatigue level alongside a robotic assistant's computational resource availability.

[0287] In a step **1320**, the system optimizes task allocation based on the cost function using the quantum-inspired token space operations detailed in the disclosure. This optimization process leverages sophisticated information theoretic principles to balance immediate task requirements with longer-term resource management considerations.

[0288] In a step **1330**, the system distributes tasks to either human or machine agents based on the optimization results. As described in the disclosure, this distribution process implements the collegiate-style knowledge exchange framework, ensuring that tasks are assigned to agents with appropriate expertise levels while maintaining overall system efficiency.

[0289] In a step **1340**, the system monitors task progress for each agent in the network using the sophisticated observer-aware processing capabilities detailed in the disclosure. This monitoring includes real-time assessment of task execution quality, resource utilization, and compliance with deontic constraints, enabling dynamic adjustment of task assignments as conditions change.

[0290] In these steps, the federated DCG features specialized human-in-the-loop (HITL) mechanisms for transformations that require professional oversight or explicit ethical confirmation before tasks can proceed. For example, a medical scenario might mandate direct physician approval for any procedure that could risk patient safety (duty of care), while a legal scenario might require lawyer review before disclosing privileged documents (professional responsibility). The system organizes computational tasks into transformation pipelines, were each transformation node processes or routes incoming data. These transformation nodes can incorporate deontic checks that detect when data or process steps cross specified ethical or regulatory thresholds—e.g., "reveals sensitive patient info," "modifies a legal document," or "requests advanced medical procedures." A deontic logic subsystem (DLS) encodes duties, obligations, and prohibitions, such as "A physician must confirm any high-risk treatment plan" or "A lawyer must review privileged records before final disclosure." The DLS operates in concert with a threshold manager that monitors the pipeline's current transformation context. Once a transformation step triggers a "sensitive" or "high-risk" classification, the threshold manager flags the pipeline to enter a HITL override state. Each pipeline can specify a role-based or domain-specific human agent (e.g., a licensed physician, an attorney) who is designated to intercept tasks. In medical contexts, if a transformation node attempts to schedule an invasive procedure without verifying the patient's condition, the pipeline routes the pending request to the on-call medical agent for explicit approval. In legal contexts, if the pipeline processes documents containing privileged attorney-client communications, the designated lawyer must confirm that disclosure is permissible under professional standards. Each

pipeline node is defined in the federated DCG domain-specific language (DSL) with metadata fields describing (i) the nature of the data processed, (ii) associated deontic constraints, and (iii) an optional HITL flag. Example DSL snippet: TransformNode {name: "HighRiskMedicalDecision" requiredRole: "LicensedPhysician" deonticConstraints: ["Obligation: Must confirm invasive procedure with doctor"] HITL: true} This snippet ensures the node's logic will automatically route the transformation request to a physician if triggered.

[0291] Deontic constraints could be specified hierarchically. A deontic constraint is a moral rule or principle that prohibits certain types of actions even when doing so would prevent more instances of that same action from occurring. Key features of deontic constraints include: prohibition of actions (such as killing innocent people, breaking promises, or stealing); non-consequentialist nature (certain actions are wrong regardless of their outcomes); absoluteness (do not allow for exceptions based on consequences).

[0292] When a pipeline execution flow reaches a node with a HITL: true flag, the system consults the deontic logic subsystem to validate that no prohibition or duty is being violated. If the transformation's operation or data classification surpasses a "safe threshold" (e.g., due to risk severity or legal constraints), the pipeline transitions into a pending state. The node compiles a context packet (metadata, partial logs, relevant data snapshots) and sends it-via secure channels in the federated DCG—to the appropriate human agent's interface.

[0293] For example, in a medical scenario, the context packet might include patient vitals, recommended drug dosages, or prior medical notes. The system obfuscates or filters out nonessential data if additional privacy constraints apply. The human agent (physician, lawyer, etc.) reviews the context packet using a human-in-the-loop override interface. This specialized interface can display relevant logs, highlight flagged constraints, and allow the agent to either approve, modify, or reject the pending transformation. The agent's decision automatically updates the node's state in the federated DCG: Approve (the pipeline continues execution, possibly with updated parameters), Modify (the pipeline reconfigures the transformation logic), or Reject (the pipeline halts and flags an override event in the logs). All hits to the HITL override mechanism generate audit trails, including timestamps, the agent's identity, the reason for override, and any changes to the transformation. These logs become part of the knowledge graph or a linked compliance database, enabling future verification, regulatory audits, and continuous system improvement. In the duty-of-care and professional responsibility integration, ethical principles are encoded in the knowledge graph. In a medical domain, duty-of-care is represented as an obligation: "Doctors must ensure patient safety above operational efficiency." In a legal domain, a prohibition might be: "Attorneys must not disclose privileged client data to outside parties without explicit client consent." Each professional agent node is associated with credentials and a role that aligns with the domain's rules—physicians must have verified medical credentials, lawyers must hold a valid bar membership. This association is stored in the federated DCG's resource registry or agent directory. A pipeline cannot proceed with a role-based HITL step if no verified human agent is assigned to that role. If the system detects urgent or emergency contexts (e.g., a critical patient status), an emergency override workflow may automatically notify the highest-priority human agent. This ensures the federated DCG respects duty-of-care obligations by not simply letting a procedure proceed unconfirmed in an emergency scenario. In a medical "invasive procedure" use case example, the system first ingests real-time vitals from sensors for a patient. The "InvasiveProcedurePlan" node sees abnormal vitals that justify an emergent procedure. The node sets a "High Risk" label, and the DLS references knowledge graph obligations stating a doctor must confirm any invasive procedure. A context packet is assembled with the patient's vital trends, proposed procedure details, and fallback therapies. The doctor's user interface displays the reason for override, and the doctor either approves the recommended procedure or modifies the dosage. Upon approval, the transformation node finalizes resource allocation; if rejected, the pipeline halts or transitions to a safer fallback plan.

[0294] The federated DCG uses TLS or analogous encryption to transmit the context packet to the human agent's interface, ensuring HIPAA compliance in medical or attorney-client privilege in legal contexts. The system can specify a maximum time window for agent decisions, after which it may escalate to a secondary human agent or revert to a safe default. Because the federated DCG is federated, multiple replicas of the decision logs may be stored on separate nodes for fault tolerance. If a node is unreachable, the system automatically reroutes the override request to another qualified human agent. The observer agent can track how often HITL overrides occur, feeding analytics back into a continuous improvement cycle.

[0295] This additional embodiment describes a dynamic "deontic circuit breaker" mechanism that goes beyond static human-in-the-loop pipeline steps, enabling real-time insertion of circuit breakers into the federated Distributed Computational based on ongoing deontic risk scoring and analysis. This approach also interfaces directly with resource-allocation and load-balancing subsystems to ensure that high-risk or ethically complex operations are automatically halted, rerouted, or escalated to human review when certain triggers are met. While standard federated DCG pipelines can embed human-in-the-loop transformations declaratively at design time (e.g., "HITL: true"), some real-world situations demand adaptive interventions. This embodiment addresses how the system computes a running "deontic risk score" (e.g., "ethical hazard index," "compliance risk rating") throughout pipeline execution. If the score spikes above a threshold, deontic circuit breakers (DCBs) are dynamically injected or activated in mid-execution to block or detour tasks, possibly requiring human authorization or alternative resource allocations.

[0296] The Deontic Risk Scoring Subsystem (DRS) continuously monitors each transformation node's operations and data attributes. This includes data classification (e.g., "private health info"), agent domain constraints, or partial analyses of upcoming tasks. Based on knowledge graph references, regulatory constraints, or machine learning risk models, the DRS computes an ongoing risk score. For instance, each new piece of data or partial result might increment the score if it is particularly sensitive or if combined with existing data it creates a privacy or compliance risk. The federated DCG includes live observer processes that tap into partial transformation outputs, scheduling logs, and resource usage. These observers feed real-time context (e.g., CPU load, data type changes, emerging con-

straints from knowledge graphs) to the DRS and also track resource metrics from the resource-ethical optimization engine. This synergy ensures the DRS has a broad, up-to-date view for scoring. When the DRS detects that the risk score surpasses a certain threshold (e.g., "≥80% chance of violating confidentiality obligations"), it can inject a specialized pipeline segment or transformation node, known as a "DCB node." These DCB nodes function as interrupt gates—they halt or suspend further pipeline execution at that point, potentially storing partial outputs in a secure buffer. Injection can also happen at the resource-allocation layer: if a node is about to schedule a task that conflicts with a deontic requirement (e.g., processing personal data in a region with strict privacy laws), the circuit breaker flags that node and denies the resource request, deferring tasks to a safer or more compliant node. Once the circuit breaker is triggered, the system may escalate to a human agent by routing the pipeline context to a designated professional (doctor, lawyer, compliance officer), re-run or reallocate by having the federated DCG's multi-objective optimization attempt to replan tasks on alternative resources or with less sensitive data transformations, or fallback where if no path can comply with the relevant deontic rules, the DCB forcibly terminates the pipeline or defers the entire job until external resolution.

[0297] Resource-Ethical Optimization continually receives updates from the DRS. If the risk score is climbing for a pipeline, the system can preemptively route tasks to "high-trust" nodes with advanced security or re-locate tasks to a different jurisdiction with more favorable regulations. Conversely, if resource constraints become severe and the system wants to schedule tasks in a less-secure environment, the DRS reevaluates the risk score. If it deems the new environment non-compliant or unethical, the circuit breaker triggers. The platform can define a set of risk thresholds that map to different actions (e.g., "medium risk=attempt partial anonymization," "high risk=immediate circuit breaker plus human override"). This balances cost-based scheduling (e.g., CPU/GPU efficiency) with compliance-based constraints, ensuring that no single dimension (performance or compliance) alone dictates final decisions. Each data item or partial result is assigned a "sensitivity level." The DRS aggregates these with relevant contextual factors (jurisdiction, agent role, prior transformations) to produce a real-time score, RiskScore(t). If RiskScore(t)≥DangerThreshold, the pipeline's next step is paused. The DRS signals the orchestrator to insert a DCB node.

[0298] The orchestrator modifies the runtime pipeline in memory, effectively splicing in a "break" step, instructing downstream transformations to hold pending tasks. A newly injected DCB node may spawn a queue or buffer for partial outputs, then either request an override from a human agent, initiate partial re-anonymization or differential privacy transformations to reduce risk, or abort the pipeline or re-route tasks to alternate resources matching the system's constraints. If a human override is granted or additional anonymization steps successfully reduce the risk score, the orchestrator removes or disables the DCB node. The pipeline continues from its paused state with an updated risk context or re-planned resource mapping. Consider an extended use-case example of a "Computation Time federated DCG for Medical Diagnosis." In a long-running computation, the system is running a large-scale distributed analysis of medical imaging to detect anomalies. Mid-analysis, a node detects the presence of extremely sensitive patient data that was not properly anonymized upstream. The DRS calculates a spiking risk score. A DCB node is injected, halting the pipeline mid-imaging analysis, and partial results are quarantined. The system notifies a hospital compliance officer who either instructs the platform to apply a stricter anonymization subroutine or confirms that the data was incorrectly labeled "anonymous." After the officer's override reclassifies the data with correct anonymization or obtains patient consent, the DCB node is disabled, and the pipeline execution resumes. For runtime modification of pipelines, the orchestrator must allow dynamic insertion or removal of nodes. This can be realized by storing pipeline definitions in a mutable graph structure in memory and using standard "topology change" events. To avoid mid-execution race conditions, pipeline modifications happen through an atomic transaction in the federated DCG's pipeline manager, ensuring other nodes see a consistent pipeline state. Each circuit breaker trigger is recorded with a cause, timestamp, and final resolution (e.g., "No override," "Human override #123 granted"). The logs can feed into the knowledge graph for future analysis or compliance reviews. The system can unify standard "human-in-the-loop" steps declared at design time with these dynamic DCB-based escalations. Both can involve the same or different human agent roles, but the DCB approach emerges from ongoing system risk calculations rather than a static pipeline design.

[0299] FIG. **14** is a flow diagram illustrating an exemplary method for integrating specialized knowledge into a knowledge graph and leveraging the platform in a simulated routine surgery. In a first step **1400**, the system initializes a scenario involving unexpected bleeding during routine surgery. As detailed in the disclosure, this initialization includes capturing vital signs, contextual information, and relevant medical history using the system's sophisticated sensor integration and contextual awareness capabilities.

[0300] In a step **1410**, the system projects specialist knowledge into token space using the quantum-inspired geometric operations detailed in the disclosure. This projection includes mapping multiple types of expertise, such as surgical knowledge, anesthesiology expertise, and emergency response protocols, into a high-dimensional representation that preserves semantic relationships and operational constraints.

[0301] In a step **1420**, the system executes a token space debate between various specialist assessments. As described in the disclosure, this debate process leverages the collegiate-style knowledge exchange framework, enabling rapid geometric interactions between different specialist perspectives while maintaining deontic constraints. For example, a trauma specialist's assessment might interact with an anesthesiologist's perspective through rapid token-space operations.

[0302] In a step **1430**, the system determines optimized output based on the token space debate using the sophisticated information theoretic principles detailed in the disclosure. This optimization process considers both immediate medical needs and longer-term implications while maintaining compliance with ethical and procedural requirements.

[0303] In a step **1440**, the system converts the final output to a human-readable format using the advanced explanation generation capabilities described in the disclosure. This conversion process ensures that complex medical decisions

are communicated clearly and effectively to human medical staff while maintaining full transparency about the reasoning process.

[0304] According to various embodiments, the system may implement advanced reasoning and control capabilities through integration of specialized languages and frameworks. These integrations enable sophisticated decision-making while maintaining compliance with deontic constraints across multiple levels of abstraction, from high-level ethical reasoning to low-level robotic control.

[0305] The system initiates a routine surgical scenario step **1400** but must adapt swiftly to unexpected bleeding. Traditionally, we rely on pre-computed knowledge graphs or large vector indexes to retrieve medical best practices, but here we demonstrate how an enhanced LazyGraphRAG can efficiently supply relevant context using an on-demand approach, blending best-first and breadth-first retrieval-without costly up-front summarization of an entire corpus. As previously stated, the system captures the patient's vital signs, medical history, and environmental sensor data to identify urgent anomalies (e.g., "blood pressure dropping, bleeding recognized in the patient's abdomen"). Instead of rummaging through a massive pre-summarized knowledge base, the system queries a lightweight concept graph representing medical knowledge. It only extracts or constructs relevant "concept nodes" on-the-fly (e.g., coagulopathy treatments, rare vascular anomalies, recommended blood transfusion protocols) that match the "unexpected bleeding" query context. The system runs a noun phrase extraction algorithm on the emergent textual data (e.g. triage notes, surgery logs). This extracts domain-specific terms such as "resected hepatic artery," "intraoperative coagulopathy," "massive transfusion protocol." These extracted concepts become part of a small, ephemeral concept graph that references known relationships (e.g. hepatic arteries→coagulopathy risk) stored at a coarse level. No LLM summarization is performed up front. We simply store minimal textual associations (co-occurrence edges, relevant snippet references) in a concept graph. The system recognizes two complementary needs: a local query for immediate next steps (e.g., "Which clamp technique do we use for an arterial bleed in the liver?") and a global query for broader policy or cross-domain knowledge (e.g., "Which hospital-wide transfusion guidelines must be followed?"). The enhanced LazyGraphRAG handles both by iteratively deepening: First, starting with a best-first approach, checking local concept alignments (arterial clamps, sedation impacts). Then, if needed (the system still sees conflicting data or missing info), it can expand to a "breadth-first" pass across additional conceptual "communities" (like blood type, ABO mismatch concerns, or rare clotting disorders). For each subquery (e.g., "arterial clamp best practices?"), the enhanced LazyGraphRAG ranks text chunks from various medical data sources (textbooks, journals, EHR notes). The system uses a small LLM-based "relevance test" to confirm the top k chunks are indeed relevant for the current query. If the system finds enough relevant chunks (or if it hits its relevance test budget-like 20 checks for local queries, 80 for broader queries), it stops searching further communities. If the system identifies a cluster of concepts labeled "transfusion guidelines," it recurses into that subgraph. If repeated checks yield no relevant text, it stops exploring that subgraph. This "iterative deepening" means minimal overhead for unneeded areas (like pediatrics, if the patient is an adult). Once relevant text chunks are confirmed, the system maps them into claim-based groupings (e.g., "Claim A: apply clamp at the proximal arterial tear," "Claim B: administer factor VII if clotting is not stabilized."). The system uses a separate LLM call for subquery-based summarization, thus deferring large summarizations until the final step. This is the "lazy" portion—no full summarization was done prior to the emergency. Surgeons or the AI assisting agent can verify the claims or ask for additional details. If a claim is contradictory or incomplete, the enhanced LazyGraphRAG can do another pass in the concept graph. For example, "Double-check if the patient is on any anti-coagulants." The system triggers a new local subquery to see if the EHR mentions warfarin or novel anticoagulants. Finally, the system selects the top claims to fit the surgical team's context window (say, 4k tokens if using a local LLM on an embedded device). It filters out extraneous details about pediatric guidelines, storing them for reference but not surfacing them in the final summary.

[0306] The integrated knowledge from the lazy retrieval approach is fed into the surgical workflow system. If the system or surgeon finds contradictions or requests more data, a new iteration of enhanced LazyGraphRAG is performed with a larger or more specialized relevance test budget. The advantages over traditional vector or full graph summarization include minimal up-front costs, improved relevance, and scalable complexity. If the system or surgeon finds contradictions or requests more data, a new iteration of enhanced LazyGraphRAG is performed with a larger or more specialized relevance test budget. The advantages over traditional vector or full graph summarization include minimal up-front costs, improved relevance, and scalable complexity. The system can still do "lazy" expansions for textual data, but also references a GeoKG with geometry-based edges. During query time, the retrieval engine merges textual similarity with spatial constraints. Entities and edges become time-stamped or carry time intervals (e.g., "road closed from 8 PM to 6 AM," "patient's medication schedule changes after 2 hours"). Inspired by TKG models like DyMemR, the system chooses which historical facts to retain in an on-demand memory pool. This helps avoid "stale" data or irrelevant time periods. At query time, we only "activate" relevant historical segments—especially crucial in real-time events where recency matters. In complex surgeries or legal disputes, certain constraints hinge on distance or elapsed time.

[0307] For example, "A neighboring county's ambulance can't arrive in under 30 minutes—this affects the immediate next steps" or "A piece of evidence that was only valid for a set time window is no longer permissible." Different agents might interpret deontic constraints differently, especially if they rely on location or time. For example, Agent 1: "We must not share data for a region outside our jurisdiction" versus Agent 2: "We are allowed to share because the patient is physically in Region B." Incorporating geometry and time clarifies when a constraint is triggered or not. Consider a scenario where a patient has an unexpected cardiac event mid brain surgery. The system knows the operating room's location, the specialized cardiologist's location, and approximate distance/time. It can quickly compute if it's feasible to bring that cardiologist in, or if an on-site general approach is mandatory. If the patient's sedation has a 2-hour maximum recommended limit, the knowledge graph could store a time-coded rule that triggers

detection, triage, escalation and alerting logic: "At time T+120 minutes, sedation limit is reached." Deontic logic can forcibly escalate or alter the approach if sedation time is nearing or other context changes. We might have opposing lawyers or confidential medical staff who each maintain a separate sub-graph. Some geometry or timelines are private while others can be shared. For example, a hospital attorney might see all state boundaries and public laws, but not the patient's exact location if it's privileged data. By embedding spatial geometry (topology, direction, distance) and temporal logic (time intervals, dynamic memory) within a knowledge graph—and combining it with an enhanced LazyGraphRAG-like on-demand retrieval—the system achieves location & time-sensitive constraints, dynamic agent roles & partial data sharing, and advanced multi-agent debates. This synergy of spatio-temporal knowledge with lazy retrieval and deontic constraints ensures deeply context-aware, location/time-cognizant, and policy-compliant reasoning. The enhanced LazyGraphRAG merges event- and location-specific data layers in real time, selectively pulling relevant historical or geospatial segments. This spatiotemporal pivot is triggered dynamically by observed cues—e.g., updated sensor data, adjacency in event graphs, or time-window expansions.

[0308] In one embodiment, the system introduces a distinctive retrieval-augmented generation technique referred to herein as the enhanced LazyGraphRAG, which diverges significantly from known or conventional RAG methodologies. Rather than pre-fetching and summarizing large corpora upfront, the enhanced LazyGraphRAG performs on-demand, iterative best-first lookups, dynamically retrieving only those knowledge graph nodes, text segments, or vector embeddings deemed contextually relevant at each partial reasoning step. Tasks are expanded in small, best-first increments only when current evidence indicates additional detail is necessary. By avoiding excessive precomputation, the system reduces overhead and mitigates data bloat. At each mini-expansion, the system evaluates newly uncovered data against obligations, permissions, and prohibitions in the deontic logic subsystem. Any conflict triggers partial redaction, anonymization, or circuit-breaker injection before data is returned to downstream components. Unlike prior chunk-based RAGs, chunking here is guided by real-time rule checks—if constraints disallow certain detail or fine-grained expansions, the system prunes that data path. This ensures that only policy-compliant embeddings are retrieved and surfaced. Collectively, these design elements produce a dynamic, compliance-aware retrieval pipeline enabling users and agents to interact with large knowledge corpora or knowledge graphs without incurring the typical overheads of all-or-nothing expansions. Crucially, the enhanced LazyGraphRAG's incremental chunking and spatiotemporal expansions—accompanied by repeated deontic checks—represent an inventive technique that goes beyond standard retrieval-augmented generation approaches. By allowing context and constraints to shape each retrieval step in real time, this system not only improves retrieval efficiency and context fidelity but also provides a robust mechanism to enforce domain-specific rules and privacy constraints.

[0309] This embodiment builds upon, and remains consistent with, the fundamental concepts of the recently introduced traditional LazyGraphRAG framework, which emphasizes on-demand iterative expansion of knowledge sources without incurring the upfront summarization costs normally required by comprehensive graph-based indexing. While the core traditional LazyGraphRAG method already demonstrates compelling advantages in balancing cost versus answer quality (particularly for global queries and large datasets), an enhanced LazyGraphRAG embodiment goes further in several notable ways: 1. Spatiotemporal integration: in addition to the noun-phrase or concept extraction proposed by the traditional LazyGraphRAG, this approach can dynamically map these extracted concepts onto spatiotemporal knowledge graphs, thereby enabling queries that consider time windows, location-aware contexts, or event sequences. Rather than treating extracted concepts in isolation, an enhanced system links them to event nodes, geospatial references, and time intervals—on demand—so that iterative expansions reflect the evolving temporal or geographical scope of a user's query; 2. Deontic Compliance Checks which utilize a deontic reasoning subsystem integrated at each retrieval iteration. As a traditional LazyGraphRAG would incrementally identify new chunks and potential sub-communities, the system automatically applies real-time checks against stored obligations, permissions, and prohibitions. If a newly surfaced chunk violates relevant constraints—e.g., disclosing forbidden details or exceeding privacy thresholds—the system prunes or redacts that path before exposing the retrieved text to a user or to subsequent pipeline steps. This "compliance-aware chunking" explicitly distinguishes the system from more general LazyGraphRAG workflows that do not account for real-time policy gates; 3. Adaptive Circuit Breakers and Role-Specific Agents: beyond the iterative deepening retrieval logic, the enhanced LazyGraphRAG introduces a mechanism for partial "circuit breaker" insertion, triggered whenever relevant expansions start to exceed defined risk scores or conflict with agent role constraints. For example, if newly discovered content must be restricted to a medical specialist or a higher clearance agent, the pipeline can automatically generate a "circuit breaker" node that halts the default expansions and escalates to a specialized persona. This extension retains the iterative best-first and breadth-first synergy of the traditional LazyGraphRAG but injects explicit human or domain-expert oversight whenever high-risk data is encountered; 4. Lazy Summarization Layers with Hierarchical Claims: while original LazyGraphRAG fully defers LLM summarization until query time, an enhanced version further dynamically layers partial summarizations. When the system identifies highly relevant or repeated text chunks across expansions, it temporarily caches micro-summaries—organized by concept cluster or sub-community—to expedite subsequent expansions in the same session or context. This partial "lazy layering" only occurs if repeated queries and expansions exceed a threshold frequency, ensuring we preserve minimal up-front cost while improving iterative retrieval speed for repeated queries within a session; 5. Hybrid Traditional-Quantum Interface: In optional embodiments, the iterative expansions within the enhanced LazyGraphRAG can call specialized quantum solvers for certain ranking or optimization subtasks. However, this quantum integration is not fundamental to the approach and is distinguished from a "quantum-inspired" concurrency references. Instead, it provides an advanced configuration that leverages hardware-accelerated or approximate quantum algorithms for large-scale concept clustering or multi-constraint re-checking. Overall, these additional capabilities preserve the advantageous cost and scalability profile of the

traditional LazyGraphRAG—namely, avoiding pre-computed entity summaries and deferring broad coverage expansions until necessary—while layering compliance checks, spatiotemporal data integration, circuit breaker triggers, and dynamic summarization. By focusing on real-time policy-enforcement and domain-oriented expansions, an enhanced LazyGraphRAG significantly expands both the types of queries addressable (e.g., spatiotemporal or policy-constrained queries) and the case with which enterprise-grade regulatory or organizational rules can be upheld in an iterative retrieval pipeline.

[0310] Although the enhanced LazyGraphRAG (or partially lazy retrieval) offers substantial advantages—particularly for incremental, on-demand exploration of unstructured data—the system is also capable of recognizing scenarios in which a pre-indexed GraphRAG structure provides unique benefits. In some embodiments, the system merges both strategies, yielding functionality that neither pure "lazy" RAG nor fully "pre-summarized" RAG alone can achieve. Specifically: a fully built "GraphRAG data index," wherein entities, relationships, or community summaries are extracted and curated, can have independent utility beyond question answering. For example, these summaries may be published as enterprise knowledge reports, compliance overviews, or analytical briefs for decision-makers. The system can automatically compile such community-level summaries at intervals (e.g., daily or weekly) to provide a human-readable snapshot of how data is evolving. This functionality transcends the real-time Q&A context, serving broader operational needs (e.g., compliance auditing, domain-specific analytics, and stakeholder reporting). The invention lies in enabling robust static indexing—while still allowing selective deferral of certain expansions to a lazy mechanism for real-time queries. Another inventive aspect arises when an existing entity-level or community-level index is integrated alongside the lazy expansions. The system can leverage those comprehensive summaries in parallel with on-demand retrieval steps. For instance, if a user's query triggers local expansions (as in classic LazyGraphRAG) but also references a global theme (e.g., "What overarching trends appear in [dataset X]?"), the system can short-circuit portions of the lazy expansion by pulling from a precompiled, higher-level "community" summary. This synergy amplifies query efficiency—since partially relevant summaries exist—and also enhances answer quality by ensuring that the system can pivot to structured insights when local expansions prove insufficient. The system is capable of supporting automated bridging between these two retrieval modes, constituting a novel method of fusing top-down and bottom-up expansions within a single RAG environment.

[0311] A further inventive principle involves designing a new style of "GraphRAG data index" explicitly optimized for supporting lazy expansions. Traditional indexing often relies on broad entity or relationship summaries that can be expensive to create and may remain static over time. In contrast, the system contemplates pre-emptive claim and topic extraction at ingestion time, but does so in a more granular, modular fashion—effectively "tagging" or "clustering" content so that lazy expansions can quickly assemble relevant subsets without fully summarizing each node. By incorporating minimal or partial pre-summarization (for example, auto-extracted claims or micro-summaries) and storing them in an index structure intentionally designed for iterative deepening, the system achieves the best of both worlds: fast local expansions (akin to classic LazyGraphRAG); immediate fallback to specialized "claim clusters" or "topic seeds" when the query demands broader context; economical overhead compared to heavy global summarizations that might be wasteful or quickly outdated. Viewed together, these enhancements demonstrate that "laziness" in graph-based RAG is not an all-or-nothing proposition. Rather, the inventive leap is to combine partial, on-demand expansions with carefully curated static elements-thereby yielding comprehensive data vantage points for tasks like global auditing, while also allowing on-demand retrieval for localized queries. This approach addresses a range of real-world usage scenarios spanning from once-off queries in ephemeral contexts to ongoing enterprise analyses where prebuilt knowledge graphs provide additional, non-Q&A benefits. Such a multi-pronged system architecture—merging robust indexing methods with lazy expansion, dynamic constraints enforcement (including deontic policy checks), and optional pre-emptive claim extraction—represents a substantial advance over purely lazy or purely index-based RAG systems. By situating each approach where it is strongest and enabling automatic switching or blending, the invention offers an improved cost-quality tradeoff and a richer set of knowledge services beyond mere question answering.

[0312] FIG. **26** is a flow diagram illustrating an exemplary method for a federated distributed graph-based computing platform. In a step **2600**, the system receives tasks and data from users or external systems. This step initiates the federated computing process, where complex computational tasks are encoded into high-level computational graphs. These graphs represent the overall structure and dependencies of the required computations, and may include additional data such as application-specific information, machine learning models, datasets, or model weightings.

[0313] In a step **2610**, the system analyzes the tasks and generates custom compute graphs for each federated node based on their capabilities and access rights. This involves examining each task to determine its specific requirements, such as computational power, data access needs, and security constraints. The system then creates tailored versions of the original computational graph, modified to fit the specific capabilities and access rights of each federated node. In a step **2620**, the system distributes tasks and corresponding compute graphs to appropriate federated nodes. This involves securely transmitting these custom compute graphs to the respective federated nodes, along with any necessary data or models. This transmission occurs through a structured pipeline, ensuring efficient and secure distribution of tasks across the federation.

[0314] In a step **2630**, tasks are executed within each federated node according to their assigned compute graphs, maintaining privacy and security constraints. The received compute graph is further broken down and distributed among internal components of each federated node. This step enables partial or blind execution, where some federated nodes may process only a portion of the overall computation, with limited visibility into the broader task. In a step **2640**, the system monitors task progress and resource utilization across all federated nodes. As computations progress, each federated node reports back through the pipeline structure. This feedback includes task progress, resource

utilization, and any issues encountered. The system aggregates this information, providing a high-level overview of the system's state.

[0315] In a step **2650**, results from federated nodes are aggregated and processed, ensuring data privacy, security, and required compliance protocols, processes and auditable records (e.g., computational processes, transformations, compute, storage, and transport localities, software versions, SBOMs) are maintained where available. The system pieces together the final output from potentially encrypted or obfuscated results, maintaining the partial blindness of the execution where necessary. In a step **2660**, the system dynamically adjusts compute graphs and task allocations based on real-time feedback and changing conditions within the federation. Based on the aggregated feedback, the system may decide to reallocate tasks or resources. It might modify compute graphs in real-time, reassign tasks to different federated nodes, or adjust resource allocations.

[0316] This process focuses on improving enablement of privacy-preserving data transformations in a federated system, explicitly including differential privacy within the workflow. This example embodiment may be inserted into the specification to more fully enable how raw data is protected across various federation nodes while still supporting system-wide analytics or AI-driven decision-making. The federated distributed graph-based computing platform (FDGCP) includes a privacy-preserving transformation pipeline that applies a combination of data anonymization, encryption, and differential privacy mechanisms before distributing any user-generated data to individual federated nodes. This architecture ensures that no single node within the federation can reconstruct raw or identifiable information, thereby complying with deontic constraints that mandate privacy preservation at each stage of distributed computation. Raw data—e.g., text inputs, medical logs, sensor readings—is first processed locally on each user device or organizational system, generating an obfuscated representation. The local component applies noise injection consistent with local differential privacy principles, such as Count Mean Sketch or Hadamard-based transformations. A per-donation privacy budget (ε) is enforced to limit the frequency and magnitude of user contributions and ensure that repeated submissions cannot be exploited to deduce personal information. Before sending the differentially private representation to any external node, device identifiers, IPs, or unique user tokens are stripped, and all communications occur over an encrypted channel. This ensures that even if intercepted, the data is already privatized and cannot be reverse-engineered to yield raw user information.

[0317] A federation manager (FM) reviews the metadata and the anonymized or differentially private data streams to determine the optimal assignment of computations among available federated nodes. This assignment is guided by constraints in the system's knowledge graphs, which encode deontic requirements, including privacy norms and obligations (e.g., "must not share raw data," "must apply at least ε=2 for medical data"). Based on each node's clearance or capability, the FM routes only the required, already-transformed data subsets (e.g., randomly hashed vector slices with injected noise). Nodes thus never view raw user data and may only see partial anonymized fragments if the system designates additional "blind execution" constraints. Each node (whether an AI agent node, an edge cluster, or a data center) receives the privatized data segments and performs local computations (e.g., statistical counts, machine learning inferences, or partial token-based transformations). To glean global insights—such as trending words, prevalent symptoms, or energy drain patterns—the FDGCP aggregates partial, noise-injected results at a central aggregator or advanced aggregator nodes. Because each node's results remain noisy and identifier-free, the aggregator only reconstructs population-level patterns once large numbers of noisy contributions are averaged. The injected noise statistically cancels out at scale, enabling meaningful analytics while preserving individual privacy. The FDGCP enforces a per-user or per-node privacy budget. Once a user's daily or weekly quota is reached, their device either halts further data submissions or further increases noise in subsequent transmissions, ensuring compliance with the user's opt-in settings. For instance, high-sensitivity data like health record usage may have a lower daily submission limit (e.g., one donation per day, ε=2).

[0318] Each user device or organizational node can display logs (e.g., "DifferentialPrivacy*" files) detailing how many data points were contributed and which transformations were applied. Users may revoke the opt-in at any time, causing future transmissions to be halted or replaced with null data. Obligations such as "apply anonymization if data pertains to personal health info" or "inject at least X amount of noise for identified privacy risks" are encoded in the rules database or knowledge graph. The federation manager checks these constraints before routing data or orchestrating computations. If a node attempts to request raw data or attempts to exceed the permitted privacy budget, the FDGCP rejects the request in real time. Automatic logs record the violation attempt and notify relevant administrators or human agents, ensuring compliance with obligations and prohibitions set forth by regulatory or organizational policies. Once aggregated, the final differentially private statistics—such as trending keyboard suggestions, frequently used medical procedure codes, or popular emojis—are shared with authorized system components or organizational stakeholders without revealing any individual-level data. The FDGCP may monitor error rates or anomalies in aggregated results and adjust the noise parameters accordingly. This dynamic tuning helps balance accuracy with privacy over time, guided by the same deontic constraints that require a minimum standard of user privacy. Through differential privacy integrated with anonymization, encryption, and partial/blind execution, this embodiment ensures the federated system can benefit from aggregated data insights while fully respecting user-level confidentiality. In every step—from local device transformations to multi-node aggregation—robust privacy constraints are automatically enforced, preserving user anonymity and adhering to the platform's deontic mandates.

[0319] FIG. **27** is a flow diagram illustrating an exemplary method for a federated distributed graph-based computing platform that includes a federation manager. In a step **2700**, the system receives task definitions and computational graphs from the central system. This initiates the process of distributed computing, where complex tasks are represented as computational graphs that can be broken down and distributed across the federation. These graphs encapsulate the structure, dependencies, and data requirements of the overall computational task.

[0320] In a step **2710**, the system analyzes and decomposes tasks into subtasks with varying levels of visibility and access requirements. This step involves breaking down the received computational graphs into smaller, manageable components. Each subtask is assigned specific visibility and access levels, enabling the system to implement partial or blind execution strategies. This decomposition allows for fine-grained control over information flow within the federated network. In a step **2720**, the system distributes tailored subtasks and compute graphs to appropriate federated nodes based on their capabilities and clearance levels. This distribution process takes into account the specific attributes of each federated node, including its computational resources, security clearance, and current workload. The system ensures that each node receives only the information and tasks it is authorized to process, maintaining the integrity of the partial blindness approach.

[0321] In a step **2730**, the system monitors real-time execution progress and resource utilization across all federated nodes. This ongoing monitoring process allows the system to track the progress of distributed tasks, assess the performance of individual nodes, and identify any bottlenecks or issues in real-time. The system collects data on task completion rates, resource usage, and any anomalies encountered during execution. In a step **2740**, the system aggregates partially obscured results from federated nodes, maintaining predetermined levels of information isolation. As federated nodes complete their assigned subtasks, they return results that may be intentionally obscured or encrypted to maintain the partial blindness of the execution. The system collects these results, ensuring that the predetermined levels of information isolation are preserved throughout the aggregation process.

[0322] In a step **2750**, the system synthesizes final outputs and provides a high-level summary to the central system, preserving the established information boundaries. This final step involves combining the partially obscured results into a coherent output that addresses the original task requirements. The system generates a high-level summary that encapsulates the results of the distributed computation while carefully maintaining the information boundaries established earlier in the process. This summary is then provided to the central system, completing the federated computation cycle while preserving the security and privacy constraints of the distributed network.

[0323] The system includes an Adaptive Persona Graph—a new subsystem where each agent can switch or blend "personas" dynamically based on real-time user context, legal constraints, or shifting objectives. Rather than having a single, static agent role (e.g., "legal agent," "medical agent"), each agent can morph into specialized micro-personas on demand—like a finance-minimizer role, a safety-checking role, or a patient-privacy role—while continuing to share relevant chain-of-thought data (when permissible) with other agents in the federation. Today's multi-agent or LLM-based systems typically have fixed roles (e.g., a "data scientist agent," a "legal agent"). By allowing real-time persona transformations, the platform could serve many more use cases with fewer "hard-coded" roles, drastically reducing integration overhead and speeding time to market. In heavily regulated industries (healthcare, finance, defense), the persona graph can dynamically spin up more "compliance-heavy" personas whenever a new regulation is triggered or the system encounters sensitive data. Agents become "shape-shifters," pulling micro-personas from a shared knowledge bank (like sub-experts). For instance, in a complex scenario (patient has unexpected allergic reaction mid-surgery), the system can activate "Allergy Specialist Persona" logic on the same agent that was previously just an "Emergency Room Persona." This flexible reconfiguration offers a powerful commercial advantage: fewer overall agents, but more "plug-and-play" domain expansions. Through the persona graph, agents can share just the relevant portion of their chain-of-thought with other newly minted or combined personas, controlled by the deontic reasoning subsystem. This partial or ephemeral chain-of-thought sharing is crucial for human auditors or cross-expert synergy but still adheres to user-defined or legally defined "do not reveal" constraints. We can license "persona modules" or "domain expansions" to enterprise clients. Each module (a new persona) can be downloaded and integrated dynamically, making the platform capable of serving as a more dynamic "one-stop shop" for specialized AI roles. This "marketplace of personas" has clear commercial potential: enterprise customers purchase or rent specialized persona expansions for specific tasks. The system maintains a central Persona Registry—a specialized knowledge structure that describes each persona's constraints, domain knowledge, and gating logic. Nodes in the Persona Graph represent either a base persona or an extension (e.g., "medical-surgical extension," "HIPAA compliance extension"). Edges indicate how they can combine or switch under certain triggers (time-based, event-based, or user-defined). Whenever the system receives new tasks, detects new constraints, or spots an agent overload or context shift, the federation manager references the Persona Graph to see if the agent should remap itself to a new persona set. For example, if the user's query is about advanced cardiology, the system merges the "medical-surgery persona" with the "cardiology extension," effectively forming a specialized persona on-the-fly. Once a persona switch is invoked, the system consults the deontic constraints to see which chain-of-thought fragments from the old persona can be safely handed over to the new persona. Some details might be redacted if they violate domain rules or privacy constraints. Chain-of-Thought Fusion occurs if the new persona can legally or ethically inherit relevant context from prior persona states.

[0324] The multi-agent debate layer uses the persona graph so that each agent with newly combined personas can produce or rebut arguments from different vantage points. If a "risk-averse" persona merges with a "cost-minimizing" persona, the debate module might see a "hybrid stance" that weighs both cost and risk in real time. By storing each persona's clearance or obligations in the knowledge graph, the system ensures that no new persona composition violates mandatory constraints. The system can also integrate short-lived ephemeral "secret persona expansions" for top-secret data. Once the relevant sub-task ends, that persona is archived or "disposed," removing any risk of unauthorized re-use. The Persona Registry is implemented as a specialized data store or extension of the knowledge graph that enumerates each persona's domain, obligations, permissible chain-of-thought scope, and "fusion eligibility" rules. When triggered, the system merges two or more persona nodes into a composite persona node, akin to unifying classes in object-oriented programming, but at runtime, guided by the deontic rules. Each persona can store partial memory or retrieval indexes (embedding-based or knowledge-graph-

based). On persona switch, memory pointers are reassigned or locked based on security levels. Every persona shift is logged with timestamps and rationales, crucial for compliance audits: "At T=12:05, agent #3 switched from persona 'ER-doctor' to persona 'ER-doctor+Cardiology extension' due to detecting arrhythmia data." We could optionally define a marketplace where third parties can develop specialized persona expansions. For instance, a recognized health authority could publish a "Pediatric Care Persona," or a big law firm could publish a "Tax-Law Persona." Enterprises buy or license these expansions, installing them into the platform. The system's federation manager ensures they only function for tasks and data streams that meet relevant constraints. Consider a user scenario: A large medical device manufacturer deploying an advanced multi-agent solution for remote surgeries and real-time compliance checks. Starting with a "General Surgery Persona" controlling an AI-driven robotic arm, when real-time vitals indicate potential heart failure, the system consults the Persona Graph and sees that a "Cardiology Persona Extension" is available from a licensed domain pack. The system merges the "General Surgery Persona"+"Cardiology Persona Extension" into a new "Cardio-Surgery Persona" while maintaining HIPAA compliance. The system verifies the newly formed persona can see the relevant chain-of-thought about bleeding or sedation but must not see certain extraneous personal info. Partial chain-of-thought is transferred, partial is masked.

Exemplary Computing Environment

[0325] FIG. **28** illustrates an exemplary computing environment on which an embodiment described herein may be implemented, in full or in part. This exemplary computing environment describes computer-related components and processes supporting enabling disclosure of computer-implemented embodiments. Inclusion in this exemplary computing environment of well-known processes and computer components, if any, is not a suggestion or admission that any embodiment is no more than an aggregation of such processes or components. Rather, implementation of an embodiment using processes and components described in this exemplary computing environment will involve programming or configuration of such processes and components resulting in a machine specially programmed or configured for such implementation. The exemplary computing environment described herein is only one example of such an environment and other configurations of the components and processes are possible, including other relationships between and among components, and/or absence of some processes or components described. Further, the exemplary computing environment described herein is not intended to suggest any limitation as to the scope of use or functionality of any embodiment implemented, in whole or in part, on components or processes described herein.

[0326] The exemplary computing environment described herein comprises a computing device **10** (further comprising a system bus **11**, one or more processors **20**, a system memory **30**, one or more interfaces **40**, one or more non-volatile data storage devices **50**), external peripherals and accessories **60**, external communication devices **70**, remote computing devices **80**, and cloud-based services **90**.

[0327] System bus **11** couples the various system components, coordinating operation of and data transmission between those various system components. System bus **11** represents one or more of any type or combination of types of wired or wireless bus structures including, but not limited to, memory busses or memory controllers, point-to-point connections, switching fabrics, peripheral busses, accelerated graphics ports, and local busses using any of a variety of bus architectures. By way of example, such architectures include, but are not limited to, Industry Standard Architecture (ISA) busses, Micro Channel Architecture (MCA) busses, Enhanced ISA (EISA) busses, Video Electronics Standards Association (VESA) local busses, a Peripheral Component Interconnects (PCI) busses also known as a Mezzanine busses, or any selection of, or combination of, such busses. Depending on the specific physical implementation, one or more of the processors **20**, system memory **30** and other components of the computing device **10** can be physically co-located or integrated into a single physical component, such as on a single chip. In such a case, some or all of system bus **11** can be electrical pathways within a single chip structure.

[0328] Computing device may further comprise externally-accessible data input and storage devices **12** such as compact disc read-only memory (CD-ROM) drives, digital versatile discs (DVD), or other optical disc storage for reading and/or writing optical discs **62**; magnetic cassettes, magnetic tape, magnetic disk storage, or other magnetic storage devices; or any other medium which can be used to store the desired content and which can be accessed by the computing device **10**. Computing device may further comprise externally-accessible data ports or connections **12** such as serial ports, parallel ports, universal serial bus (USB) ports, and infrared ports and/or transmitter/receivers. Computing device may further comprise hardware for wireless communication with external devices such as IEEE 1394 ("Firewire") interfaces, IEEE 802.11 wireless interfaces, BLUETOOTH® wireless interfaces, and so forth. Such ports and interfaces may be used to connect any number of external peripherals and accessories **60** such as visual displays, monitors, and touch-sensitive screens **61**, USB solid state memory data storage drives (commonly known as "flash drives" or "thumb drives") **63**, printers **64**, pointers and manipulators such as mice **65**, keyboards **66**, and other devices **67** such as joysticks and gaming pads, touchpads, additional displays and monitors, and external hard drives (whether solid state or disc-based), microphones, speakers, cameras, and optical scanners.

[0329] Processors **20** are logic circuitry capable of receiving programming instructions and processing (or executing) those instructions to perform computer operations such as retrieving data, storing data, and performing mathematical calculations. Processors **20** are not limited by the materials from which they are formed or the processing mechanisms employed therein, but are typically comprised of semiconductor materials into which many transistors are formed together into logic gates on a chip (i.e., an integrated circuit or IC). The term processor includes any device capable of receiving and processing instructions including, but not limited to, processors operating on the basis of quantum computing, optical computing, mechanical computing (e.g., using nanotechnology entities to transfer data), and so forth. Depending on configuration, computing device **10** may comprise more than one processor. For example, computing device **10** may comprise one or more central processing units (CPUs) **21**, each of which itself has multiple processors or multiple processing cores, each capable of independently or semi-independently processing programming instructions

based on technologies like complex instruction set computer (CISC) or reduced instruction set computer (RISC). Further, computing device **10** may comprise one or more specialized processors such as a graphics processing unit (GPU) **22** configured to accelerate processing of computer graphics and images via a large array of specialized processing cores arranged in parallel. Further computing device **10** may be comprised of one or more specialized processes such as Intelligent Processing Units, field-programmable gate arrays or application-specific integrated circuits for specific tasks or types of tasks. The term processor may further include: neural processing units (NPUs) or neural computing units optimized for machine learning and artificial intelligence workloads using specialized architectures and data paths; tensor processing units (TPUs) designed to efficiently perform matrix multiplication and convolution operations used heavily in neural networks and deep learning applications; application-specific integrated circuits (ASICs) implementing custom logic for domain-specific tasks; application-specific instruction set processors (ASIPs) with instruction sets tailored for particular applications; field-programmable gate arrays (FPGAs) providing reconfigurable logic fabric that can be customized for specific processing tasks; processors operating on emerging computing paradigms such as quantum computing, optical computing, mechanical computing (e.g., using nanotechnology entities to transfer data), and so forth. Depending on configuration, computing device **10** may comprise one or more of any of the above types of processors in order to efficiently handle a variety of general purpose and specialized computing tasks. The specific processor configuration may be selected based on performance, power, cost, or other design constraints relevant to the intended application of computing device **10**.

[0330] System memory **30** is processor-accessible data storage in the form of volatile and/or nonvolatile memory. System memory **30** may be either or both of two types: non-volatile memory and volatile memory. Non-volatile memory **30***a* is not erased when power to the memory is removed, and includes memory types such as read only memory (ROM), electronically-erasable programmable memory (EEPROM), and rewritable solid state memory (commonly known as "flash memory"). Non-volatile memory **30***a* is typically used for long-term storage of a basic input/output system (BIOS) **31**, containing the basic instructions, typically loaded during computer startup, for transfer of information between components within computing device, or a unified extensible firmware interface (UEFI), which is a modern replacement for BIOS that supports larger hard drives, faster boot times, more security features, and provides native support for graphics and mouse cursors. Non-volatile memory **30***a* may also be used to store firmware comprising a complete operating system **35** and applications **36** for operating computer-controlled devices. The firmware approach is often used for purpose-specific computer-controlled devices such as appliances and Internet-of-Things (IoT) devices where processing power and data storage space is limited. Volatile memory **30***b* is erased when power to the memory is removed and is typically used for short-term storage of data for processing. Volatile memory **30***b* includes memory types such as random-access memory (RAM), and is normally the primary operating memory into which the operating system **35**, applications **36**, program modules **37**, and application data **38** are loaded for execution by processors **20**. Volatile memory **30***b* is generally faster than non-volatile memory **30***a* due to its electrical characteristics and is directly accessible to processors **20** for processing of instructions and data storage and retrieval. Volatile memory **30***b* may comprise one or more smaller cache memories which operate at a higher clock speed and are typically placed on the same IC as the processors to improve performance.

[0331] There are several types of computer memory, each with its own characteristics and use cases. System memory **30** may be configured in one or more of the several types described herein, including high bandwidth memory (HBM) and advanced packaging technologies like chip-on-wafer-on-substrate (CoWoS). Static random access memory (SRAM) provides fast, low-latency memory used for cache memory in processors, but is more expensive and consumes more power compared to dynamic random access memory (DRAM). SRAM retains data as long as power is supplied. DRAM is the main memory in most computer systems and is slower than SRAM but cheaper and more dense. DRAM requires periodic refresh to retain data. NAND flash is a type of non-volatile memory used for storage in solid state drives (SSDs) and mobile devices and provides high density and lower cost per bit compared to DRAM with the trade-off of slower write speeds and limited write endurance. HBM is an emerging memory technology that provides high bandwidth and low power consumption which stacks multiple DRAM dies vertically, connected by through-silicon vias (TSVs). HBM offers much higher bandwidth (up to 1 TB/s) compared to traditional DRAM and may be used in high-performance graphics cards, AI accelerators, and edge computing devices. Advanced packaging and CoWoS are technologies that enable the integration of multiple chips or dies into a single package. CoWoS is a 2.5D packaging technology that interconnects multiple dies side-by-side on a silicon interposer and allows for higher bandwidth, lower latency, and reduced power consumption compared to traditional PCB-based packaging. This technology enables the integration of heterogeneous dies (e.g., CPU, GPU, HBM) in a single package and may be used in high-performance computing, AI accelerators, and edge computing devices.

[0332] Interfaces **40** may include, but are not limited to, storage media interfaces **41**, network interfaces **42**, display interfaces **43**, and input/output interfaces **44**. Storage media interface **41** provides the necessary hardware interface for loading data from non-volatile data storage devices **50** into system memory **30** and storage data from system memory **30** to non-volatile data storage device **50**. Network interface **42** provides the necessary hardware interface for computing device **10** to communicate with remote computing devices **80** and cloud-based services **90** via one or more external communication devices **70**. Display interface **43** allows for connection of displays **61**, monitors, touchscreens, and other visual input/output devices. Display interface **43** may include a graphics card for processing graphics-intensive calculations and for handling demanding display requirements. Typically, a graphics card includes a graphics processing unit (GPU) and video RAM (VRAM) to accelerate display of graphics. In some high-performance computing systems, multiple GPUs may be connected using NVLink bridges, which provide high-bandwidth, low-latency interconnects between GPUs. NVLink bridges enable faster data transfer between GPUs, allowing for more efficient parallel processing and improved performance in applications such as machine learning, scientific simulations, and graphics

rendering. One or more input/output (I/O) interfaces **44** provide the necessary support for communications between computing device **10** and any external peripherals and accessories **60**. For wireless communications, the necessary radio-frequency hardware and firmware may be connected to I/O interface **44** or may be integrated into I/O interface **44**. Network interface **42** may support various communication standards and protocols, such as Ethernet and Small Form-Factor Pluggable (SFP). Ethernet is a widely used wired networking technology that enables local area network (LAN) communication. Ethernet interfaces typically use RJ45 connectors and support data rates ranging from 10 Mbps to 100 Gbps, with common speeds being 100 Mbps, 1 Gbps, 10 Gbps, 25 Gbps, 40 Gbps, and 100 Gbps. Ethernet is known for its reliability, low latency, and cost-effectiveness, making it a popular choice for home, office, and data center networks. SFP is a compact, hot-pluggable transceiver used for both telecommunication and data communications applications. SFP interfaces provide a modular and flexible solution for connecting network devices, such as switches and routers, to fiber optic or copper networking cables. SFP transceivers support various data rates, ranging from 100 Mbps to 100 Gbps, and can be easily replaced or upgraded without the need to replace the entire network interface card. This modularity allows for network scalability and adaptability to different network requirements and fiber types, such as single-mode or multi-mode fiber.

[0333] Non-volatile data storage devices **50** are typically used for long-term storage of data. Data on non-volatile data storage devices **50** is not erased when power to the non-volatile data storage devices **50** is removed. Non-volatile data storage devices **50** may be implemented using any technology for non-volatile storage of content including, but not limited to, CD-ROM drives, digital versatile discs (DVD), or other optical disc storage; magnetic cassettes, magnetic tape, magnetic disc storage, or other magnetic storage devices; solid state memory technologies such as EEPROM or flash memory; or other memory technology or any other medium which can be used to store data without requiring power to retain the data after it is written. Non-volatile data storage devices **50** may be non-removable from computing device **10** as in the case of internal hard drives, removable from computing device **10** as in the case of external USB hard drives, or a combination thereof, but computing device will typically comprise one or more internal, non-removable hard drives using either magnetic disc or solid state memory technology. Non-volatile data storage devices **50** may be implemented using various technologies, including hard disk drives (HDDs) and solid-state drives (SSDs). HDDs use spinning magnetic platters and read/write heads to store and retrieve data, while SSDs use NAND flash memory. SSDs offer faster read/write speeds, lower latency, and better durability due to the lack of moving parts, while HDDs typically provide higher storage capacities and lower cost per gigabyte. NAND flash memory comes in different types, such as Single-Level Cell (SLC), Multi-Level Cell (MLC), Triple-Level Cell (TLC), and Quad-Level Cell (QLC), each with trade-offs between performance, endurance, and cost. Storage devices connect to the computing device **10** through various interfaces, such as SATA, NVMe, and PCIe. SATA is the traditional interface for HDDs and SATA SSDs, while NVMe (Non-Volatile Memory Express) is a newer, high-performance protocol designed for SSDs connected via PCIe. PCIe SSDs offer the highest performance due to the direct connection to the PCIe bus, bypassing the limitations of the SATA interface. Other storage form factors include M.2 SSDs, which are compact storage devices that connect directly to the motherboard using the M.2 slot, supporting both SATA and NVMe interfaces. Additionally, technologies like Intel Optane memory combine 3D XPoint technology with NAND flash to provide high-performance storage and caching solutions. Non-volatile data storage devices **50** may be non-removable from computing device **10**, as in the case of internal hard drives, removable from computing device **10**, as in the case of external USB hard drives, or a combination thereof. However, computing devices will typically comprise one or more internal, non-removable hard drives using either magnetic disc or solid-state memory technology. Non-volatile data storage devices **50** may store any type of data including, but not limited to, an operating system **51** for providing low-level and mid-level functionality of computing device **10**, applications **52** for providing high-level functionality of computing device **10**, program modules **53** such as containerized programs or applications, or other modular content or modular programming, application data **54**, and databases **55** such as relational databases, non-relational databases, object oriented databases, NoSQL databases, vector databases, knowledge graph databases, key-value databases, document oriented data stores, and graph databases.

[0334] Applications (also known as computer software or software applications) are sets of programming instructions designed to perform specific tasks or provide specific functionality on a computer or other computing devices. Applications are typically written in high-level programming languages such as C, C++, Scala, Erlang, GoLang, Java, Scala, Rust, and Python, which are then either interpreted at runtime or compiled into low-level, binary, processor-executable instructions operable on processors **20**. Applications may be containerized so that they can be run on any computer hardware running any known operating system. Containerization of computer software is a method of packaging and deploying applications along with their operating system dependencies into self-contained, isolated units known as containers. Containers provide a lightweight and consistent runtime environment that allows applications to run reliably across different computing environments, such as development, testing, and production systems facilitated by specifications such as containerd.

[0335] The memories and non-volatile data storage devices described herein do not include communication media. Communication media are means of transmission of information such as modulated electromagnetic waves or modulated data signals configured to transmit, not store, information. By way of example, and not limitation, communication media includes wired communications such as sound signals transmitted to a speaker via a speaker wire, and wireless communications such as acoustic waves, radio frequency (RF) transmissions, infrared emissions, and other wireless media.

[0336] External communication devices **70** are devices that facilitate communications between computing device and either remote computing devices **80**, or cloud-based services **90**, or both. External communication devices **70** include, but are not limited to, data modems **71** which facilitate data transmission between computing device and the Internet **75** via a common carrier such as a telephone company or internet service provider (ISP), routers **72** which

facilitate data transmission between computing device and other devices, and switches **73** which provide direct data communications between devices on a network or optical transmitters (e.g., lasers). Here, modem **71** is shown connecting computing device **10** to both remote computing devices **80** and cloud-based services **90** via the Internet **75**. While modem **71**, router **72**, and switch **73** are shown here as being connected to network interface **42**, many different network configurations using external communication devices **70** are possible. Using external communication devices **70**, networks may be configured as local area networks (LANs) for a single location, building, or campus, wide area networks (WANs) comprising data networks that extend over a larger geographical area, and virtual private networks (VPNs) which can be of any size but connect computers via encrypted communications over public networks such as the Internet **75**. As just one exemplary network configuration, network interface **42** may be connected to switch **73** which is connected to router **72** which is connected to modem **71** which provides access for computing device **10** to the Internet **75**. Further, any combination of wired **77** or wireless **76** communications between and among computing device **10**, external communication devices **70**, remote computing devices **80**, and cloud-based services **90** may be used. Remote computing devices **80**, for example, may communicate with computing device through a variety of communication channels **74** such as through switch **73** via a wired **77** connection, through router **72** via a wireless connection **76**, or through modem **71** via the Internet **75**. Furthermore, while not shown here, other hardware that is specifically designed for servers or networking functions may be employed. For example, secure socket layer (SSL) acceleration cards can be used to offload SSL encryption computations, and transmission control protocol/internet protocol (TCP/IP) offload hardware and/or packet classifiers on network interfaces **42** may be installed and used at server devices or intermediate networking equipment (e.g., for deep packet inspection).

[0337] In a networked environment, certain components of computing device **10** may be fully or partially implemented on remote computing devices **80** or cloud-based services **90**. Data stored in non-volatile data storage device **50** may be received from, shared with, duplicated on, or offloaded to a non-volatile data storage device on one or more remote computing devices **80** or in a cloud computing service **92**. Processing by processors **20** may be received from, shared with, duplicated on, or offloaded to processors of one or more remote computing devices **80** or in a distributed computing service **93**. By way of example, data may reside on a cloud computing service **92**, but may be usable or otherwise accessible for use by computing device **10**. Also, certain processing subtasks may be sent to a microservice **91** for processing with the result being transmitted to computing device **10** for incorporation into a larger processing task. Also, while components and processes of the exemplary computing environment are illustrated herein as discrete units (e.g., OS **51** being stored on non-volatile data storage device **51** and loaded into system memory **35** for use) such processes and components may reside or be processed at various times in different components of computing device **10**, remote computing devices **80**, and/or cloud-based services **90**. Also, certain processing subtasks may be sent to a microservice **91** for processing with the result being transmitted to computing device **10** for incorporation into a larger processing task. Infrastructure as Code (IaaC) tools like Terraform can be used to manage and provision computing resources across multiple cloud providers or hyperscalers. This allows for workload balancing based on factors such as cost, performance, and availability. For example, Terraform can be used to automatically provision and scale resources on AWS spot instances during periods of high demand, such as for surge rendering tasks, to take advantage of lower costs while maintaining the required performance levels. In the context of rendering, tools like Blender can be used for object rendering of specific elements, such as a car, bike, or house. These elements can be approximated and roughed in using techniques like bounding box approximation or low-poly modeling to reduce the computational resources required for initial rendering passes. The rendered elements can then be integrated into the larger scene or environment as needed, with the option to replace the approximated elements with higher-fidelity models as the rendering process progresses.

[0338] In an implementation, the disclosed systems and methods may utilize, at least in part, containerization techniques to execute one or more processes and/or steps disclosed herein. Containerization is a lightweight and efficient virtualization technique that allows users, applications, or agents to package and run applications and their dependencies in isolated environments called containers. One of the most popular containerization platforms is containerd, which is widely used in software development and deployment. Containerization, particularly with open-source technologies like containerd and container orchestration systems like Kubernetes, is a common approach for deploying and managing applications. Containers are created from images, which are lightweight, standalone, and executable packages that include application code, libraries, dependencies, and runtime. Images are often built from a containerfile or similar, which contains instructions for assembling the image. Containerfiles are configuration files that specify how to build a container image. Systems like Kubernetes natively support containerd as a container runtime. They include commands for installing dependencies, copying files, setting environment variables, and defining runtime configurations. Container images can be stored in repositories, which can be public or private. Organizations often set up private registries for security and version control using tools such as Harbor, JFrog Artifactory and Bintray, GitLab Container Registry, or other container registries. Containers can communicate with each other and the external world through networking. Containerd provides a default network namespace, but can be used with custom network plugins. Containers within the same network can communicate using container names or IP addresses.

[0339] Remote computing devices **80** are any computing devices not part of computing device **10**. Remote computing devices **80** include, but are not limited to, personal computers, server computers, thin clients, thick clients, personal digital assistants (PDAs), mobile telephones, watches, tablet computers, laptop computers, multiprocessor systems, microprocessor based systems, set-top boxes, programmable consumer electronics, video game machines, game consoles, portable or handheld gaming units, network terminals, desktop personal computers (PCs), minicomputers, mainframe computers, network nodes, virtual reality or augmented reality devices and wearables, and distributed or multiprocessing computing environments. While remote comput-

ing devices **80** are shown for clarity as being separate from cloud-based services **90**, cloud-based services **90** are implemented on collections of networked remote computing devices **80**.

[0340] Cloud-based services **90** are Internet-accessible services implemented on collections of networked remote computing devices **80**. Cloud-based services are typically accessed via application programming interfaces (APIs) which are software interfaces which provide access to computing services within the cloud-based service via API calls, which are pre-defined protocols for requesting a computing service and receiving the results of that computing service. While cloud-based services may comprise any type of computer processing or storage, three common categories of cloud-based services **90** are serverless logic apps, microservices **91**, cloud computing services **92**, and distributed computing services **93**.

[0341] Microservices **91** are collections of small, loosely coupled, and independently deployable computing services. Each microservice represents a specific computing functionality and runs as a separate process or container. Microservices promote the decomposition of complex applications into smaller, manageable services that can be developed, deployed, and scaled independently. These services communicate with each other through well-defined application programming interfaces (APIs), typically using lightweight protocols like HTTP, protobuffers, gRPC or message queues such as Kafka. Microservices **91** can be combined to perform more complex or distributed processing tasks. In an embodiment, Kubernetes clusters with containerized resources are used for operational packaging of system.

[0342] Cloud computing services **92** are delivery of computing resources and services over the Internet **75** from a remote location. Cloud computing services **92** provide additional computer hardware and storage on as-needed or subscription basis. Cloud computing services **92** can provide large amounts of scalable data storage, access to sophisticated software and powerful server-based processing, or entire computing infrastructures and platforms. For example, cloud computing services can provide virtualized computing resources such as virtual machines, storage, and networks, platforms for developing, running, and managing applications without the complexity of infrastructure management, and complete software applications over public or private networks or the Internet on a subscription or alternative licensing basis, or consumption or ad-hoc marketplace basis, or combination thereof.

[0343] Distributed computing services **93** provide large-scale processing using multiple interconnected computers or nodes to solve computational problems or perform tasks collectively. In distributed computing, the processing and storage capabilities of multiple machines are leveraged to work together as a unified system. Distributed computing services are designed to address problems that cannot be efficiently solved by a single computer or that require large-scale computational power or support for highly dynamic compute, transport or storage resource variance or uncertainty over time requiring scaling up and down of constituent system resources. These services enable parallel processing, fault tolerance, and scalability by distributing tasks across multiple nodes.

[0344] Although described above as a physical device, computing device **10** can be a virtual computing device, in which case the functionality of the physical components herein described, such as processors **20**, system memory **30**, network interfaces **40**, NVLink or other GPU-to-GPU high bandwidth communications links and other like components can be provided by computer-executable instructions. Such computer-executable instructions can execute on a single physical computing device, or can be distributed across multiple physical computing devices, including being distributed across multiple physical computing devices in a dynamic manner such that the specific, physical computing devices hosting such computer-executable instructions can dynamically change over time depending upon need and availability. In the situation where computing device **10** is a virtualized device, the underlying physical computing devices hosting such a virtualized computing device can, themselves, comprise physical components analogous to those described above, and operating in a like manner. Furthermore, virtual computing devices can be utilized in multiple layers with one virtual computing device executing within the construct of another virtual computing device. Thus, computing device **10** may be either a physical computing device or a virtualized computing device within which computer-executable instructions can be executed in a manner consistent with their execution by a physical computing device. Similarly, terms referring to physical components of the computing device, as utilized herein, mean either those physical components or virtualizations thereof performing the same or equivalent functions.

[0345] The skilled person will be aware of a range of possible modifications of the various aspects described above. Accordingly, the present invention is defined by the claims and their equivalents.

What is claimed is:

1. A computing system for an AI agent decision platform with deontic reasoning, the computing system comprising:

one or more hardware processors configured for:

receiving a plurality of tasks at a network of specialized agents, wherein each agent comprises domain-specific knowledge and is bound by deontic constraints comprising at least one of either obligations, permissions, or prohibitions stored in knowledge graphs;

forwarding the plurality of tasks to a centralized distributed graph-based system;

analyzing the tasks using a deontic reasoning subsystem to evaluate compliance with the stored deontic constraints;

generating a plurality of compute graphs that represent the plurality of subtasks;

decomposing compliant tasks into subtasks based on agent domain expertise and associated deontic constraints;

generating compute graphs that represent the subtasks with their associated deontic constraints;

distributing the compute graphs to agents within the network based on the agents' domain expertise and deontic permissions; and

executing the subtasks while maintaining compliance with the stored deontic constraints.

2. The computing system of claim **1**, wherein agents may be human or non-human agents.

3. The computing system of claim **1**, wherein agents receive feedback and adjust task allocation based on the feedback.

4. The computing system of claim 1, wherein knowledge graphs are updated based on a plurality of contextual data and sensor data.

5. The computing system of claim 4, wherein sensor data includes but is not limited to Internet of Things (IoT) data, medical device data, wearable device data, video data, and image data.

6. The computing system of claim 1, wherein the system further comprises a resource-ethical optimization module that applies multi-objective optimization across both computational cost metrics and compliance metrics derived from deontic constraints, thereby dynamically allocating tasks to nodes or agents that best satisfy performance objectives while minimizing ethical risk.

7. The computing system of claim 1, wherein the system further comprises a dynamic deontic breaker subsystem configured to:

monitor deontic risk scores during runtime execution of federated distributed computational graph pipelines;

automatically inject circuit breaker nodes when a calculated risk score exceeds a predefined threshold;

halt or redirect task processing upon circuit breaker activation; and

require either human agent authorization or implementation of additional anonymization measures before allowing pipeline resumption.

8. The computing system of claim 7, wherein the dynamic deontic circuit breaker subsystem integrates with a multi-objective resource allocation and load-balancing framework to:

preemptively escalate high-risk tasks for human review;

redirect tasks to nodes with enhanced security capabilities; or

automatically terminate task execution when no compliant resource allocation path exists.

9. The computing system of claim 1, wherein the system applies privacy-preserving transformations to raw data before federation node assignment through:

implementing a least one of data anonymization, encryption, homomorphic encryption, tokenization, and differential privacy;

maintaining deontic privacy constraint compliance throughout data processing; and

enabling partial or blind execution capabilities across the federation network.

10. A computer-implemented method for an AI agent decision platform with deontic reasoning, the computer-implemented method comprising the steps of:

receiving a plurality of tasks at a network of specialized agents, wherein each agent comprises domain-specific knowledge and is bound by deontic constraints comprising at least one of either obligations, permissions, or prohibitions stored in knowledge graphs;

forwarding the plurality of tasks to a centralized distributed graph-based system;

analyzing the tasks using a deontic reasoning subsystem to evaluate compliance with the stored deontic constraints;

generating a plurality of compute graphs that represent the plurality of subtasks;

decomposing compliant tasks into subtasks based on agent domain expertise and associated deontic constraints;

generating compute graphs that represent the subtasks with their associated deontic constraints;

distributing the compute graphs to agents within the network based on the agents' domain expertise and deontic permissions; and

executing the subtasks while maintaining compliance with the stored deontic constraints.

11. The method of claim 10, wherein agents may be human or non-human agents.

12. The method of claim 10, wherein agents receive feedback and adjust task allocation based on the feedback.

13. The method of claim 10, wherein knowledge graphs are updated based on a plurality of contextual data and sensor data.

14. The method of claim 13, wherein sensor data includes but is not limited to Internet of Things (IoT) data, medical device data, wearable device data, video data, and image data.

15. The method of claim 10, wherein the method further comprises applying multi-objective optimization across both computational cost metrics and compliance metrics derived from deontic constraints using a resource-ethical optimization module, thereby dynamically allocating tasks to nodes or agents that best satisfy performance objectives while minimizing ethical risk.

16. The method of claim 10, wherein the method further comprises a dynamic deontic breaker subsystem configured to:

monitor deontic risk scores during runtime execution of federated distributed computational graph pipelines;

automatically inject circuit breaker nodes when a calculated risk score exceeds a predefined threshold;

halt or redirect task processing upon circuit breaker activation; and

require either human agent authorization or implementation of additional anonymization measures before allowing pipeline resumption.

17. The method of claim 16, wherein the dynamic deontic circuit breaker subsystem integrates with a multi-objective resource allocation and load-balancing framework to:

preemptively escalate high-risk tasks for human review;

redirect tasks to nodes with enhanced security capabilities; or

automatically terminate task execution when no compliant resource allocation path exists.

18. The method of claim 10, wherein the method applies privacy-preserving transformations to raw data before federation node assignment through:

implementing a least one of data anonymization, encryption, homomorphic encryption, tokenization, and differential privacy;

maintaining deontic privacy constraint compliance throughout data processing; and

enabling partial or blind execution capabilities across the federation network.

19. A system for an AI agent decision platform with deontic reasoning, comprising one or more computers with executable instructions that, when executed, cause the system to:

receive a plurality of tasks at a network of specialized agents, wherein each agent comprises domain-specific knowledge and is bound by deontic constraints comprising at least one of either obligations, permissions, or prohibitions stored in knowledge graphs;

forward the plurality of tasks to a centralized distributed graph-based system;

analyze the tasks using a deontic reasoning subsystem to evaluate compliance with the stored deontic constraints;

generate a plurality of compute graphs that represent the plurality of subtasks;

decompose compliant tasks into subtasks based on agent domain expertise and associated deontic constraints;

generate compute graphs that represent the subtasks with their associated deontic constraints;

distribute the compute graphs to agents within the network based on the agents' domain expertise and deontic permissions; and

execute the subtasks while maintaining compliance with the stored deontic constraints.

20. The system of claim **19**, wherein agents may be human or non-human agents.

21. The system of claim **19**, wherein agents receive feedback and adjust task allocation based on the feedback.

22. The system of claim **19**, wherein knowledge graphs are updated based on a plurality of contextual data and sensor data.

23. The system of claim **22**, wherein sensor data includes but is not limited to Internet of Things (IoT) data, medical device data, wearable device data, video data, and image data.

24. The system of claim **19**, wherein the system further comprises a resource-ethical optimization module that applies multi-objective optimization across both computational cost metrics and compliance metrics derived from deontic constraints, thereby dynamically allocating tasks to nodes or agents that best satisfy performance objectives while minimizing ethical risk.

25. The system of claim **19**, wherein the system further comprises a dynamic deontic breaker subsystem configured to:

monitor deontic risk scores during runtime execution of federated distributed computational graph pipelines;

automatically inject circuit breaker nodes when a calculated risk score exceeds a predefined threshold;

halt or redirect task processing upon circuit breaker activation; and

require either human agent authorization or implementation of additional anonymization measures before allowing pipeline resumption.

26. The system of claim **25**, wherein the dynamic deontic circuit breaker subsystem integrates with a multi-objective resource allocation and load-balancing framework to:

preemptively escalate high-risk tasks for human review;

redirect tasks to nodes with enhanced security capabilities; or

automatically terminate task execution when no compliant resource allocation path exists.

27. The system of claim **19**, wherein the system applies privacy-preserving transformations to raw data before federation node assignment through:

implementing a least one of data anonymization, encryption, homomorphic encryption, tokenization, and differential privacy;

maintaining deontic privacy constraint compliance throughout data processing; and

enabling partial or blind execution capabilities across the federation network.

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