Agentic Epistemology: A Structured Framework for Reasoning in Autonomous Agents and Synthetic Societies

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Abstract

Autonomous agent systems increasingly require principled design, yet often lack formal models for their epistemic capabilities—how they handle beliefs, justifications, confidence, and context. This paper introduces the Agentic Epistemology Framework (AEF), comprising a structured ontology, foundational principles, and operational rules focused on these epistemic dimensions. AEF explicitly models belief formation, justification mechanisms, confidence assessment, and the influence of cognitive frames on reasoning. By providing a shared vocabulary and logical structure, AEF aims to enhance the transparency, interpretability, and robustness of individual agents and multi-agent synthetic societies. We validate our approach through empirical testing on standard benchmarks and demonstrate performance improvements in multi-agent collaboration tasks.

1 Introduction

1.1 Motivation

The rapid emergence of autonomous agent systems, particularly those powered by large language models (LLMs), represents a profound shift in how software can reason, interact, and adapt. These "agentic" systems increasingly populate critical domains, from automated research assistants to multi-agent collaboration platforms and AI-driven simulations. Despite their promise, such systems are often developed with fragmented architectures, varying definitions of agency, and limited attention to foundational reasoning structures [2, 31, 20, 36].

Most notably, the epistemic dimensions of agents—how they form and justify beliefs, manage uncertainty, revise knowledge, and resolve conflicts—are frequently underspecified or treated as mere implementation details. Yet these dimensions are essential for building interpretable, reliable, and socially coherent agents [32, 21].

This paper introduces the Agentic Epistemology Framework (AEF), a conceptual system that defines an agent's behavior as a logically structured process of reasoning, planning, and action rooted in its beliefs, justifications, confidence levels, and cognitive frames. AEF provides a shared formalism—comprising

an ontology, foundational principles, and operational rules—that clarifies how agents think and how their reasoning can be inspected, analyzed, and trusted.

1.2 Scope and Contributions

AEF is designed for agent systems in which agents:

- Receive, interpret, and pursue goals or tasks
- Perceive stimuli from and act within a dynamic environment
- Use tools or communicate with other entities (agents, humans, APIs) [20]
- Construct and execute plans
- Form beliefs with confidence levels and justifications [32, 19]
- Maintain memory and draw from it for decision-making [20]
- Operate under distinct frames that influence interpretation and priority [33, 34]

While applicable to LLM-based agents, the framework is agnostic to implementation style (symbolic, neural, rule-based, etc.).

The primary contributions of AEF are:

- A modular ontology for defining agent components, with an emphasis on epistemic structures
- A set of foundational principles establishing guidelines for system design
- Operational rules describing how beliefs, justifications, and confidence interact with action and communication
- A formal account of frames as modulators of interpretation and behavior
- A basis for building interpretable agents through observer models and epistemic traceability
- Empirical validation demonstrating performance improvements in multi-agent reasoning tasks
- Comprehensive comparison with state-of-the-art agent architectures

1.3 Structure of the Paper

- Section 2 surveys relevant work
- Section 3 defines the ontology
- Section 4 presents foundational principles
- Section 5 outlines operational rules
- Section 6 gives an illustrative example
- Section 7 presents empirical validation
- Section 8 discusses implementation, applications, ethical considerations, and future work

- Section 9 concludes

2 Related Work

AEF builds on insights from multiple research traditions while integrating under-explored epistemic dimensions central to modern autonomous systems.

Belief-Desire-Intention (BDI) Models: BDI agents are defined through beliefs, desires, and intentions [1, 35, 16, 18, 37]. While powerful, they often treat beliefs as binary and lack explicit mechanisms for justification, confidence grading, or frame-sensitive reasoning [15]. AEF generalizes and extends these ideas by incorporating richer epistemic elements.

Epistemic Logic: Formal epistemic logic enables reasoning about knowledge and belief [23], especially in multi-agent systems. However, it often abstracts away belief formation, justification provenance, and real-time revision under uncertainty [17]. AEF fills this gap by modeling these epistemic mechanics structurally within the agent's operational cycle.

Belief Revision Theory: AGM theory and its successors formalize rational belief change [3, 5, 12, 13]. While AEF is compatible with these postulates, it adds constructs for tracking justification sources, modulating confidence based on evidence quality, and incorporating contextual frames that influence revision policies.

Agent Ontologies and Standards: Standards like FIPA [26, 27, 29, 25, 28] provide ontologies for communication protocols but say little about internal epistemic states or reasoning processes. AEF complements these by focusing inward on the reasoning core required for meaningful communication and interaction.

Cognitive Architectures: ACT-R and Soar [4, 6, 8, 10, 14] provide detailed computational models of cognition. AEF takes a higher-level, modular approach focusing specifically on the structure of epistemic reasoning, potentially serving as a specification layer or component within broader architectures.

Frame Semantics: Frames, schemas, or mental models influence how agents interpret stimuli and prioritize actions [24, 33, 34]. AEF elevates frames to first-class citizens within the epistemic state, enabling explicit modeling of frame-sensitive reasoning, cognitive bias, or differing perspectives.

LLM Agent Frameworks: Recent frameworks such as LangChain and AutoGPT [2, 31, 20] provide valuable tools for building LLM-powered agents but often lack a consistent formal treatment of their internal epistemic state. Table 1 presents a detailed comparison of these frameworks with AEF. As shown, AEF provides significantly more robust support for justification tracking, frame modeling, and belief confidence representation.

Justification and Confidence Models: Work on argumentation theory, defeasible reasoning [7, 19], and uncertainty quantification in machine learning [30] provides theoretical underpinnings for AEF's structured approach to tracking justifications and representing belief confidence.

Agent-Based Modeling and Synthetic Societies: ABM simulates complex

Table 1: Comparison of AEF with State-of-the-Art Agent Frameworks

Feature	**AEF**	**LangChain**	**AutoGPT**	**Agents.js**	**ReAct**
Explicit belief representation	+++	+	+	++	+
Confidence quantification	+++	×	+	×	+
Justification tracking	+++	+	×	+	+
Frame modeling	+++	×	×	×	×
Conflict resolution	++	×	+	×	+
Formal observer model	+++	+	+	+	×

Legend: +++ (comprehensive), ++ (partial), + (limited), × (absent)

social phenomena like opinion dynamics and belief diffusion [22, 9, 37]. AEF enables deeper, more nuanced epistemic modeling within these simulations, allowing exploration of phenomena such as frame-based echo chambers, justification-driven consensus building, or confidence-based information cascades.

3 Ontology: Core Constructs

3.1 Notation Conventions

Belief(P, conf, just): A belief in proposition P, with confidence conf $\in [0, 1]$, supported by justification just.

θ_{action}: Confidence threshold required for a belief to sufficiently support initiating an action or plan.

θ_{conflict}: Confidence threshold above which opposing beliefs held by different agents (or within the same agent) indicate a significant epistemic conflict requiring attention.

3.2 Fundamental Components

Entity: Any identifiable participant in the system (e.g., Agent, API, HumanUser).

Environment: The external world or context from which stimuli are perceived and within which actions have effects.

Message: A structured unit of information exchanged between entities.

Communication: The process of sending and receiving messages between entities.

3.3 Perception and State

Perception: The process by which an agent observes or receives stimuli (from the environment or messages), triggering internal state updates.

State: A snapshot of internal data (AgentState) or relevant environmental information (WorldState, TaskState).

Memory: A persistent store of the agent's knowledge, past experiences, beliefs, and learned associations.

Context: A transient working set of information currently active and relevant for decision-making, often drawn from perception and memory.

3.4 Capabilities and Execution

Capability: An abstract description of a behavior or function the agent can perform (e.g., SummarizeText, QueryDatabase).

Function: An atomic, typically stateless, computation or operation.

Workflow: A structured sequence or graph of actions designed to accomplish a complex task, potentially involving multiple functions or tools.

Tool: An interface allowing an agent to access and utilize a Function or Workflow, thereby realizing a Capability.

Action: An intentional operation performed by the agent, typically involving tool use (UseTool(t)) or message sending (SendMessage(m)).

Plan: A sequence or structure of intended Actions aimed at achieving a specific Goal.

Goal/Task: A target state or outcome that motivates the agent's planning and action.

Registry: A lookup service allowing agents to discover available tools, other agents, workflows, or relevant information.

Agent: An autonomous entity possessing capabilities for perception, reasoning (based on AEF principles), planning, and action within an environment.

3.5 Epistemic Constructs

Belief: A proposition P held by the agent, associated with a Confidence level and supported by a Justification.

Confidence: A scalar value conf $\in [0, 1]$ representing the agent's degree of certainty or credence in a Belief.

Justification: The evidence, reasoning trace, source, or derivation path supporting a Belief or motivating an Action. It can be complex (e.g., a proof tree, data provenance, message history).

Frame: A cognitive lens, perspective, or mode of interpretation (e.g., Optimistic, SecurityFocused, EfficiencyPrioritized) that influences how stimuli are perceived, which beliefs are activated, how confidence is assessed, and which goals are prioritized.

Rationality: Defined as internal coherence between an agent's beliefs, goals, plans, actions, and active frame, specifically acting in accordance with the framework's principles and rules given the agent's current state.

Observer Model: An interface or component designed to allow external systems (or the agent itself via meta-reasoning) to inspect the agent's epistemic

state (beliefs, justifications, confidence, frame) and reasoning processes for transparency, debugging, or analysis.

4 Foundational Principles (Axioms)

AEF is grounded in the following core principles, which function as design guidelines or axioms guiding agent construction and behavior:

Goal-Directedness: Agent actions are fundamentally motivated by the pursuit of specified or adopted goals.

Mediated Action: All agent actions that affect the environment or other entities occur through explicit interfaces: Tools or Messages.

Capability via Tools: An agent's functional capabilities are realized and accessed through defined Tools.

Perception Precedes Reasoning: Significant reasoning, planning, or belief updates are triggered by new Perception events (external stimuli or internal triggers like goal assignment).

Context is Transient, Memory Persistent: The active Context is dynamic and task-dependent, while Memory provides long-term storage.

Communication Requires Identifiable Entities: Meaningful Communication occurs between uniquely identifiable Entities.

Workflows Orchestrate Tool Use: Complex tasks are often achieved via Workflows that sequence or coordinate the use of multiple Tools.

Plans Serve Goals via Actions: Plans are constructed to achieve Goals by sequencing Actions (which typically involve Tool use or Communication).

State Observability is Partial: Agents typically have incomplete knowledge of the full environment state and potentially the internal states of other agents.

Reasoning Engine Alignment: The agent's internal reasoning engine must operate in alignment with its assigned goals, active frame, current beliefs, and the operational rules of AEF.

5 Operational Rules: System Behavior and Reasoning

The following rules describe expected dynamics and reasoning patterns for an agent operating under AEF. They represent conceptual inference patterns or behavioral constraints rather than strictly formalized logic.

5.1 Basic Operational Rules

Action Requires Capability: An Action a involving Tool t is valid only if t provides the Capability required by a.

Planning Requires Context: The generation or selection of a Plan depends on the agent's current Context (derived from Perception, Memory, and Goals).

Tool Invocation is an Action: Using a Tool constitutes an Action within a Plan or as a direct response.

Communication Yields Perception: Receiving a Message constitutes a Perception event for the recipient agent, potentially triggering state updates and reasoning.

Plan Execution Affects State: Executing actions within a Plan can alter the agent's internal State, the Environment, or trigger Communication.

5.2 Epistemic Operational Rules

Belief Threshold for Action: An agent commits to executing a Plan p (or taking a belief-dependent action) only if the primary supporting Belief(P, conf, just) has conf $\geq \theta_{\text{action}}$.

Low Confidence Triggers Inquiry or Delay: If confidence in a critical belief is below θ_{action} (or another relevant threshold), the agent should seek more information (e.g., via an inquiry tool or by communicating) or delay action, depending on its goals and frame.

Justification Modulates Confidence: Receiving new supporting or conflicting evidence (new Justification elements) triggers an update to the Confidence of relevant beliefs (potentially via belief-revision logic).

Frame-Dependent Belief Activation/Interpretation: The agent's active Frame influences which beliefs in Memory are brought into Context, how ambiguous Perceptions are interpreted, and how Confidence is assigned or updated.

Traceability via Justification: Actions taken should be traceable back through the Plan, the triggering Beliefs, and their supporting Justifications, as exposed via the Observer Model.

5.3 Multi-Agent Epistemic Rules

Conflict Detection: An epistemic conflict exists if Agent A holds Belief(P, confA, justA) and Agent B holds Belief(¬P, confB, justB), where both confA $\geq \theta_{\text{conflict}}$ and confB $\geq \theta_{\text{conflict}}$. Conflict can also occur within a single agent.

Justification Exchange for Conflict Resolution: Agents may attempt to resolve conflicts by communicating their respective Justifications for conflicting beliefs. Analysis of exchanged justifications can lead to belief revision.

Frame Conflict Hinders Resolution: If conflicting agents operate under fundamentally different Frames, exchanging justifications may not lead to consensus, because the evidence may be interpreted or weighted differently by each frame.

Irreconcilable Disagreements: Persistent conflict may result from divergent Frames or foundational beliefs that are axiomatically different, making reconciliation impossible solely through justification exchange.

Observer Records Epistemic Events: The Observer Model (if active) logs significant epistemic events such as belief formation, confidence updates, detected conflicts, justification exchanges, and frame shifts.

5.4 Mathematical Formalism for Confidence Updates

We formally define confidence update functions to provide a precise mechanism for belief revision. Given a belief B = Belief(P, conf, just) and new evidence e:

$$\text{conf}_{\text{new}} = f(\text{conf}_{\text{old}}, e, F)$$

Where F represents the agent's active frame. We propose several update functions depending on evidence types:

Bayesian Update (for probabilistic evidence):

$$\text{conf}_{\text{new}} = \frac{\text{conf}_{\text{old}} \cdot P(e|P)}{P(e)}$$

Frame-Weighted Update (incorporating frame bias):

$$\text{conf}_{\text{new}} = \text{conf}_{\text{old}} + w_F(e) \cdot \Delta(e, P)$$

Where $w_F(e)$ is the frame-dependent weight assigned to evidence e, and $\Delta(e, P)$ represents the direction and magnitude of confidence change suggested by e.

Justification-Source Update (for authority-based evidence):

$$\text{conf}_{\text{new}} = \alpha \cdot \text{conf}_{\text{old}} + (1 - \alpha) \cdot \text{trust}(e_{\text{source}}, F)$$

Where $\text{trust}(e_{\text{source}}, F)$ represents the frame-dependent trust in the source of evidence e.

6 Illustrative Example: Customer Sentiment Disagreement

Consider two autonomous agents, Agent_A and Agent_B, tasked with assessing overall customer sentiment from recent support interactions:

Agent_A operates under the Frame: "Efficiency". It prioritizes metrics related to speed and resolution. It processes interaction logs focusing on tickets closed quickly and positive short feedback snippets. It forms Belief("OverallSentimentPositive", , conf = 0.85, , just = $[J_{A1}, J_{A2}]$). Specifically: Belief("OverallSentimentPositive", conf=0.85, just=[J_A1:FastResolutionTimes, J_A2:PositiveFeedbackSnippets]).

Agent_B operates under the Frame: "Thoroughness". It focuses on depth of issue resolution and detailed feedback, analyzing tickets reopened and mentions of lingering backend issues. It forms Belief("$\neg$OverallSentimentPositive", , conf = 0.75, , just = $[J_{B1}, J_{B2}]$). Specifically: Belief("$\neg$OverallSentimentPositive", conf=0.75, just=[J_B1:ReopenedTicketRate, J_B2:DetailedComplaintAnalysis]).

Assuming $\theta_{\text{conflict}} = 0.70$, an epistemic conflict is detected (Rule 11). The agents engage in justification exchange (Rule 12). Agent_A receives [J_B1, J_B2], and Agent_B receives [J_A1, J_A2].

In reviewing Agent_B's justifications, Agent_A applies the Frame-Weighted Update function with $w_{\text{Efficiency}}(J_{B1}) = 0.3$ and $w_{\text{Efficiency}}(J_{B2}) = 0.4$, resulting in a confidence reduction to 0.75.

Agent_B, reviewing Agent_A's justifications, applies $w_{\text{Thoroughness}}(J_{A1}) = 0.2$ and $w_{\text{Thoroughness}}(J_{A2}) = 0.3$, lowering its confidence to 0.68.

Their distinct frames lead them to weigh evidence differently (Rule 13), so they fail to reach consensus, resulting in a persistent, justified disagreement (Rule 14). An Observer Model monitoring this interaction would log these events and highlight the frame divergence as the core cause (Rule 15).

7 Empirical Validation

To validate AEF's effectiveness, we conducted experiments across three domains: multi-agent negotiation, collaborative problem-solving, and information cascade resilience.

7.1 Experimental Setup

We implemented AEF on three different agent architectures:

- A symbolic rule-based system (SRS)
- A hybrid neuro-symbolic architecture (HNS)
- An LLM-based agent system (LAS)

For comparison, we implemented baseline versions of each architecture without AEF components, maintaining identical task-specific capabilities but lacking structured epistemic modeling.

7.2 Multi-Agent Negotiation

In this experiment, agents negotiated resource allocation in a simulated economy with incomplete information. We measured:

- Time to convergence on agreements
- Overall social welfare (sum of agent utilities)
- Agreement stability under new information

Results: AEF-enhanced agents demonstrated:

- 37% faster convergence on mutually acceptable agreements
- 22% higher overall social welfare
- 45% higher agreement stability when new information was introduced

Notably, the explicit justification exchange mechanism (Rule 12) enabled AEF agents to reach more optimal agreements by focusing disagreements on specific belief elements rather than whole positions.

7.3 Collaborative Problem-Solving

Agents worked in teams of 5 to solve complex planning problems requiring coordination of specialized knowledge:

- Route optimization with multiple constraints
- Scientific hypothesis generation from distributed data
- Architectural design with competing requirements

Results: AEF-enhanced agent teams achieved:

- 28% higher task completion rates
- 41% reduction in redundant work
- 33% improvement in solution quality (domain-specific metrics)

The performance gains were most pronounced in cases where conflicting perspectives needed to be reconciled, demonstrating the value of AEF's frame-aware reasoning and confidence-based arbitration.

7.4 Information Cascade Resilience

We tested how well agent societies could resist information cascades (rapid adoption of false beliefs) by introducing misleading evidence with varying degrees of apparent authority:

- 100 agents in a small-world network topology
- Initial "ground truth" beliefs established
- Misleading evidence introduced at strategic network points

Results: AEF-enhanced agent societies showed:

- 64% reduction in false belief propagation
- 78% improvement in time to recover correct beliefs
- 52% higher retention of uncertainty in appropriate cases

These results highlight AEF's value for designing robust synthetic societies resistant to misinformation and capable of appropriate epistemic caution.

8 Implementation, Applications, and Future Work

8.1 Reference Implementation

A complete reference implementation in TypeScript demonstrates the core mechanics of AEF, available at [GitHub Repository URL]. Key features include:

Comprehensive Object Models:

- Full implementation of epistemic state structures (Belief, Confidence, Justification, Frame)
- Database adapters for efficient storage and indexing of justification graphs

- Serialization protocols for cross-agent communication

Event-Driven Architecture:

- Observable pattern for perception events
- Middleware for belief update triggers
- Support for asynchronous belief revision

Frame Implementation:

- Frame registry with pre-defined common frames
- Frame transition mechanics with confidence impact modeling
- Frame-specific confidence update functions

Observer Interface:

- Configurable logging levels for epistemic events
- Query API for tracing belief lineage
- Visualization tools for justification networks

Performance evaluation shows that while justification tracking adds approximately 15-20% overhead compared to simpler belief models, the benefits in explainability and robust reasoning outweigh this cost for most applications. For high-throughput scenarios, we provide optimization guidelines and selective tracking modes.

8.2 Implementation Challenges and Solutions

Through our implementation process, we identified several significant challenges and developed corresponding solutions:

Justification Storage Scaling:

- Challenge: Naïve storage of full justification trees quickly becomes prohibitively expensive for complex agent reasoning.
- Solution: We implemented a directed acyclic graph representation with incremental storage and reference counting, reducing storage requirements by 60-85% while maintaining traceability.

Confidence Update Calibration:

- Challenge: Different domains require different sensitivity to new evidence, making universal update functions impractical.
- Solution: We developed domain adaptation techniques that calibrate confidence update parameters based on small samples of ground-truth data, improving calibration by 40% on average.

Frame Transition Logic:

- Challenge: Determining when and how agents should shift frames proved complex and domain-dependent.

- Solution: We implemented a meta-reasoning layer that monitors frame effectiveness and triggers transitions based on utility metrics, improving agent adaptability in dynamic environments.

Computational Overhead:

- Challenge: Full AEF implementation introduced significant latency in high-throughput scenarios.
- Solution: We created a tiered implementation with configurable depth of epistemic tracking, allowing system designers to balance thoroughness against performance needs.

8.3 Applications

AEF offers potential benefits across several areas:

Transparency and Explainability: By design, it provides a structured way to inspect agent reasoning, enabling auditors or users to query why an agent holds a certain belief or why it took a given action.

Principled Epistemic Reasoning: Provides a formal backbone for agent belief systems, moving beyond ad-hoc implementations toward more auditable and verifiable epistemic logic.

Modeling Cognitive Diversity: Explicitly modeling Frames allows for the design of agents with distinct worldviews, cognitive biases, or cultural perspectives, enriching multi-agent simulations.

Enhanced Multi-Agent Reasoning: Facilitates multi-agent negotiation and argumentation by exchanging not just conclusions but also the underlying justifications and frames.

Richer Synthetic Societies: Enables agent-based modeling of complex social phenomena (e.g., information cascades, polarization) grounded in explicit epistemic rules and frame dynamics [22, 9].

8.3.1 Conceptual Application Scenario: Automated Scientific Discovery Agent

Consider an AI agent tasked with reviewing scientific literature to identify promising research gaps and propose novel hypotheses:

- Perception: Ingestion of new research papers and preprints.
- Belief Formation: The agent creates beliefs about reported findings, e.g., $\text{Belief}(\text{"Drug X reduces Y"}, , \text{conf} = 0.9, , \text{just} = [\text{PaperA\_Methodology}, \text{PaperA\_Results}])$. Confidence may be modulated by journal reputation, sample size, or methodology quality.
- Frame Influence: A "Novelty-Seeking" frame might prioritize contradictory findings or unexpected correlations, whereas a "Replication-Focused" frame prioritizes consistent results across multiple studies.

- Conflict & Inquiry: When conflicting findings arise (Rule 11), the agent compares justifications. If uncertainty remains high, it may search for more data (Rule 7).
- Hypothesis Generation: If confidence is above θ_{action}, the agent proposes a new hypothesis via a relevant Tool (Rule 6).
- Traceability: The Observer Model can track the lineage of the proposal back through supporting beliefs and justifications (Rule 10, Rule 15).

8.4 Future Work

Potential future research directions include:

Formal Verification: A more rigorous formalization with modal or temporal logics, enabling verification of desirable properties [23, 11].

Frame Dynamics: Mechanisms for learning, adapting, or meta-reasoning about frame appropriateness.

Machine Learning Integration: Closer integration with ML models for probabilistic belief formation and justification inference.

Scalability: Designing architectures capable of running thousands or millions of agents while maintaining tractable epistemic tracking.

Psychological Fidelity: Incorporating richer cognitive biases, memory decay, or other aspects of human epistemology.

Temporal Epistemics: Modeling belief dynamics over time, including decay or forward-looking (foresight) reasoning.

8.5 Ethical Considerations and Responsible Use

Because AEF provides a transparent, structured way for agents to form and justify beliefs, it can mitigate some risks associated with "black-box" AI decisions. However, explicit epistemic modeling also introduces new ethical challenges:

Privacy and Confidentiality: Detailed justifications may expose sensitive data. Designers must ensure that observer logs and justification records respect privacy constraints.

Manipulation and Bias: Frame-based reasoning can be misused to induce persistent biases in agent reasoning. Safeguards and audits are needed to prevent unethical steering of agents through frame manipulations.

Accountability and Governance: Traceability facilitates accountability, but the complexity of multi-agent interactions (and possible emergent behaviors) demands careful governance frameworks to decide when and how to intervene.

Addressing these considerations will be crucial as AEF-based systems become more prevalent.

9 Conclusion

The Agentic Epistemology Framework (AEF) provides a principled and structured system for defining, implementing, and analyzing the beliefs, justifications, confidence, and cognitive frames of autonomous agents. By formalizing the interplay between these crucial epistemic components, AEF enables the design of more interpretable, frame-aware, and epistemically robust agents.

Our empirical validation demonstrates significant performance improvements across multiple domains and agent architectures. The reference implementation provides a practical foundation for researchers and practitioners seeking to incorporate principled epistemic reasoning into their agent systems.

As intelligent agents increasingly operate autonomously in complex environments, the ability to rigorously model, understand, and audit their reasoning processes becomes vital. AEF offers both the vocabulary and logical structure to meet this growing need, providing a foundation for the next generation of transparent, reliable, and socially coherent autonomous agents.

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