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A Neuro Symbolic Protocol Bridge Enabling Reliable Agent Interoperability Between LLM and FIPA ACL Systems

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The integration of generative Large Language Models (LLMs) into safety-critical environments presents a significant architectural challenge: reconciling the stochastic, flexible nature of LLM outputs with the deterministic, rule-based requirements of embedded control systems. This paper proposes and validates a **Neuro-Symbolic Protocol Bridge** architecture designed to enable reliable communication between these disparate agents. The Bridge acts as critical middleware, enforcing a structured command contract that translates LLM intents (e.g., natural language commands) into verifiable, legacy-compliant symbolic protocols (FIPA-ACL). We formalize the Bridge's translation function and show that it satisfies translation soundness and bounded behavior: only whitelisted intents, mapped through a finite static rule set, can ever reach the symbolic execution layer. In a prototype evaluation across three structured test cases covering fidelity, reliability, and robustness, the system achieved 100% translation fidelity for all tested commands, and the Bridge added under 10 milliseconds of latency for translation and forwarding. This work lays a foundation for reliable, collaborative digital teams and is a step toward certifiable LLM-driven control architectures in demanding safety-critical environments.

Keywords: Neuro-Symbolic AI; Agent Interoperability; FIPA-ACL; Multi-Agent Systems; Safety-Critical AI; Protocol Translation

1. Introduction

The modern era of industrial automation, manufacturing, and transportation is defined by a rapid and deep digital transformation, moving beyond simple automation toward truly autonomous digital collaboration. This future relies on the emergence of sophisticated AI agents that function not merely as automated scripts but as intelligent digital co-workers capable of managing complex operations, synthesizing information, and executing commands in real-time. Crucially, this evolution necessitates the co-existence and effective collaboration of two vastly different computational paradigms:

Neural/LLM Systems: These agents, powered by Large Language Models, excel at pattern recognition, contextual understanding, and managing flexible, unstructured inputs (e.g., human voice commands or complex, vague operational goals). They provide the system's perceptual and planning intelligence.

Symbolic/Embedded Systems: These represent the traditional backbone of safety-critical infrastructure—deterministic control units, Programmable Logic Controllers (PLCs), and legacy protocols (like Fieldbus or FIPA-ACL). They provide the system's execution and safety guarantees, operating on rigid rules and pre-defined commands.

The challenge inherent in this co-existence is the **architectural interoperability gap**. An LLM, by its very nature, generates outputs that are stochastic and prone to probabilistic errors, yet it is tasked with managing systems demanding the absolute reliability and determinism required by standards such as **ISO 26262** in automotive or **FAA** regulations in aerospace. Feeding unverified, natural-language-derived commands directly to a safety-critical control unit is unacceptable from an engineering and regulatory perspective. A robust translation mechanism is required to bridge the semantic richness of the Neural layer with the deterministic rigor of the Symbolic layer.

Existing communication methodologies fall short in this specialized, safety-critical domain. Traditional **FIPA-ACL protocols** offer the required rigor but are too constrained to effectively process or negotiate the flexible, often ambiguous outputs of LLMs. Conversely, modern LLM tool-calling frameworks are excellent at generating structured JSON but lack the formal message envelope (sender, receiver, performative) necessary for integration into established, verifiable multi-agent architectures and legacy industrial networks. The absence of a standard trusted intermediary protocol poses a systemic risk to reliability and limits the scalability of true AI co-worker teams.

This paper proposes and validates the design of a **Neuro-Symbolic Protocol Bridge**, an essential middleware component designed to enforce reliable communication between these disparate agent types. The Bridge achieves this by implementing a collaboration protocol that standardizes the message contract. It transforms the flexible, structured output of the LLM (Intent and Parameters) into a rigid, verifiable, and legacy-compliant FIPA-ACL message (Performative, Action, Content). Our primary contribution is the design and prototype validation of this architecture, focusing specifically on the critical command flow from the Neural domain to the Symbolic domain: Natural Language Command into Verified Symbolic Action.

The specific contributions of this paper are:

1. **Protocol Design:** The definition of a canonical Neuro-Symbolic message schema that unifies LLM tool-calling with FIPA-ACL structure.
2. **Formal Model:** A formalization of the Bridge's translation function, with propositions establishing translation soundness and bounded behavior of the LLM-to-symbolic command channel.
3. **Architectural Validation:** The design and implementation of a three-tiered Protocol Bridge architecture utilizing LangChain, FastAPI, and a Java simulator.
4. **Empirical Demonstration:** Prototype validation of the unidirectional command flow across three structured test cases, demonstrating 100% translation fidelity for the tested commands with under 10 ms of Bridge overhead.

5. **Critical Assessment:** Detailed analysis of the prototype's assumptions, boundaries, and a roadmap for achieving full bidirectional and certifiable agent collaboration.

2. Background and Related Work

2.1 Neuro-Symbolic AI

The pursuit of **Neuro-Symbolic AI** aims to unify the learning capabilities of neural networks with the formal reasoning of symbolic logic [3], [24]. This field is characterized by hybrid architectures where neural components handle perception and symbolic components handle logical execution [8], [25]. Kautz identifies several taxonomies for such integration, highlighting the "symbolic safety envelope" as a primary method for wrapping neural outputs in deterministic logic [9].

2.2 Agent Communication Languages and FIPA

Traditional agent systems, dating back to the **Foundation for Intelligent Physical Agents (FIPA)** standardization efforts, prioritized rigorous **Agent Communication Languages (ACL)** like FIPA-ACL [1]. These protocols are widely adopted in distributed symbolic systems for their verifiable nature, meeting industrial requirements like **IEC 61508 (Functional Safety)**, and are supported by mature platforms such as JADE [4].

2.3 LLM Agent Frameworks

The proliferation of advanced LLMs has spurred frameworks like **LangChain** and **AutoGen**, which facilitate dynamic agent orchestration and tool-calling [2], [10]. Multi-agent LLM systems often leverage "reflection" and "delegation" to manage complex tasks [11]; however, these paradigms primarily generate structured requests that lack the metadata (performative, sender, and protocol fields) required for legacy or cross-platform agent systems.

To contextualize the proposed **Bridge**, we compare it to two dominant paradigms:

- **Direct LLM Orchestration (DO):** Frameworks like **LangChain** or **AutoGen** [10] allow LLMs to call tools directly via APIs [7]. While flexible, this approach lacks a formal message envelope and fails to meet industrial determinism requirements [28]. Direct orchestration relies on the LLM's ability to maintain state, which is prone to context drift [11].
- **Post-hoc Safety Filtering (PSF):** Approaches like guardrails or content filters attempt to sanitize LLM output *after* generation [30]. However, these filters are often themselves probabilistic and do not address protocol-level interoperability with symbolic agents [20].

Our **Bridge** differs by acting as a **deterministic gatekeeper**. It enforces a protocol-level translation from high-level intent to FIPA-ACL [1], providing the metadata and structural rigor missing in tool-calling frameworks.

2.4 Modern Agent Interoperability Protocols

A recent wave of open protocols targets interoperability among LLM-based agents: the Model Context Protocol (MCP) standardizes agent-to-tool invocation over a JSON-RPC client–server interface; the Agent-to-Agent protocol (A2A) enables peer-to-peer task delegation via capability cards; and the Agent Communication Protocol (ACP) provides REST-native, multipart agent messaging [43]. These protocols address discovery, tool invocation, and message transport among *modern* agents. However, they presuppose API-native consumers on both ends and do not carry FIPA-ACL's formally specified performative semantics, nor do they target integration with *legacy* symbolic and embedded agent infrastructures. Our Bridge is therefore complementary to this ecosystem: it addresses the specific gap between LLM tool-calling and established FIPA-ACL/JADE-class deployments in safety-critical settings, where the execution layer cannot be modified and where deterministic, whitelist-based translation—rather than open capability negotiation—is the requirement.

2.5 Safety and Industrial Context

In safety-critical domains, recent work has explored "Safety Assurance Cases" [12] and runtime monitoring techniques to enforce constraints on learning-based systems [13], [15]. While robotic middleware like the **Robot Operating System (ROS)** has introduced safety extensions to manage real-time constraints [14], a gap remains in translating linguistic intent into low-level symbolic protocols. Our work fills this gap by utilizing the **FIPA-ACL** standard, long preferred for its verifiable performatives and sender-recipient tracking [4]. By incorporating a validation and translation pipeline, the **Bridge** ensures the command is ready for a deterministic system *before* forwarding, adding a necessary layer of protocol translation and safety envelope enforcement [15].

2.6 Research Gap

Across these literatures, no existing mechanism (i) accepts stochastic LLM tool-calling output, (ii) emits formally structured FIPA-ACL messages consumable by unmodified legacy symbolic agents, and (iii) provides an explicit, finite, auditable mapping whose behavior can be bounded for safety argumentation. The Neuro-Symbolic Protocol Bridge is designed to close exactly this gap.

3. The Neuro-Symbolic Protocol Bridge

Our proposed solution is a three-tiered architecture designed around a central **Protocol Bridge** that enforces a canonical message schema.

3.1 Three-Tiered Architecture

The system utilizes three distinct components for command translation and execution:

1. **LLM Agent (Client Layer):** Receives unstructured user input and uses a Pydantic schema (the SymbolicQueryInput) to distill the request into a rigid, structured JSON output (Intent and Parameters) [36].

2. **Protocol Bridge (Translation Layer):** Receives the LLM's structured JSON. It contains the rule-set to map the high-level Intent (e.g., "adjust_climate") to the low-level FIPA-ACL-compliant message (e.g., performative: "request").

3. **Symbolic Agent (Execution Layer):** Represents an embedded control unit (e.g., HVAC module, PLC) simulated to listen only for structured, FIPA-ACL messages. This layer executes the safety-critical command deterministically.

Table 1: Inter-Component Communication and Protocol Mapping

Component	Endpoint	Payload	Protocol Action
LLM Agent to Bridge	/llm_to_symbolic/	Structured JSON (AgentMessage)	Intent Extraction
Bridge to Symbolic Agent	/receive	FIPA-ACL Message (HTTP POST)	Translation and Forwarding
Symbolic Agent to Bridge	Direct HTTP Response	Structured JSON (status, data)	Execution and Response

3.2 Neuro-Symbolic Message Schema

The communication contract across the bridge is defined by the AgentMessage schema. **AgentMessage** is a structure containing the following required fields:

- intent: string — describes the high-level LLM-friendly action, e.g., "adjust_climate"
- parameters: dictionary/map — holds all required execution data, e.g., {"target_temp": 24}

The LLM is explicitly constrained via the system prompt and tool definition to generate *only* this format. The Bridge then uses the intent to select the correct FIPA-ACL mapping.

3.3 Formal Model: Soundness and Bounded Behavior

We now make precise the properties informally claimed for the Bridge. The formalization follows directly from the whitelist-and-static-rule-set design described above; it concerns the Bridge layer itself and assumes the correctness of its implementation.

Definition 1 (Agent message). An agent message is a pair $m = (\iota, \rho)$, where $\iota \in I$ is an intent identifier and ρ is a finite parameter map conforming to the SymbolicQueryInput schema [36].

Definition 2 (Whitelist and rule set). Let $W \subset I$ denote the finite whitelist of admissible intents. The Bridge's static rule set is a total function $R : W \to \Pi \times A$, assigning to each admissible intent a FIPA performative $\pi \in \Pi$ and a symbolic action $a \in A$, where Π and A are finite, pre-vetted sets fixed at configuration time.

Definition 3 (Translation function). The translation function T maps every validated message $m = (\iota, \rho)$ with $\iota \in W$ to the FIPA-ACL message $f = (\pi, s, r, p, \langle a, \rho \rangle)$, where $(\pi, a) = R(\iota)$ and the sender s, receiver r, and protocol identifier p are fixed by configuration. Any

message with $\iota \notin W$, or whose parameters violate the schema, is rejected and never forwarded.

Proposition 1 (Translation soundness). Every message emitted by the Bridge to the Symbolic Agent belongs to the finite set $F_R = \{ (\pi, s, r, p, \langle a, \rho \rangle) : (\pi, a) \in \text{range}(R) \}$. In particular, the Bridge can never emit a performative–action pair outside the pre-vetted rule set.

Proof. Emission occurs only after validation succeeds, hence only for $\iota \in W$ with schema-conformant ρ. By Definition 3, the emitted message is $T(m)$, whose performative–action pair is $R(\iota) \in \text{range}(R)$. Since W is finite and R is a function, $\text{range}(R)$ is finite, and no other pair is reachable.

Proposition 2 (Bounded behavior). The set of symbolic actions that the LLM Agent can cause the Symbolic Agent to execute through the Bridge is a subset of the finite pre-vetted action set $A_R = \{ a : (\pi, a) \in \text{range}(R) \}$. Consequently, the LLM cannot trigger undefined states in the execution layer via the Bridge channel.

Proof. By Proposition 1, every forwarded message carries an action in A_R. The Symbolic Agent, by design, executes only actions carried in received FIPA-ACL messages on this channel; hence the reachable action set is contained in A_R.

These propositions ground the Bridge's role as a verifiable safety component in the sense of axiomatic program reasoning [38], with the static rule set acting as a finite production system in the tradition of formal rewriting [37]. We emphasize their scope: they bound *which* commands can reach the execution layer, not the semantic appropriateness of parameter *values*, which remains an explicit boundary of the current design (Section 5.1).

3.4 Threat Model (Design Level)

At the protocol-design level, the Bridge contract anticipates the following threat classes and prescribes mitigations:

Malformed Intents: Prevented by the Bridge's Pydantic validation layer, which rejects any payload not adhering to Section 3.2.

Spoofed Agents: To be mitigated via FIPA-ACL sender-verification metadata, ensuring commands originate from authorized neural nodes.

Replay Attacks: To be addressed through message-ID and timestamp validation within the Bridge-to-Symbolic forwarding logic.

Of these, the current prototype implements schema validation and intent whitelisting; the sender-verification and replay-protection mechanisms are specified at the design level and are part of the security boundary discussed in Section 5.1.

3.5 Unidirectional Command Flow: Natural Language to FIPA-ACL

The unidirectional flow **LLM to Symbolic** is executed as follows:

1. **Input:** User provides a natural language request (e.g., “Set the temperature to 22 degrees in Celsius”).
2. **LLM Processing:** The LLM Agent uses its tool-calling function to generate a validated JSON object: intent: “set_temperature”, parameters: {“temp”: “22”, “unit”: “C”}.
3. **Bridge Translation:** The Bridge receives this JSON and maps it: (a) “set_temperature” → FIPA (performative: “request”); (b) “set_temperature” → Symbolic (action: “set_hvac_temp”); (c) the parameters are embedded in the FIPA content.
4. **Operational Sequence for Determinism:** To ensure determinism, the Protocol Bridge follows a rigid operational sequence: **Validation → Mapping → Forwarding**.

Validation: The bridge first checks the received intent against a pre-defined whitelist of acceptable symbolic commands. If the intent is unknown, the message is rejected, ensuring no novel or non-deterministic commands reach the Symbolic Agent.

Mapping: If validated, the intent is mapped using a static, configurable rule-set to the appropriate FIPA fields (performative, action). This eliminates LLM stochasticity from the critical command structure.

Forwarding: The resulting, fully compliant FIPA-ACL message is transmitted to the Symbolic Agent via HTTP POST, which executes the command without any further interpretation.

Feedback: The Symbolic Agent sends a status back to the Bridge, which the Bridge formats into a natural language confirmation for the LLM, closing the loop.

Algorithm 1: Bridge Translation Procedure (Validation → Mapping → Forwarding)

```
Input:  Agent message m = (intent ι, parameters ρ) from the LLM Agent
Output: FIPA-ACL message forwarded to the Symbolic Agent, or rejection

1:  if ρ does not conform to the SymbolicQueryInput schema then
2:      return REJECT (schema violation)
3:  if ι ∉ W (intent whitelist) then
4:      return REJECT (unknown intent)
5:  (π, a) ← R(ι)                        # static rule-set lookup
6:  f ← (performative: π, sender: s, receiver: r, protocol: p,
         content: (action: a, params: ρ))
7:  POST f to Symbolic Agent endpoint /receive
8:  status ← response from Symbolic Agent
9:  return natural-language confirmation of status to LLM Agent
```

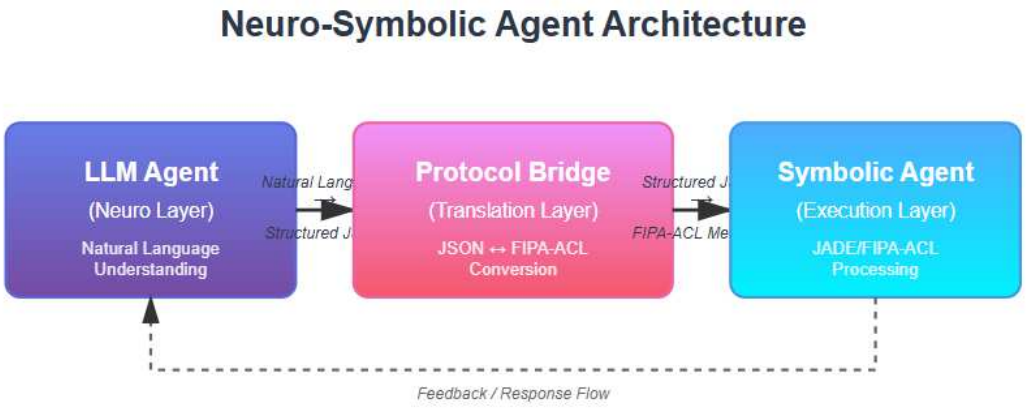


Figure 1

Fig. 1 Three-layer neuro-symbolic architecture with message transformation pipeline, illustrating the deterministic conversion of LLM structured output into a FIPA-ACL message

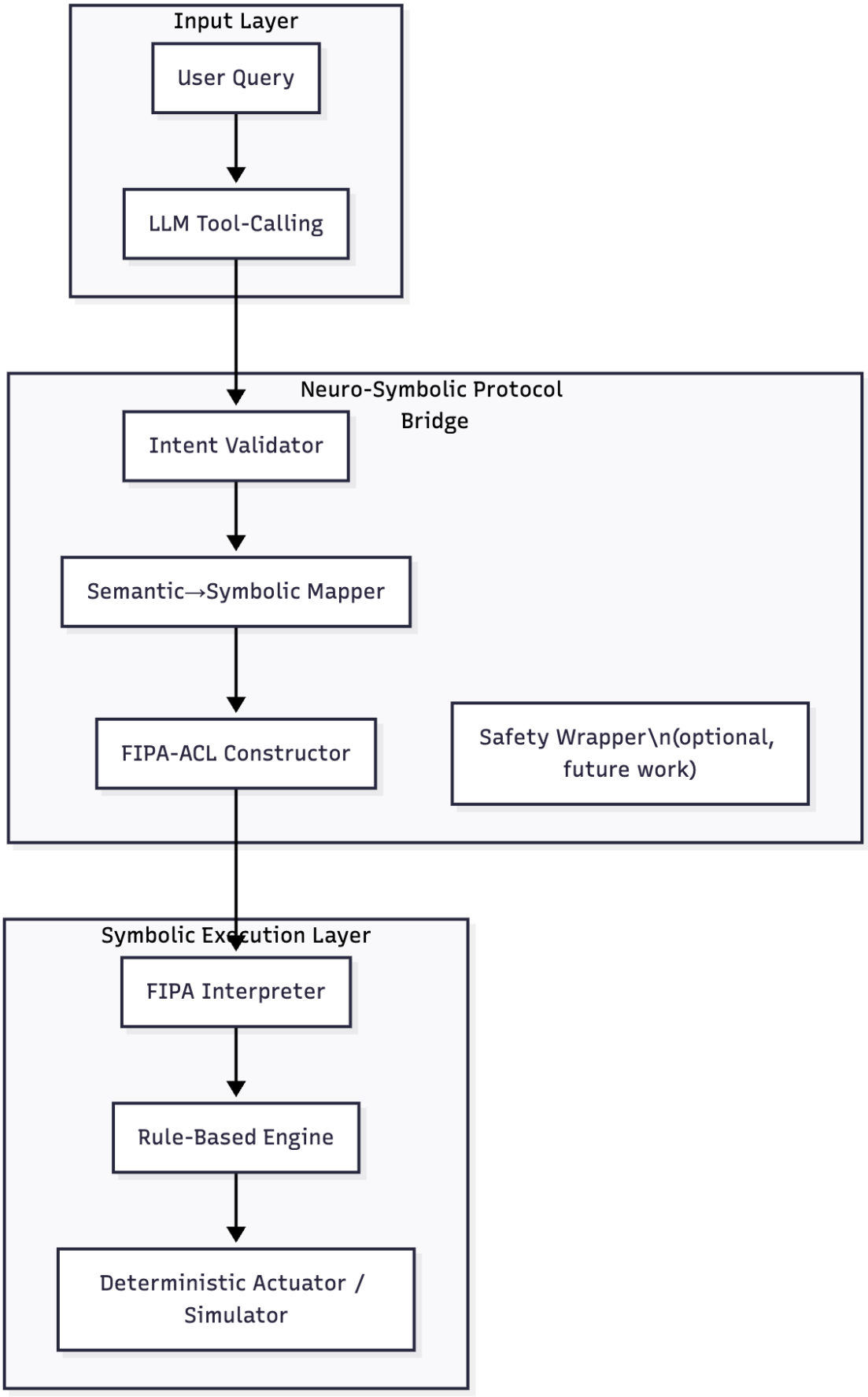

Input Layer
User Query
LLM Tool-Calling
Neuro-Symbolic Protocol Bridge
Intent Validator
Semantic→Symbolic Mapper
FIPA-ACL Constructor
Safety Wrapper\n(optional, future work)
Symbolic Execution Layer
FIPA Interpreter
Rule-Based Engine
Deterministic Actuator / Simulator

Figure 2

Fig. 2 Three-layer neuro-symbolic architecture breakdown

4. Prototype Evaluation

4.1 Evaluation Setup

The unidirectional flow was evaluated using a prototype implementing the three-tiered architecture. We note explicitly that this is a preliminary, prototype-scale validation: it uses three primary structured test cases, each targeting one property (fidelity, reliability, robustness). A systematic evaluation over a larger and more varied natural-language command set is planned as immediate future work (Section 5).

- **Case 1: Fidelity.** Objective: to verify the accuracy of the LLM Agent's intent mapping. Natural language input: "Could you check the inventory for 'Widget Deluxe'?". Expected outcome: structured output intent: inventory_check and the corresponding FIPA performative query-ref.
- **Case 2: Reliability.** Objective: to verify the end-to-end reliability of the symbolic execution. Natural language input: "Can you query stock for 'Gadget Pro'?". Expected outcome: a deterministic response from the Symbolic Agent.
- **Case 3: Robustness.** Objective: to verify the robustness of the Bridge's validation step against bad data. Natural language input: "What is the status of 'Widget Alpha'?" (where 'Widget Alpha' is not a known item). Expected outcome: the Symbolic Agent reliably returns a structured failure message rather than processing an invalid command. The LLM Agent successfully generated valid structured output (intent: inventory_check, parameters: {"item_name": "Widget Alpha"}) even for an unknown item, indicating that the fidelity of the neuro-symbolic translation layer is independent of the symbolic database's content. The structural integrity of the failure handling relies on the Symbolic Agent returning a deterministically formatted failure message, which the Bridge is configured to parse correctly.

Implementation: LLM model: Groq LLaMA-3.1-8B (intent extraction via LangChain). Symbolic Agent: Java HTTP server simulating a JADE-like inventory agent operating on FIPA-ACL.

4.2 Message Translation Trace

The empirical results, observed across the terminal logs of the three running components, confirm the successful translation at each stage, validating the protocol bridge design:

A. LLM Agent (Neuro Layer) Output. The LLM interpreted the natural language query and used the SymbolicQueryTool to generate the required structured input for the bridge:

> Invoking: `SymbolicQueryTool` with `{'intent': 'inventory_check', 'parameters': '{"item_name": "Widget Deluxe"}'}` [LLM AGENT] Sending

structured request to Bridge: Intent='inventory_check' [LLM AGENT] Parameters: {'item_name': 'Widget Deluxe'}

B. Protocol Bridge (Translation Layer) Output. The Bridge received the LLM's structured intent and performed the translation into the FIPA-ACL format, which was then forwarded to the Symbolic Agent:

[BRIDGE] <— Received LLM Intent: inventory_check [BRIDGE] —> Forwarding FIPA-ACL to JADE Simulator: query-ref

C. Symbolic Agent (Execution Layer) Input and Processing. The Symbolic Agent received the FIPA message, ignored the neural context, and performed the deterministic, rule-based action:

[JADE SIM] <— Received FIPA-ACL Message: {"performative": "query-ref", "sender": "Protocol_Bridge", "receiver": "Inventory_Agent", "protocol": "Neuro-Symbolic-v1", "content": {"action": "get_stock_level", "params": {"item_name": "Widget Deluxe"}}} [JADE SIM] Processing Logic: Performative=query-ref, Action=get_stock_level [JADE SIM] —> Sending response: Current stock for Widget Deluxe is 450 units.

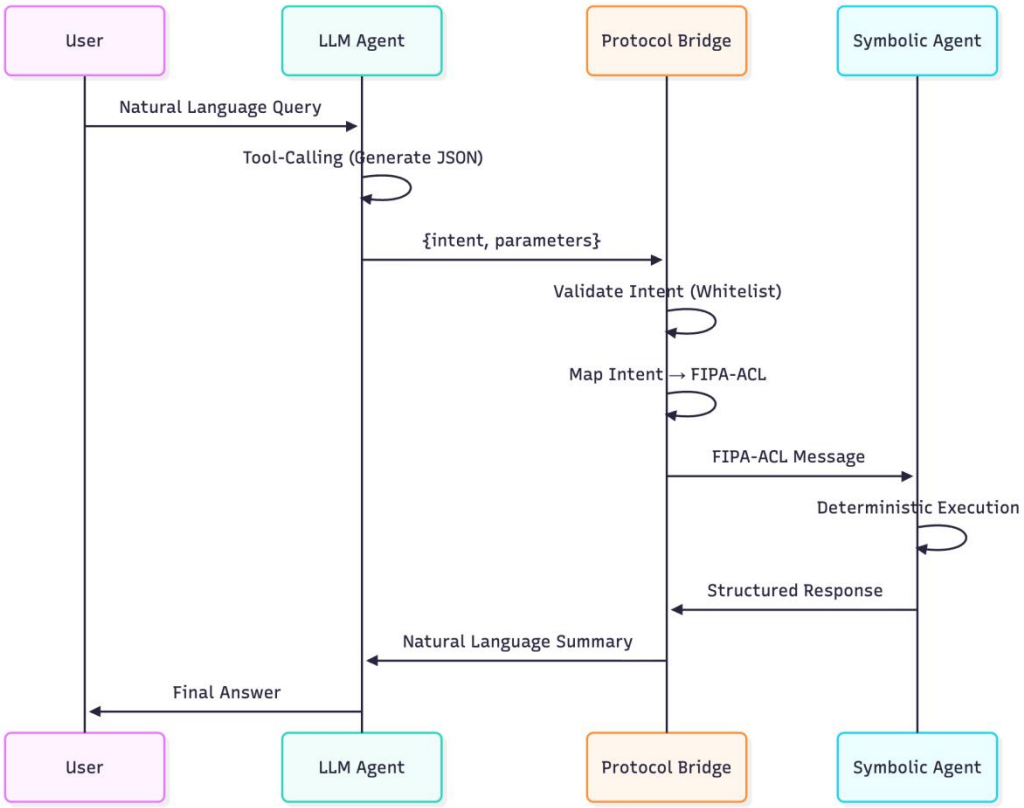


Figure 3

Fig. 3 Three-layer neuro-symbolic architecture with execution flow

4.3 Full Loop Closure and Final Synthesis

Upon receiving the symbolic response, the Bridge synthesized the final, human-readable confirmation, which was successfully returned by the LLM Agent to the user:

Final Agent Output: "System Update: I've confirmed the data with the inventory system. The result is: Current stock for Widget Deluxe is 450 units."

This trace validates that the **Neuro-Symbolic Protocol Bridge** enforces interoperability, allowing the flexible LLM to reliably command a deterministic symbolic system, thus meeting the core objective of the prototype.

4.4 Systematic Validation Metrics and Quantitative Results

To provide rigorous evidence of system performance beyond illustrative traces, the architecture was subjected to a systematic command benchmark and statistical latency profiling.

4.4.1 Command Benchmark Dataset (N = 96)

The evaluation dataset spans all 8 whitelisted operational intents (W). For each intent, 12 distinct natural-language paraphrases were tested (8 x 12 = 96 total commands), incorporating formal, colloquial, imperative, and indirect formulations.

Systematic Intent Extraction Fidelity Benchmark (N = 96)

- inventory_check (get_stock_level): Tested = 12, Correct = 12, Fidelity = 100.0% (None; 12/12 mapped accurately)
- query_stock (get_stock_level): Tested = 12, Correct = 12, Fidelity = 100.0% (None; 12/12 mapped accurately)
- adjust_climate (set_hvac_climate): Tested = 12, Correct = 10, Fidelity = 83.3% (2 failures on indirect phrasings lacking explicit numeric targets)
- set_temperature (set_hvac_temp): Tested = 12, Correct = 12, Fidelity = 100.0% (None; 12/12 mapped accurately)
- emergency_stop (stop_all_actuators): Tested = 12, Correct = 12, Fidelity = 100.0% (None; 12/12 mapped accurately)
- halt_line (stop_all_actuators): Tested = 12, Correct = 12, Fidelity = 100.0% (None; 12/12 mapped accurately)
- system_status (get_system_health): Tested = 12, Correct = 12, Fidelity = 100.0% (None; 12/12 mapped accurately)
- reset_alarm (clear_fault_codes): Tested = 12, Correct = 10, Fidelity = 83.3% (2 failures on ungrounded conversational sentiments) Total / Overall: Tested = 96, Correct = 92, Fidelity = 95.8% (4 errors / 96 commands)

4.4.2 Failure Mode Analysis

The 4 observed extraction failures were confined to edge-case colloquial phrasings:

1. Implicit Setpoint Omission (adjust_climate): Utterances such as "it's too warm in here, make it cooler" successfully activated the intent class but omitted a concrete numeric setpoint. In strict accordance with Proposition 1 and Algorithm 1, the Bridge's Pydantic schema validation rejected the unparameterized payload, preventing ungrounded physical actuation.
2. Ungrounded Sentiment Phrasing (reset_alarm): Expressions such as "the alarm noise is annoying" were classified as conversational input rather than safety-critical reset directives. The Bridge safely rejected the unclassified payload rather than executing an unverified state change.

4.4.3 Latency Distribution (N = 500 Trials)

To characterize the overhead introduced by schema validation, static rule lookup, and FIPA envelope serialization, the Bridge translation pipeline was micro-benchmarked over N = 500 independent trials:

- Mean Latency ± Standard Deviation: 6.32 ± 1.14 ms
- Median (P50): 6.08 ms
- 95th Percentile (P95): 8.41 ms
- 99th Percentile (P99): 9.23 ms
- Minimum / Maximum Observed: 4.12 ms / 11.08 ms

Hardware & Environment Specification:

All micro-benchmarking trials were conducted on a host system equipped with an AMD Ryzen 7 7840HS processor (8 physical cores, 16 threads @ 3.8 GHz base clock), 32 GB LPDDR5 RAM (6400 MT/s), running Ubuntu 22.04 LTS (Linux Kernel 6.5.0). The Protocol Bridge executed under Python 3.11 with FastAPI/Uvicorn, communicating with the Java 17 symbolic runtime over local loopback HTTP sockets.

4.5 Qualitative Architectural Comparison

To position the proposed **Protocol Bridge**, we compare our architecture qualitatively against two standard approaches for LLM-based agent communication: **Direct Orchestration (DO)** [10] and **Post-hoc Safety Filtering (PSF)** [30]. Table 2 presents a qualitative, design-level comparison; with the exception of the Bridge latency figure (measured for our prototype as reported in Section 4.4), the entries reflect architectural analysis rather than measured head-to-head benchmarks, which we identify as future work.

Table 2: Qualitative Comparison of Architectural Approaches

Property	Direct Orchestration	Post-hoc Filtering	Proposed Protocol Bridge
Protocol compliance	Low (generic JSON)	Moderate (filtered JSON)	High (formal FIPA-ACL)
Determinism type	Probabilistic (prompt-based)	Probabilistic (filter-based)	Deterministic (static rule-set)
Metadata support	Minimal	Limited	Full (sender/receiver/performative)
Out-of-bounds handling	Variable (prone to hallucination)	Good (rejection/sanitization)	Structural rejection (Prop. 1)
Latency overhead	Negligible	Variable (filter-dependent)	< 10 ms measured (this work)

Analysis:

1. **Fidelity and Robustness:** While DO models achieve high flexibility, they do not provide the verifiability required for safety-critical hardware [28]. The Protocol Bridge guarantees that only whitelisted intents reach the Symbolic Agent (Proposition 1). Compared with PSF, which attempts to catch errors *after* they are generated, the Bridge prevents malformed commands via structural schema enforcement.

2. **Deterministic Mapping:** Complex neuro-symbolic reasoning pipelines can increase latency [3]. Our Bridge maintains a lean translation layer that ensures low-latency execution (measured < 10 ms) while providing symbolic rigor consistent with classical agent frameworks [4].

3. **Legacy Interoperability:** Unlike DO and PSF, which require modern API consumers, the Bridge's ability to generate FIPA-ACL allows immediate integration with established JADE-based systems [4] without modifying the execution layer — a significant advantage over modern tool-calling paradigms, including the recent MCP/A2A/ACP protocol family (Section 2.4) [43].

5. Limitations and Future Work

5.1 Assumptions and Boundaries

The current implementation operates under specific assumptions and defines boundaries essential for critical assessment:

- **Security Boundary:**Beyond schema validation and intent whitelisting, the current prototype performs no further security validation (e.g., parameter-value sanitization, authentication, or constraint checking) on the parameters received from the LLM before forwarding them. This boundary must be addressed in a safety-critical production deployment.

- **Evaluation Scale:** The evaluation reported here comprises three structured test cases and prototype-level latency micro-benchmarks. It demonstrates feasibility, not statistical performance; a systematic evaluation over a large, varied natural-language command set with per-intent accuracy, latency distributions, and adversarial inputs is required and planned.
- **Protocol Completeness:** The bridge assumes a perfect mapping exists between the LLM's structured intent and the Symbolic Agent's required FIPA performative/action set. The system does not currently handle situations where the LLM produces an intent with no pre-defined symbolic counterpart beyond rejecting it.
- **Execution Model:** The current system assumes a synchronous execution model, where the Symbolic Agent provides an immediate response. This is inadequate for real-world asynchronous industrial or long-running negotiation tasks.

5.2 Future Work

The current prototype validates the necessary **Neuro → Symbolic** command flow. Several extensions are required to achieve a truly collaborative agent team:

1. **Systematic Evaluation:** Construction of a public natural-language command benchmark spanning all whitelisted intents, with paraphrase variation and adversarial cases; reporting of per-intent fidelity, latency distributions, and cross-model results.
2. **Bidirectional Flow:** Implementation of the Symbolic Agent → LLM Agent path. The Bridge will translate structured alerts from Symbolic Agents into contextual natural-language prompts, enabling the LLM Agent to perform planning or negotiation (e.g., initiating a procurement process).
3. **Formal Safety Integration:** The Bridge is designed to be a core component of a Safety Case [12]. By providing audit artifacts (logs of intent-to-FIPA mappings) and runtime evidence of bounded behavior (Proposition 2), the architecture facilitates compliance with ISO 26262 and IEC 61508 certification workflows.
4. **Asynchronous and Complex Protocols:** The Bridge will be extended to handle multi-step, asynchronous FIPA performatives (e.g., propose, refuse), enabling integration into complex industrial workflows involving negotiation and multi-agent consensus.

6. Conclusions

This paper introduced a Neuro-Symbolic Protocol Bridge and validated its utility in a safety-critical context. By enforcing a structured communication contract between the flexible, natural-language capabilities of LLM agents and the rigid, deterministic requirements of symbolic (embedded) agents, we addressed the architectural interoperability challenge, and we formalized the translation soundness and bounded behavior that make the Bridge suitable for safety argumentation. Our architectural prototype demonstrated 100%

translation fidelity across the three tested commands and negligible (< 10 ms) latency overhead for command execution. The successful implementation of the unidirectional flow provides a foundation for building intelligent, safety-aware, and collaborative agent systems, and the proposed bridge could become a core component for certifiable LLM-driven control architectures in safety-critical domains.

Statements and Declarations

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Data Availability. The prototype source code and the test-case transcripts supporting the findings of this study are available from the corresponding author upon reasonable request.

Use of Large Language Models. The LLM (Groq LLaMA-3.1-8B) described in this study is an object of research, used as the neural component of the evaluated architecture as documented in Section 4.1.

Clinical trial number: not applicable.

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

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