# MERL-T: a Multi-Expert architecture for trustworthy Artificial Legal Intelligence

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**Abstract**: *Contemporary Large Language Models fail to capture the fundamental epistemic structure of legal reasoning. Law operates through a constitutive duality: abstract principles providing interpretive scaffolding and concrete rules governing specific situations. Generic LLMs collapse this duality into undifferentiated text, producing plausible but epistemically unfounded outputs. We introduce MERL-T (Multi-Expert Retrieval Legal Transformer), a five-layer pipeline architecture operationalizing legal epistemology through specialized components that preserve the heterogeneity of legal reasoning itself. MERL-T implements epistemic fidelity through: (1) a knowledge graph (KG) encoding legal relationships as explicit, navigable structures rather than implicit weights, distinguishing normative, conceptual, jurisprudential, and doctrinal entities with temporal versioning; (2) orchestrated retrieval agents integrating heterogeneous sources (structured norms, case law, doctrine) through LLM-based dynamic planning; (3) four expert modules grounded in distinct legal philosophies—literal interpretation (legal positivism), systemic-teleological reasoning (legal teleology), principles balancing (constitutional principalism), and precedent analysis (legal realism)—each maintaining internal coherence according to its epistemic commitments; (4) a synthesis layer employing convergent mode when experts agree on conclusions but reason differently, and divergent mode when disagreement reflects genuine legal ambiguity, refusing to force false consensus. Unlike monolithic approaches that collapse methodological plurality into single outputs, MERL-T preserves epistemic plurality by maintaining multiple valid interpretations when legal materials genuinely support divergent readings. Our architectural analysis demonstrates how each design choice follows necessarily from the epistemic requirements of legal reasoning itself, providing a model for trustworthy AI in specialized domains where reasoning structure matters as much as linguistic fluency.*

**Keywords:** Legal Epistemology, Multi-Expert Systems, Knowledge Graphs, Legal Reasoning, Artificial Legal Intelligence

**JEL Classification:** *C45; C55; K00; K40; O31.*

**Note:** *the full version of this abstract is available in the references (Allega & Puzio, 2025b)*

# 1. Introduction

Legal reasoning is specialized practical rationality operating through distinctive epistemic structures (Hart, 1961): abstract principles (constitutional values, fundamental rights) providing conceptual scaffolding, and concrete rules (statutory provisions, regulatory requirements) governing particular situations (Dworkin, 1977). Competent legal reasoning requires navigating between these levels through multiple interpretive methodologies. Contemporary LLMs, trained on undifferentiated corpora, fail to respect this epistemic structure, producing outputs that are linguistically fluent but epistemically unfounded through: (1) epistemic opacity - cannot explain why interpretations are legally valid, (2) structural blindness - miss hierarchical relationships structuring legal knowledge, and (3) methodological monism - collapse different interpretive approaches into single undifferentiated output.

If the problem is epistemic, the solution must be architectural: build epistemic structure into system design. MERL-T (Allega & Puzio, 2025b) operationalizes legal epistemology through specialized components that (1) represent legal knowledge structure explicitly (Allega & Puzio, 2025a), (2) reason according to distinct legal methodologies, and (3) preserve epistemic plurality when disagreement reflects genuine ambiguity (Allega & Puzio, 2025c). This has three architectural consequences: *Explicit Knowledge Representation* (structured knowledge graph (KG) capturing relationships between concepts, norms, principles, precedents), *Methodological Specialization* (distributed across specialized expert modules grounded in distinct legal philosophies), and *Uncertainty Preservation* (preserve disagreement when multiple interpretations are valid). MERL-T implements these through five layers: *Preprocessing* (query understanding + KG enrichment), *Orchestration* (LLM-based routing + retrieval agents), *Reasoning* (four specialized experts + synthesis), *Storage* (multi-database architecture), and *Learning* (community feedback with uncertainty preservation) (Allega & Puzio, 2025c).

# 2. Literature Review on the Five-layer architecture

MERL-T processes Italian legal queries through five interconnected layers:

1. **Preprocessing Layer:** six-stage adaptive processing: abbreviation expansion, entity extraction, concept mapping, intent classification, complexity estimation, temporal detection. KG Enrichment Engine maps concepts to norms/principles/precedents through graph traversal. (Hamilton et al., 2017)
2. **Orchestration Layer:** LLM-based Router generates dynamic execution plans selecting retrieval agents (KG Agent, API Agent, VectorDB Agent) and reasoning experts based on query characteristics (Brown et al., 2020; Anthropic, 2024).
3. **Reasoning Layer:** four specialized experts (Literal Interpreter, Systemic-Teleological Reasoner, Principles Balancer, Precedent Analyst) perform legal analysis grounded in distinct epistemological frameworks. Synthesizer combines outputs through convergent or divergent synthesis. (Kipf & Welling, 2017)
4. **Storage Layer:** Neo4j KG for structured relationships, ChromaDB for semantic search, PostgreSQL for metadata. Data ingestion pipeline processes legislation, jurisprudence, doctrine. (Bordes et al., 2013; Lehmann et al., 2015).
5. **Learning Layer:** community feedback with dynamic authority weighting enables progressive improvement while maintaining epistemic fidelity (Allega, 2025; Allega & Puzio 2025c).

# 3. Knowledge graph: encoding legal epistemology

The KG is an epistemic structure making implicit legal relationships explicit and navigable, serving three functions: conceptual scaffolding (representing abstract legal concepts and relationships), provenance grounding (linking concepts to authoritative sources), and temporal navigation (maintaining temporal versions for historical queries).

The KG is a labeled directed graph G=(V,E,λ,τ) where V represents legal entities, E⊆V×V represents typed relationships, λ:V→T assigns node types, and τ:V→2^T assigns temporal validity. Node types include: *Normative* (it. “Norma”, “Principio”, “Comma/Lettera/Numero”), *Conceptual* (it. “Concetto Giuridico”, “Definizione Legale”), *Jurisprudential* (it. “Sentenza”, “Massima”, “Caso”), and *Doctrinal* (it. “Dottrina”, “Commentario”). Edge types represent: *Structural Relations* (it. “CONTIENE”, “MODIFICA”, “ABROGA”), Semantic Relations (it. “REGOLA”, “DEFINISCE”, “PRESUPPONE”), *Jurisprudential Relations* (it. “APPLICA”, “INTERPRETA”, “SOSTITUISCE”), and *Principled Relations* (it. “CONFLIGGE”, “BILANCIA”, “DERIVA\_DA”).

For temporal versioning, each Norma node *n* maintains Versions(n)={(v₁,[t₁ˢ,t₁ᵉ]),...,(vₖ,[tₖˢ,tₖᵉ])} enabling queries at specific times. The KG ensures three epistemic properties: *Explicitness* (implicit relationships become explicit edges), *Navigability* (traverse from concepts to related norms/principles/cases), and *Provenance* (every node/edge includes source metadata). While vector embeddings provide semantic similarity, explicit graph structure distinguishes relationship types, supports complex queries, and makes semantics queryable and explainable. MERL-T uses both: KG for epistemic structure, vectors for flexible retrieval.

# 4. Multi-Expert Reasoning

Legal reasoning is heterogeneous - four methodologies (literal, teleological, principled, precedential) reflect fundamentally different epistemic commitments: literal treats law as text (semiotic analysis), teleological as purposive system (intentionalist hermeneutics), principled as normative hierarchy (value reasoning), precedential as social practice (analogical reasoning). Attempting all four in a single forward pass produces epistemically confused outputs. MERL-T implements methodological specialization through four distinct experts:

1. **Literal Interpreter (legal positivism):** strict grammatical analysis and ordinary meaning (Kelsen, 1960). Prohibits considering legislative purpose, case law, or constitutional principles. Activated for clear rules, validity checks. Example: (it.) Art. 1350 c.c. requires written form for real estate - literal interpretation: oral contract is void.
2. **Systemic-teleological Reasoner (legal teleology):** identifies the *ratio legis* and interprets text to achieve purpose while maintaining systemic consistency. Activated for ambiguous text, incomplete norms. Example: (it.) Art. 1350 - why written form? Ensure certainty. Therefore interpret to include electronic signatures providing equivalent certainty.
3. **Principles Balancer (constitutional principlism):** resolves principle conflicts through proportionality analysis (legitimate aim, suitability, necessity, proportionality) (Dworkin, 1977, 1986; Alexy, 2002). Activated for constitutional questions, rights conflicts. Example: defamation balances free expression vs. honor, with journalists receiving more protection due to public interest.
4. **Precedent Analyst (legal realism):** analyzes how courts actually applied norms in analogous cases (Holmes, 1897). Extracts *ratio decidendi*, tracks temporal evolution, weights by authority. Activated for novel applications, evolving standards. Example: "good faith" in (it.) Art. 1337 c.c. requires consulting Supreme Court decisions (Bench-Capon & Sartor, 2003).

Why four experts? Each embodies distinct epistemic commitment about legal meaning - commitments mutually exclusive within a single reasoning chain. Separating experts ensures internal coherence according to epistemic commitments. Each methodology requires specialized context (e.g., only Principles Balancer receives constitutional precedents). Separation makes methodology choice visible: which expert(s) consulted, what reasoning each provided, how outputs synthesized.

# 5. LLM-Based orchestration

The Router must decide: which retrieval agents, which experts, what synthesis mode, when to iterate. Traditional MoE systems use gating networks (Jacobs et al., 1991; Shazeer et al., 2017) - non-interpretable, rigid, context-insensitive. MERL-T uses LLM-based orchestration: Router is itself an LLM reasoning about optimal execution strategy. It receives query context, enriched context, conversation history and produces *ExecutionPlan* (structured JSON) specifying *retrieval\_plan*, *reasoning\_plan*, *iteration\_strategy* with explicit rationale.

This offers four advantages: *Interpretability* (explicit rationale for every decision), Adaptability (adapts to novel queries without retraining), *Learning* (improves through feedback on execution plans), and *Compositionality* (decomposes complex queries into sub-plans). The *Iteration Controller* evaluates *ProvisionalAnswer* after each cycle based on confidence, expert consensus, norm ambiguity, and retrieval sufficiency, generating refinement plans when needed until stopping conditions are satisfied.

# 6. Synthesis: preserving epistemic plurality

The Synthesizer integrates expert outputs through two modes: *Convergent Synthesis* (when experts agree on conclusion but reason differently) extracts common conclusion, integrates multiple reasoning lines, preserves methodology attribution, and builds composite provenance. Example: minor's contract - Literal Interpreter cites Art. 2 c.c. (capacity at 18), Systemic-Teleological notes protective purpose. Synthesized answer provides both textual clarity and purposive coherence. *Divergent Synthesis* (when experts disagree substantively) identifies divergence points, explains sources, presents multiple perspectives with reasoning, and makes methodology visible. Example: journalist publishing private photos - Principles Balancer applies proportionality test (permitted if newsworthy/proportional), Precedent Analyst cites Supreme Court trend (permitted for public figures). Both favor permission with different justifications - boundary context-dependent requiring case-by-case assessment.

Why preserve disagreement? Legal ambiguity is often a genuine feature of legal materials. Forcing false consensus: (1) misrepresents epistemic state, (2) obscures methodology, (3) reduces practical value. Divergent synthesis respects epistemic plurality - tells the truth about legal complexity.

# 7. Preliminary Empirical Evidence

MERL-T is currently in an early implementation phase. We present preliminary empirical evidence demonstrating proof-of-concept feasibility while acknowledging the significant validation work that remains. Full access to the repository is available via Github.

## 7.1 Knowledge Graph Implementation

The Knowledge Graph component has been implemented and populated with Italian legal sources. Data ingestion achieved 100% completion for the fourth book of Italian Civil Code (887 articles) and Constitution (139 articles), with 92% doctrine enrichment.

***Table 1: Knowledge Graph Statistics***

|  |  |  |
| --- | --- | --- |
| **Metric** | **Value** | **Interpretation** |
| Total Nodes | 27,740 | Includes articles, commi, references |
| Total Relationships | 43,935 | Semantically typed |
| Nodes per Article | ~2.9 | Reflects hierarchical structure |
| Relationships per Node | 1.58 | Moderately connected graph |

The node-to-article ratio (~2.9) reflects the hierarchical structure of Italian law: each article generates separate nodes for commi (paragraphs), lettere (letters), and temporal versions (multivigenza). The relationship density (1.58) is typical for legal documents with cross-references.

***Table 2: Node Type Distribution***

|  |  |  |
| --- | --- | --- |
| **Type** | **Percentage** | **Example** |
| Norma (Norm) | 45.1% | Laws, decrees, regulations |
| Articolo (Article) | 29.6% | Base legal units |
| Comma (Paragraph) | 14.8% | Numbered subdivisions |
| Concetto (Concept) | 6.5% | Abstract concepts (e.g., "buona fede") |
| Principio (Principle) | 2.3% | Fundamental principles |
| Sentenza (Sentence) | 1.8% | Court rulings |

## 7.2 Retrieval Performance

Semantic search performance was evaluated on a gold standard of 30 queries:

***Table 3: Retrieval Benchmark Results***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Metric** | **Value** | **Target** | **Status** | **Industry Benchmark** |
| NDCG@5 | 0.869 | 0.60 | +44.8% | 0.70-0.85 |
| Hit Rate@5 | 96.67% | 90% | +7.4% | 85-95% |
| MRR | 0.850 | 0.70 | +21.4% | 0.70-0.85 |
| Perfect Match | 93.3% | 80% | +16.6% | 75-90% |
| Latency (vector) | 93 ms | <200 ms | ✓ | 50-150 ms |

***Table 4: Performance by Query Type***

|  |  |  |
| --- | --- | --- |
| **Query Type** | **Recall@5** | **Example** |
| Institutional | 96.7% | "Art. 1453 risoluzione contratto" (contract resolution) |
| Numeric | 93.3% | "Articolo 2043 codice civile" (civil liability) |
| Conceptual | 61.1% | "Cos'è la buona fede contrattuale?" (good faith) |
| Procedural | 58.3% | "Come si calcola il risarcimento?" (compensation) |

*Critical Observation: The system excels at finding specific articles (96.7% for institutional queries) but shows significant degradation on conceptual queries (61.1%). This gap reveals a fundamental limitation of semantic search for concepts distributed across multiple articles—a target for future work.*

## 7.3 Multi-Expert Pipeline Validation

The four-expert system was tested on 9 legal queries with full pipeline tracing. This validates that the architectural components described in Sections 3-6 operate as designed.

***Table 5: Expert Latency Breakdown***

|  |  |  |  |
| --- | --- | --- | --- |
| **Expert** | **Mean Latency** | **95% CI** | **% Total** |
| Literal Interpreter | 8,682 ms | [7,155, 9,922] | 15.0% |
| Systemic-Teleological | 11,864 ms | [9,922, 13,535] | 20.5% |
| Principles Balancer | 10,228 ms | [7,673, 12,115] | 17.7% |
| Precedent Analyst | 11,133 ms | [10,166, 12,192] | 19.3% |
| Orchestrator | ~15,875 ms | - | 27.5% |
| Total Pipeline | 57,782 ms | [53,782, 61,565] | 100% |

The Systemic-Teleological expert is the slowest (20.5% of time) because it must verify consistency with the broader legal system. The Orchestrator consumes 27.5% for intelligent routing and final synthesis.

***Table 6: Expert Confidence Scores***

|  |  |  |  |
| --- | --- | --- | --- |
| **Expert** | **Mean Confidence** | **95% CI** | **Interpretation** |
| Literal | 0.822 | [0.611, 0.944] | High - explicit text |
| Systemic | 0.811 | [0.600, 0.933] | High - clear references |
| Principles | 0.700 | [0.400, 0.900] | Medium - broader interpretation |
| Precedent | 0.789 | [0.589, 0.900] | High - citable jurisprudence |
| Weighted Mean | 0.788 | [0.584, 0.909] | - |

The Principles Balancer shows lower confidence (0.70) and wider confidence intervals because it operates on abstract concepts (e.g., "good faith") requiring broader interpretation, compared to other experts working with concrete sources.

## 7.4 Source Grounding Analysis

Comparison of Expert System vs. baseline LLM (20 queries, EXP-020):

***Table 7: Expert System vs. Baseline LLM***

|  |  |  |  |
| --- | --- | --- | --- |
| **Metric** | **Expert System** | **Baseline LLM** | **Delta** |
| Source Grounding | 100.0% | 96.6% | +3.4% |
| Hallucination Rate | 0.0% | 3.4% | -3.4% |
| Citations per Response | 16.7 | 2.1 | +695% |
| Average Latency | 14,012 ms | 9,940 ms | +41% |

## 7.5 Methodological Limitations

1. Sample size: only 30 gold standard queries (N=30) and 9 pipeline traces (N=9). Statistical power is borderline; N≥100 coming in Phase 2.

2. Italian Law Only: Current implementation is specific to Italian legal system. Generalization requires architectural adaptation.

***Table 9: Hypothesis Success Rate***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Category** | **Tested** | **Passed** | **Failed** | **Rate** |
| Data Ingestion | 10 | 10 | 0 | 100% |
| Knowledge Graph | 4 | 4 | 0 | 100% |
| RAG Retrieval | 15 | 11 | 4 | 73% |
| Expert System | 10 | 4 | 6 | 40% |
| Total | 39 | 29 | 10 | 74% |

*The pattern is clear: foundational components (ingestion, KG) are mature at 100%, while higher-level components (expert reasoning) require iteration*

# 8. Discussion

## 8.1 Architectural necessity

We claim this architecture is necessary for trustworthy legal AI. Legal reasoning requires navigating principles/rules through multiple methodologies (Premise1). This epistemic structure cannot be adequately represented in implicit weights - it must be externalized in explicit components (Premise2). Different methodologies embody mutually exclusive commitments and must be separated for coherence (Premise3). Therefore, trustworthy legal AI must implement explicit knowledge structures (KG), separated interpretive specialists (Experts), and transparent synthesis through orchestrated pipelines. MERL-T's architecture follows necessarily from epistemic requirements of legal reasoning.

## 8.2 Comparative advantages

Compared to monolithic LLMs: explicit KG structure vs. implicit weights, four specialized methodologies vs. undifferentiated reasoning, dynamic planning vs. fixed forward pass, convergent/divergent synthesis vs. single output, full provenance vs. opacity, prompt evolution vs. retraining required, high epistemic fidelity vs. collapsed plurality. Compared to standard RAG (Lewis et al., 2020): KG enrichment guides retrieval semantically and structurally vs. pure similarity, orchestrates heterogeneous sources vs. single corpus, provides expert interpretations with provenance vs. document chunks.

## 8.3 Limitations and future work

The four-expert model captures major methodologies but not all approaches (economic analysis, critical legal studies exist). KG requires ongoing curation for new legislation/case law/doctrine (Chalkidis et al., 2020; Ashley, 2017). Multi-expert architecture requires multiple LLM calls increasing latency/cost vs. monolithic models (mitigated through parallel execution, caching, custom models for simpler steps). Current design reflects the Italian legal system - other jurisdictions require adapted architectures. Future work: cross-jurisdictional extension, production optimization, empirical validation with practitioners, integration with additional reasoning paradigms.

## 8.4 Broader implications

For Legal AI Research: architectural choices matter epistemically - system structure determines reasoning capabilities and domain fidelity. For AI Ethics (EU’s High-Level Expert Group on Artificial Intelligence, 2019): trustworthy AI requires epistemic fidelity where reasoning structure respects domain norms - MERL-T proves such fidelity can be operationalized. For Legal Practice: multi-expert architecture has pedagogical value, making methodologies explicit and comparing outputs to enhance critical thinking about legal reasoning (Allega, 2025; Allega & Puzio, 2025a).

# 9. Conclusion

Trustworthy legal AI requires architectural commitment to epistemic fidelity: system structure must mirror legal reasoning's epistemic structure. Generic LLMs cannot capture law's dual nature (principles vs. rules) or methodological plurality. MERL-T operationalizes legal epistemology through five layers: KG making implicit relationships explicit, LLM-based Router for dynamic planning, Specialized Experts grounded in distinct philosophies, Synthesis preserving epistemic plurality, and learning enabling evolution through community feedback (Allega & Puzio, 2025c). The result is a system that reasons legally - navigating between principles and rules, applying distinct methodologies, preserving uncertainty when appropriate, providing full provenance. This is not a black box but a glass box making legal reasoning transparent, auditable, and epistemically grounded. For legal AI, architecture is epistemology. The way we structure the system determines what it can know, how it can reason, and whether outputs are trustworthy. MERL-T demonstrates that architectural choices can operationalize complex domain epistemology, providing a model for trustworthy AI in specialized domains where reasoning structure matters as much as linguistic fluency.

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