
A survey of neurosymbolic artificial intelligence: foundations, advances, and future trajectories

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Abstract

Neurosymbolic artificial intelligence seeks to integrate the strengths of learning and symbolic reasoning to deliver systems that are effective, interpretable, reliable, and accountable. This survey compiles advances from 2020 to mid-2026, organized into four themes: performance, understandability, reliability, and ethics.

We treat an approach as neurosymbolic only when symbolic structures with well-defined semantics participate directly in learning or inference; retrieval or external tool use without such coupling is treated as adjacent context. Within this scope, we describe recurring interface patterns - in practical terms, the ways neural components consume, produce, or are constrained by symbolic representations and reasoning operators (e.g., programs/queries, constraints, or structured traces). We use these patterns to organize and compare approaches across the functional roles they target in AI systems (perception, knowledge, reasoning, planning/control, and oversight).

Keywords

neurosymbolic artificial intelligence, survey, performance, understandability, reliability, ethics

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Abbreviations

Abbreviation	Expansion
Venues and journals	
AAAI	Association for the Advancement of Artificial Intelligence
ACL	Association for Computational Linguistics (Annual Meeting)
AISTATS	International Conference on Artificial Intelligence and Statistics
EMNLP	Empirical Methods in Natural Language Processing
ICLR	International Conference on Learning Representations
ICML	International Conference on Machine Learning
IJCAI	International Joint Conference on Artificial Intelligence
NAACL	North American Chapter of the Association for Computational Linguistics
NeurIPS	Advances in Neural Information Processing Systems
PMLR	Proceedings of Machine Learning Research
WWW	The Web Conference
Methods and concepts	
AI	Artificial Intelligence
ASP	Answer Set Programming
DNN	Deep Neural Network
GNN	Graph Neural Network
HCI	Human-Computer Interaction
HIL	Human-in-the-Loop
ILP	Inductive Logic Programming
JEPA	Joint Embedding Predictive Architecture
KG	Knowledge Graph
KGQA	Knowledge Graph Question Answering
KR	Knowledge Representation
LLM	Large Language Model
MLN	Markov Logic Network
NAS	Neural Architecture Search
NeSy	Neurosymbolic
NLP	Natural Language Processing
QA	Question Answering
QALD	Question Answering over Linked Data
RAG	Retrieval-Augmented Generation
RL	Reinforcement Learning
SAT	Boolean Satisfiability
SMT	Satisfiability Modulo Theories
TD	Temporal-Difference
XAI	Explainable Artificial Intelligence

1 Introduction

Neurosymbolic artificial intelligence (NeSy AI) aims to combine the strengths of statistical learning with explicit knowledge and reasoning in order to build systems that are effective, interpretable, reliable, and accountable. We set the stage by briefly revisiting the symbolic and neural traditions and the case for integration, then articulating the problem this survey addresses, its scope and novelty, and the contributions it makes.

1.1 Background: Symbolic vs. Neural and the Case for Integration

Artificial intelligence has advanced through two intertwined traditions. In the symbolic lineage, early systems demonstrated task-oriented language interaction and structured manipulation within constrained domains (e.g., *ELIZA* and *SHRDLU*) (Weizenbaum, 1966; Winograd, 1971). This line of work also established long-running debates about representation, symbol grounding (the classical sense: relating symbols to what they denote in the world; we return in Section 2.4 to a second, looser sense in which contemporary language-model pipelines use “grounding” for retrieval, citation, or tool grounding, which does not on its own imply semantic grounding or correctness guarantees), and the relationship between symbols and procedures (Moran, 1973; Cohen, 1983; Sloman et al., 1983). Subsequent critiques clarified limitations of purely symbolic accounts and emphasized the role of execution, procedures, and *operational semantics* (how a procedure executes step by step, rather than only what it is intended to compute) (Touretzky & Minton, 1985; Dahlback, 1989; Russell, 1989). Empirical comparisons and early integration attempts in the late 1980s and 1990s explored how symbolic structure and neural learning can be combined in practice (Barnden, 1989; Frixione & Spinelli, 1989; Mooney et al., 1989). Case-based reasoning provided additional evidence that explicit representations and retrieval can support structured reasoning in applied settings (Ashley & Alevan, 1997; Rosa & Franeozo, 1999).

In parallel, the connectionist lineage established core learning principles and scalable representations, from early perceptrons and associative memory through backpropagation and modern deep learning (Rosenblatt, 1958; Hopfield, 1982; Rumelhart et al., 1986; Bengio et al., 2021). Subsequent work extended these capabilities to attention-based architectures and large-scale generative models that support broad task coverage (Vaswani et al., 2017; Ramesh et al., 2021). Neural systems paired with explicit search provide a reference point for how learning and planning can be composed in complex decision-making (Silver et al., 2016). Domain-specialized

language models illustrate both the gains and the limitations of purely neural approaches in knowledge-intensive settings: large models trained on biomedical corpora (for example *BioMegatron*) match or surpass general-purpose baselines on in-domain benchmarks, while general NLP textbooks document the recurring failure modes (factual inconsistency, brittle reasoning chains, opaque error attribution) that motivate the explicit knowledge representations and structured operators developed in the rest of this survey (Shin et al., 2020; Jurafsky & Martin, 2025).

Viewed through a broader historical lens, the field alternates between symbolic and neural emphases, and position pieces argue for integration as a recurring response to limitations in either approach (Kautz, 2022). Surveys and textbooks motivate neurosymbolic systems as a way to combine learned percepts with explicit, inspectable representations and operators (Garcez et al., 2019; Garcez & Lamb, 2020; Russell & Norvig, 2020). Recent neurosymbolic surveys emphasize practical architectures, evaluation concerns, and the role of explicit knowledge representation (KR — symbolic structures with defined operators, as opposed to learned distributed representations) in modern pipelines (Hitzler et al., 2022, 2024). Cognitive perspectives provide a functional motivation for pairing fast pattern recognition with deliberative reasoning (Kahneman, 2011; Laird et al., 2017). Human-centric perspectives emphasize systems that can explain, align, and collaborate rather than replace (Horvatić & Lipic, 2021).

Experiences from large-scale deployments illustrate both the potential and fragility of purely data-driven methods, reinforcing the need for auditable, knowledge-guided reasoning within AI pipelines (Strickland, 2019). Conceptual roadmaps and position pieces articulate why and how to integrate neural competence with symbolic structure to achieve generality with accountability (Marcus, 2020; Sheth et al., 2023a,b). Complementary perspectives emphasize system-level design choices and integration trade-offs (Sheth & Roy, 2024; Ganguly & Mukherjee, 2025). Together, these lines of evidence motivate a neurosymbolic agenda: retain the strengths of scalable learning, perception, and generation, while introducing explicit knowledge, inference, and control to support interpretation, transfer, and reliable decision-making across complex tasks.

1.2 *Problem Statement: A Fragmented and Rapidly Evolving Landscape*

Foundation models have accelerated rapidly, expanding the scope of tasks that can be addressed by learned systems while exposing new limitations and open questions about evaluation and control. Reports on frontier LLMs describe broad, cross-domain

capability alongside uneven reliability and opaque failure modes, underscoring the need for principled assessment beyond benchmark-by-benchmark comparisons (Bubeck et al., 2023). Recent stress-tests of frontier reasoning models sharpen the same finding: controlled symbolic perturbations of grade-school math problems cause systematic accuracy drops in instruction-tuned LLMs even when the perturbed problem is logically equivalent to the original, and chain-of-thought traces from larger reasoning models continue to fail in characteristic ways when the underlying symbolic structure of the problem changes rather than its surface form (Mirzadeh et al., 2025; Shojaee et al., 2025). We cite these analyses here as motivation for why explicit symbolic structure — typed artifacts and operators that the model is required to interact with rather than only to imitate — continues to matter; they are not promoted to evidenced rows in the per-theme evidence tables because they characterise neural-only systems rather than a neural–symbolic coupling. At the same time, progress signals remain difficult to compare across subfields: evaluation measures differ, data and tasks shift, and there is no universally accepted quantitative lens for characterizing improvement. Recent work proposes technology-improvement-rate measurements using patent citation networks to quantify and compare advancement across AI subdomains, but such instruments are only beginning to connect to practice-level evaluation in research benchmarks (Rezazadegan et al., 2024).

These dynamics also interact with ongoing challenges in reproducibility and reporting. Earlier audits quantified documentation gaps in empirical AI research (Gundersen & Kjensmo, 2018), and while community norms and tooling have improved since then, more recent analyses still find that software and experimental artifacts are provided unevenly and that reproduction can remain non-trivial in practice (Wolter et al., 2025). In neurosymbolic AI, the coupling between learned components and explicit knowledge/reasoning further increases sensitivity to implementation and documentation choices; recent systematic review practice has therefore used code availability as an explicit inclusion criterion (Colelough & Regli, 2025). We therefore pose the problem addressed by this survey as one of synthesis and normalization: to chart what the community is doing across rapidly evolving lines of work, to relate methods to common system functions and evaluation levers, and to consolidate practical, theme-oriented guidance that supports comparability, reproducibility, and decision-making across applications (Bubeck et al., 2023; Rezazadegan et al., 2024).

1.3 Novelty of this Synthesis and Scope

The novelty of this survey is its perspective. We use four *goal* themes (performance, understandability, reliability, ethics) to ask what a neurosymbolic interface is meant to improve, and we couple them with an *interface-pattern* vocabulary (codes I0–I8, Section 2.4, Table 2) that subsumes Kautz’s six integration patterns (Kautz, 2022) but extends them with two practical codes that recur in 2020–mid-2026 work: tool augmentation (I0), which is recorded as adjacent context unless paired with a *typed artifact* (an explicit machine-readable structure such as a logical query, program, plan, or proof; defined in Section 2.4), and accountability / human-revision workflows (I8), which capture the oversight loop that ethics evidence requires. The combination is then instantiated in four per-theme evidence tables (one per theme; Section 2.5, Tables 5–9) built from paper-level coding against the documented dimensions (Section 2.3). Temporal scope is primarily 2020 to mid-2026 with foundational anchors when essential for context. Domain coverage spans NLP, vision, knowledge graphs, planning/control/RL, robotics, and verification.

Scope boundary (what counts as neurosymbolic evidence in this survey). We treat a method as neurosymbolic evidence only when it includes (i) an explicit symbolic representation with defined operators/semantics (logic/rules, executable programs, KGs with query/entailment operators, planners/controllers, SAT/SMT constraints, proof traces) and (ii) an explicit coupling where those operators constrain, check, or otherwise participate directly in training or inference. Retrieval-augmented generation, tool calling, and natural-language reasoning traces are treated as adjacent context unless they produce typed/executable artifacts that are executed or checked by explicit operators (for example, emitting a query/program and validating it against a KG/reasoner, or enforcing constraints via checking or *shields* — runtime safety filters from safe RL that block disallowed actions; see Table 2 row I4).

What this survey adds beyond closest concurrent surveys. The closest concurrent reviews each emphasize a different lens, and the differences below describe *what we add on top of them* rather than a ranking.

- Compared to broad capability reports such as (Bubeck et al., 2023) and method-improvement-rate measurements such as (Rezazadegan et al., 2024), we add a survey-scale evidence protocol (Section 2.6) that scopes each comparative claim to a task, dataset, and measure rather than to a model family.

- Compared to the systematic mapping by (Colelough & Regli, 2025), we add (a) goals-first thematic organization, (b) explicit Kautz crosswalk, (c) per-paper trade-off and limitation columns in the per-theme evidence tables.
- Compared to the trustworthy-NeSy review by (Michel-Deletie & Sarker, 2025), we extend coverage from interpretability/trustworthiness to all four themes, with separate evidence-tagged rows for each theme.
- Compared to the broad taxonomy by (Bhuyan et al., 2024), we replace the rigid taxonomy assignment with per-theme evidence tables in which a paper can appear in multiple rows along the triple (theme = the goal, interface = how neural and symbolic components couple, function role = where in the system the coupling does work; defined in Section 2.4, Tables 1–3) when its contributions span themes.
- Compared to KG-reasoning surveys such as (DeLong et al., 2025), we widen scope outside KG reasoning while keeping KG-reasoning rows comparable through the same artifact + operator columns.
- Compared to visual reasoning surveys such as (Khan et al., 2025), we keep visual reasoning as one I1/perception family, contextualized by the rest of the matrix.

The bullets above name the closest concurrent comparator surveys for the contribution claim. Table 11 in Section 4 reuses the four method-organising surveys among them ((Bhuyan et al., 2024; DeLong et al., 2025; Michel-Deletie & Sarker, 2025; Colelough & Regli, 2025)) and adds (Renkhoff et al., 2024) for verification / validation framing; the broad capability and method-rate references (Bubeck et al., 2023; Rezazadegan et al., 2024) are not survey-format works and are kept as context citations, while (Khan et al., 2025) is the visual-reasoning anchor for Section 3.2. The contribution is therefore a goals-first synthesis that connects what a neurosymbolic coupling is intended to achieve, what operator actually enforces or checks it, and what evidence supports the claim, in a single matrix that other reviews can be mapped into.

1.4 Contributions

The paper offers, in order:

- (i) A goals-first compilation of 2020 to mid-2026 literature organized around four themes (performance, understandability, reliability, ethics) coupled to an interface-pattern vocabulary that subsumes Kautz’s integration patterns and extends them with

codes for tool augmentation (I0) and accountability/human-revision workflows (I8). Sections 2.4, 2.5, and 3; Tables 1, 2.

- (ii) Four per-theme evidence tables (Tables 5, 7, 8, 9) built from paper-level coding against the dimensions defined in Section 2.4, mapping each paper to one or more (theme, interface, function-role) rows with associated artifact + operator, evidence tag, and trade-off/limitation columns.
- (iii) An evidence protocol (Section 2.6, Table 4) that scopes every comparative claim to a task, dataset, and measure, with explicit tags (measured, formal/scoped, claimed, not evaluated) and explicit citation roles (definitional, pattern exemplar, evidence, context/background, position/opinion).
- (iv) A cross-theme analysis of recurring trade-offs (cost overhead, guarantee scope, artifact-validity risk, deployment/governance risk), recorded in the per-theme evidence tables so trade-off claims are tied to specific rows rather than to high-level architecture families.
- (v) Future directions and open challenges with concrete evaluation criteria and test considerations (Section 5). The scope of the present synthesis is stated separately in Section 4.3 so it does not occupy contribution claims.

1.5 Overview of the Survey

This subsection provides a roadmap. Section 2 sets out the source-selection, screening, and tagging process and defines the categorization system (themes, interface patterns, function roles) together with the evidence protocol. Section 3 presents the four core themes; each theme section opens with its per-theme evidence table (Tables 5, 7, 8, 9) and narrates the rows along interface-pattern families. Section 4 positions the survey relative to prior reviews and discusses broader implications. Section 5 articulates future directions with evaluation criteria and test considerations. Section 6 offers a concise recap. Appendix material reports source-specific queries, selection counts, and the data-extraction dimensions.

2 Methods of the Survey

This section describes how evidence was collected and how it is organized for the rest of the paper. It first sets out source selection, screening, and tagging (Sections 2.1–2.3), then defines the categorization system used throughout the paper (Section 2.4): three row-generating dimensions (theme, interface pattern, function role), the per-theme evidence tables that combine them (Section 2.5), and the evidence protocol that scopes every claim (Section 2.6). The categorization is described once here so that each subsequent theme section can be read as an instantiation of the same vocabulary on the same evidence base.

2.1 Source Selection

We focused on peer-reviewed work from 2020 to mid-2026, supplemented with foundational anchors when essential for context. Sources included prominent AI venues (AAAI, IJCAI, NeurIPS, ICML/AISTATS via PMLR, ICLR, ACL/EMNLP/NAACL/Findings, WWW) and journals/publishers relevant to neurosymbolic AI and KR, including this journal (Neurosymbolic Artificial Intelligence, IOS Press), Semantic Web (IOS Press), ACM, IEEE venues, and Nature/Nature Communications. We also considered relevant Springer publications and reputable preprints from arXiv when at least one of the following was true: (i) the preprint was already used as current evidence in adjacent peer-reviewed work that explicitly cited it as the source of the claim; or (ii) the preprint supplied a recent benchmark, dataset, or systematic review not yet available in archival form. When a preprint had a later conference or journal version, we treated the published version as the citable target and used the preprint only to locate or compare metadata. ArXiv-only items therefore appear in the bibliography only when one of the two conditions above applies, and are identifiable by the absence of a published-venue field. Searches were performed over digital libraries and indexing services using neurosymbolic integration keywords (logic, KGs, differentiable reasoning, planning/control, verification, explainability, symbol grounding, tool grounding) combined with venue and year filters. Query formulations differ across sources because each platform exposes a different query DSL and indexes a different subset of venues; the appendix (Section A) records the source-specific keyword and filter combinations actually run. Inclusion prioritized works that (i) integrate neural and symbolic elements, (ii) provide empirical or formal evaluation, and (iii) report sufficient methodological detail for assessment. Exclusions included purely neural or purely symbolic works without a substantive integration point, and position papers lacking concrete contribution.

To accelerate screening at scale, we used ASReview for AI-aided prioritization of records during title/abstract screening (Van De Schoot et al., 2021); final inclusion decisions were made by the authors. Selection counts are reported in the Appendix (Section B).

2.2 Thematic Organization

The four themes that organize the manuscript — performance, understandability, reliability, and ethics — were predefined at the start of the survey and then refined during reading rather than derived bottom-up from clusters of papers. The vocabulary is described in Section 2.4 (Table 1). Each included paper received a primary theme tag based on the dominant evidenced contribution, and zero or more secondary theme tags when the paper provided distinct evidence for additional themes (for example, a verifier that also exposes audit trails is coded both *reliable* and *ethical*, but only when both contributions are independently evidenced). The four themes are not disjoint method categories: a single neurosymbolic system can improve more than one of them, and we keep this explicit by allowing the same paper to appear in multiple rows of the per-theme evidence tables introduced in Section 2.5. The themes are a synthesis grouping over goals and they sit alongside an architecture-oriented vocabulary (interface patterns; Section 2.4) which describes *how* a coupling is built.

2.3 Critical Analysis and Synthesis

For each included study we extracted: (i) the problem abstraction and integration pattern, (ii) the evaluation design, datasets, and reported measures, and (iii) the limitations and threats to validity. Reproducibility considerations (dataset/publication clarity, code/data availability, and “remove-one-component” tests for robustness) are reported when available and inform the future-directions discussion.

To make this synthesis auditable, the paper-level coding protocol summarised in Appendix C was applied to each included paper against the documented dimensions (theme, interface pattern, function role, artifact + operator, evidence tag, trade-off / limitation). The coding produced **313 accepted (theme, interface pattern, function role) rows from 152 distinct papers**, grouped into the **65 evidenced combinations** that populate the per-theme evidence tables (Section 2.5). The remaining included studies are retained as bibliographic context: comparator surveys, position papers, foundational anchors, and entries where the neurosymbolic coupling did not meet the evidence-row promotion criteria. Rows that required clarification before promotion were flagged for

reread and resolved by the authors before the row was either accepted with a coding note (tag *A* in the per-theme evidence tables) or demoted to context. The full codebook is reported in the methods supplement rather than inlined here; the scope of that deferral is recorded in Section 4.3.

2.4 Categorization System

To avoid forcing systems into a single “paradigm” bin, we describe neurosymbolic AI as the engineering of interfaces between (i) statistical learners over continuous representations and (ii) explicit symbolic representations with defined operators (logic, programs, graphs, planners, constraint solvers). The categorization system used in this paper has three row-generating dimensions and three optional cell-level dimensions.

Row-generating dimensions (one row per evidenced combination).

1. **Theme** (*performant, understandable, reliable, ethical*) — the goal that the coupling is intended to support. Vocabulary in Table 1.
2. **Interface pattern** (codes *I0–I8*) — how the neural and symbolic components are coupled at the artifact/operator level. The codes form an interface-centric vocabulary that subsumes Kautz’s six integration patterns (Kautz, 2022); the per-code Kautz mapping is given in the same table. Vocabulary in Table 2.
3. **Function role** (*perception, knowledge/KR, reasoning, planning/control, oversight*) — where in the system the coupling does work. “Knowledge/KR” is a function role because many systems revolve around explicit knowledge assets that are created, updated, queried, or enforced by operators; “explaining” is not a separate role because explanation is an outcome of knowledge, reasoning, or oversight components and is captured by the artifact + operator instead. Vocabulary in Table 3.

Cell-level dimensions (recorded per paper-level row where possible).

1. **Artifact + operator** — the explicit symbolic object the paper exposes and the operator/workflow that acts on it (for example, *query + KG engine, rules/constraints + loss, proof trace + checker, policy + compliance workflow*).
2. **Evidence scope/tag** — whether the claim is *measured, claimed, not evaluated*, or *formal/scoped* (Table 4).

3. **Trade-off/limitation** — the row-level limitation visible in the cited evidence, in one of four short types: *cost overhead*, *guarantee scope*, *artifact validity risk*, *deployment/governance risk*.

Boundary rules used during coding. The interface-pattern vocabulary makes scope explicit. Tool augmentation (retrieval, RAG, function calls) is coded as *I0* and treated as adjacent context unless the paper also produces a typed/executable artifact and runs it through an explicit operator (which then becomes *I1* or *I3*); chain-of-thought traces are not symbolic by default and become symbolic only when they have a typed structure and an operator that can check or execute them (Mialon et al., 2023; Qiao et al., 2023). Governance workflows are coded *I8* only when the paper exhibits an explicit accountability artifact (policy, audit log, revision trace) and a workflow that operates on it; bare position papers about governance are recorded as comparators, not as method rows.

This perspective is consistent with earlier structured views of integration that emphasize the learning cycle and the roles of representation and extraction (Bader & Hitzler, 2005; Garcez et al., 2019) and with survey work that argues for characterizing systems along shared dimensions rather than bins (Raedt et al., 2020; Feldstein et al., 2024; Marra et al., 2024; Marra, 2024). It also keeps measurable trade-offs (cost, guarantee scope) as first-class comparison axes (Hitzler et al., 2022; Hamilton et al., 2024), supports transparent reporting of verification scope (Renkhoff et al., 2024; Michel-Deletie & Sarker, 2025), and treats code/data availability as evidence context (Colelough & Regli, 2025).

The Kautz crosswalk. The “Kautz mapping” column in Table 2 below references the six integration patterns from (Kautz, 2022), which we list here so the table can be read without leaving the page:

- *Symbolic-Neuro-Symbolic* — a symbolic input is processed by a neural component and a symbolic output is produced (canonical example: neural machine translation operating on symbolic surface forms).
- *Symbolic[Neuro]* — a primarily symbolic system invokes a neural subroutine for pattern recognition (canonical example: a game engine that calls learned policy or value networks).
- *Neuro|Symbolic* — neural and symbolic components run in cascade, with the symbolic stage consuming the neural stage’s typed output.

Table 1. Dimension 1 (themes). Four goal-oriented themes that the manuscript uses to organize the surveyed literature. The themes are a synthesis grouping over goals; a paper can appear in more than one theme when the paper provides distinct evidence for each.

Theme	Operational question	Typical claim type	Boundary note
performant	Does the coupling improve capability, efficiency, scalability, or task success?	Accuracy/utility; sample efficiency; cost/performance trade-off; scalable execution.	Scoped to a task, workload, benchmark, or system setting.
understandable	Does the coupling make behavior, reasoning, or knowledge inspectable?	Explanation provenance; faithful human usefulness; editable concepts/rules.	Explanation is an outcome of knowledge/reasoning/oversight, not its own function role.
reliable	Does the coupling improve robustness, validity, safety, or verifiability?	Constraint satisfaction; invalid-output reduction; robustness under shift; formal or scoped guarantee.	Guarantees are property- and assumption-scoped, not global safety claims.
ethical	Does the coupling support accountability, alignment, fairness, oversight, or governance?	Norm encoding; audit trail; human revision loop; policy/compliance redress workflow.	Requires an explicit accountability artifact and a workflow that uses it.

- *Neuro:Symbolic*→*Neuro* — symbolic rules or constraints are compiled into the training process of a neural model.
- *Neuro_{Symbolic}* — a neural model produces predictions that are interpreted through, or constrained by, an embedded symbolic schema (a fixed type system, constraint set, or finite vocabulary the model is forced to predict over).
- *Neuro[Symbolic]* — a neural model whose architecture incorporates explicit symbolic reasoning steps (canonical examples: differentiable-logic and proof-trace systems).

The codes I0–I8 in Table 2 preserve the six-pattern crosswalk while extending it with two practical codes that recur in 2020 to mid-2026 work and that the original Kautz schema does not name: tool grounding / augmentation (I0; adjacent context unless paired with a typed artifact and an explicit operator) and accountability / human-revision workflows (I8; the oversight loop that ethics evidence requires).

2.5 Per-Theme Evidence Tables: Theme by Interface Pattern by Function Role

The categorization system in Section 2.4 produces evidenced (theme, interface pattern, function role) combinations: each combination is a row in which each cell lists the

Table 2. Dimension 2 (interface patterns). Nine codes (I0–I8) describe the artifact/operator coupling between neural and symbolic components, with a crosswalk to Kautz’s integration patterns (Kautz, 2022) (named and explained in the preceding paragraph). The crosswalk is indicative: one system can instantiate more than one pattern. I0 (tool augmentation) is adjacent context unless paired with a typed artifact and explicit operator.

Code	Interface pattern	Counts as NeSy evidence when...	Typical artifact + operator	Kautz mapping
I0	tool grounding / augmentation	adjacent unless paired with a typed/executable artifact checked by an explicit operator	retrieved documents/tool calls + retriever/tool/checker	— (tool-grounding extension; not in original Kautz schema)
I1	neuro → symbolic extraction	a learned component emits a typed symbolic artifact that a symbolic operator consumes	query/program/plan/scene graph + parser/executor/reasoner	Symbolic-Neuro-Symbolic; Neuro Symbolic
I2	symbolic → neuro injection / constraints-in-loss	symbolic rules/constraints/ontology shape training or learned representations	rules/constraints/ontology + loss/regularizer/compiler	Neuro:Symbolic→Neuro; Neuro_{Symbolic}
I3	symbolic execution/checking of neural proposals	neural outputs are executed, checked, accepted, rejected, repaired, or interpreted by a symbolic operator	query/program/proof/plan + executor/reasoner/checker	Symbolic-Neuro-Symbolic; Neuro Symbolic; Neuro{Symbolic}
I4	inference-time enforcement	constraints restrict output or action space at inference/deployment	grammar / safety rule / shield (runtime safety filter from safe-RL) / policy + filter / verifier / controller	Neuro Symbolic; Neuro{Symbolic}
I5	verifier-in-the-loop / certified checking	a formal or semi-formal checker verifies a property under explicit assumptions	specification/property/certificate + SMT/SAT/model checker	Neuro Symbolic; Neuro{Symbolic}
I6	symbolic solver calls a neural subroutine	a symbolic process delegates a subtask to a neural component while retaining symbolic orchestration	search/proof/decomposition state + solver/planner/prover	Symbolic[Neuro]
I7	hybrid bidirectional loop	neural and symbolic modules iteratively exchange artifacts, feedback, or repairs	candidate artifact/repair/feedback + verifier/reasoner/planner	Neuro Symbolic; Symbolic-Neuro-Symbolic
I8	accountability / human revision workflow	explicit artifacts are logged, audited, governed, or revised by a defined workflow	norm/policy/audit log/change record + workflow/checker/reviewer	— (workflow-level extension; not in original Kautz schema)

representative systems that instantiate that combination, together with the optional dimensions described above. The synthesis contains **65 evidenced combinations** grouped from **313 accepted rows** drawn from **152 distinct papers**, produced by the paper-level coding protocol described in Section 2.3 (see Appendix B for the corresponding inclusion counts). The combinations are presented per-theme so that each theme section can be read as an instantiation of the same vocabulary on the same evidence

Table 3. Dimension 3 (function roles). Where the neural–symbolic coupling does work inside a system. Knowledge/KR is a function role because KR assets (KGs, rules, ontologies, constraints) are manipulated by operators; “explaining” is not a separate role because explanation is an outcome of knowledge, reasoning, or oversight.

Function role	Operational meaning	Typical artifacts/operators	Boundary note
perception	Coupling acts on raw or learned perceptual representations (vision, language, sensors, multimodal).	scene graphs; concept variables; symbolic abstractions; perceptual constraints.	Use when the interface changes what is detected or extracted from inputs.
knowledge/KR	Coupling creates, updates, queries, constrains, or governs explicit knowledge assets.	KGs; ontologies; rules; constraints; query engines; entailment operators.	A function role because KR assets are manipulated by operators.
reasoning	Coupling supports inference, deduction, abduction, proof, query answering, structured problem solving.	logic programs; proofs; queries; theorem provers; differentiable logic.	Use when symbolic operators contribute to deriving or validating conclusions.
planning/control	Coupling supports action selection, sequencing, policy learning, execution, or control under constraints.	planners; controllers; shields; policies; temporal-logic constraints.	Use for sequential decision-making, RL, robotics, autonomous systems.
oversight	Coupling supports monitoring, explanation, auditing, intervention, governance, or human review.	audit logs; provenance traces; editable rules/concepts; policy checks; review workflows.	Explanation is an outcome.

base; the four per-theme tables (Tables 5, 7, 8, 9) collectively cover the (theme, interface pattern, function role) space.

The per-theme tables share a common vocabulary and a common evidence bar; a paper that supports more than one theme appears in more than one table, each appearance independently evidenced. The per-theme tables are the survey’s primary cross-paper reference: comparative claims later in the survey point back to the specific rows that support them.

2.6 Evidence and Citation Protocol

To balance breadth (citing the full bibliography) with defensible claims, we use an explicit evidence protocol that distinguishes *how* a reference is used from *what* it proves. Bibliographic metadata were managed in Zotero and exported to BibTeX. We do not treat broad technique families (for example, “LLM prompting” or “RAG”) as neurosymbolic evidence unless an explicit symbolic representation and operator-level coupling is present.

Citation roles (how we use a reference).

- **Definitional:** supports definitions, boundary rules, and dimension vocabularies (Tables 1, 2, 3, 4).
- **Pattern exemplar:** provides a concrete instance of an interface pattern (for example, constraints-in-loss; verifier-in-the-loop; neuro → symbolic extraction).
- **Evidence:** supports a measured claim (task/dataset/measure) or a formal guarantee (theorem/checked property), with explicit scope.
- **Context/background:** provides adjacent framing (for example, LLM or KG surveys) without being treated as evidence of neurosymbolic coupling or guarantees.
- **Position/opinion:** used only as “argues/suggests”.

Evidence tags (attached to evaluative statements). When a statement is comparative (for example, “improves reliability”) or appears as a table cell, we tag it with one of the four tags in Table 4 and keep scope explicit (task/domain, dataset/benchmark). This pre-empts overgeneralization from benchmark results and aligns with critiques that commonsense and reasoning benchmarks can be flawed proxies for the intended capability (Davis, 2023).

Table 4. Evidence tags used in tables and comparative statements. Each tag specifies what the corresponding citation supports. Tags are applied per dimension and read with explicit scope (task/domain, dataset/benchmark in the cited paper).

Tag	Operational meaning
Measured	The paper reports an explicit experimental setup (task/dataset/measure) that supports the claim.
Formal/scoped	The paper reports a formal statement (theorem, checked property, certificate) under explicit assumptions that supports the claim.
Claimed	The paper asserts the claim but does not directly evaluate it with an explicit measure/setting or provide a formal guarantee.
Not evaluated	The paper does not evaluate the dimension in question (cost, robustness, faithfulness, guarantee scope), so we do not infer it.
Annotated (A)	In the per-theme evidence tables (Tables 5, 7, 8, 9) the code <i>A</i> marks a row that was retained with a coding note attached (e.g., scope downgrade, partial-evidence promotion, or split between adjacent interface-pattern codes). The detail of each <i>A</i> decision is summarised in Section 2.3; the code is not used in this dimension table directly.

3 Core Themes in Neurosymbolic artificial intelligence

We now organize the surveyed literature around four themes – performance, understandability, reliability, and ethics. The themes are anchored to system functions and to the interface patterns and evaluation measures introduced in Section 2.4; rather than a single cross-theme summary table, we present one per-theme evidence table (Tables 5, 7, 8, 9) so that each evidenced (interface pattern, function role) row can be inspected in its theme context. Each theme follows the same micro-structure (problem framing, representative advances by interface-pattern family, evaluation and measures, limitations, theme takeaway) so that design trade-offs are recorded directly in the per-theme evidence tables and recapped in Section 6.

3.1 Performance: Efficiency and Capability

This theme covers the largest evidence cluster in the synthesis: 23 evidenced (interface pattern, function role) rows aggregated from the paper-level coding. Table 5 presents those rows for this theme; the rest of this subsection narrates the table by interface-pattern family and ties each family to the dominant performance trade-off and to the function role(s) it most often serves. Three structural patterns dominate the table: (a) **training-time coupling (I2)** — symbolic rules, constraints, KGs, or ontologies shape training or learned representations via loss, regularizer, or compiler — which spans all four function roles and accounts for the largest share of measured performance gains in the paper-level coding (rows I2/KR, I2/perception, I2/planning-control, I2/reasoning); (b) **inference-time coupling via typed artifacts (I1, I3)** — a learned component emits a query, program, plan, scene graph, or proof that a symbolic operator consumes (I1) or checks/executes (I3), with cost-overhead and artifact-validity risk as the main trade-offs; and (c) **solver-orchestrated coupling (I6) and bidirectional loops (I7)** — a symbolic solver, planner, or prover calls neural subroutines or iteratively repairs neural proposals, used mainly in reasoning and planning/control. Tool augmentation (I0) appears only as adjacent context: only two performance rows are coded I0, and even those are paired with typed-artifact consumers. The rest of this subsection treats each family in turn before turning to evaluation/measures and the theme takeaway.

Table 5. Per-theme evidence table: *performant* theme. Rows are evidenced (interface pattern, function role) combinations. Tag codes: M=measured, F=formal / scoped, C=claimed, NE=not evaluated, A=annotated coding note. Limitation codes: cost=cost overhead, guar.=guarantee scope, artifact=artifact validity risk, deploy=deployment / governance risk, risk=risk noted. Each cell lists every paper coded under the row's (interface pattern, function role) combination; per the citation-role vocabulary defined in Section 2.6, a cited paper may appear either as an evidence reference (tagged M / F / C / NE / A in the evidence column) or as a pattern-exemplar reference (no evidence tag; the paper instantiates the row's interface-pattern coupling without itself supporting a measured, formal, claimed, or not-evaluated evaluative statement at the row's grain). The evidence and limitation columns aggregate counts only over the evidence-tagged subset.

Code	Function role	Representative references	Evidence tags	Limitations
I0	knowledge / kr	(Garcez et al., 2015; Gao et al., 2023; Schick et al., 2023)	M:2	
I0	reasoning	(Schick et al., 2023)	M:1	
I1	knowledge / kr	(Garcez et al., 2015; Bosselut et al., 2019; Fang et al., 2021; Cambria et al., 2022; Gao et al., 2023; Glauer et al., 2023; Liu et al., 2023; Bougzime et al., 2025; Sha et al., 2025)	M:9	artifact:2, cost:1
I1	perception	(Evans & Grefenstette, 2018; Daniele et al., 2023; Hsu et al., 2023; Aryan et al., 2024; Saha et al., 2024; Choi et al., 2025a; Jahangard et al., 2025; Kabir et al., 2025; Murtas et al., 2025; Sha et al., 2025)	M:9	artifact:5, cost:2, deploy:1, guar.:1
I1	planning / control	(James, 2018; Asai & Muise, 2020; Núñez-Molina, 2022; Pallagani et al., 2023; Shah, 2023; Siyaev et al., 2023; McDonald et al., 2024; Hao et al., 2025; Leung et al., 2025)	M:8, F:1, C:1	cost:5, guar.:4, artifact:4, risk:3
I1	reasoning	(Besold et al., 2017; Selsam et al., 2018; Mao et al., 2019a; Tsamoura et al., 2021; Chanin & Hunter, 2023; Järv et al., 2023; Siyaev et al., 2023; Sohn et al., 2025)	M:6	cost:3, artifact:2, guar.:1
I2	knowledge / kr	(Hopfield, 1982; Rosa & Franeozo, 1999; Minato et al., 2007; Bordes et al., 2013; Serafini & Garcez, 2016; Cohen et al., 2017; Han et al., 2018; Speer et al., 2018; Chen et al., 2019; Tan et al., 2020; Fang et al., 2021; Hwang et al., 2021; Oltramari et al., 2021; Badreddine et al., 2022; Li et al., 2022; Yasunaga et al., 2022; Smirnov et al., 2024; Strader et al., 2024; Werner, 2024; Saucedo et al., 2025; Sengupta & Rekik, 2025)	M:16, C:1	cost:7, artifact:7, guar.:1, risk:1

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Table 5 – continued from previous page

Code	Function role	Representative references	Evidence tags	Limitations
I2	perception	(Hu et al., 2016; Donadello et al., 2017; Serafini et al., 2017; Chen & Yang, 2021; Benetatos et al., 2023; Huang et al., 2024; Saha et al., 2024; Savazzi et al., 2025; Zhou et al., 2025)	M:8	cost:4, artifact:3, guar.:1
I2	planning / control	(Dong et al., 2019; Asai & Muise, 2020; Kimura et al., 2021; Karia & Srivastava, 2022; Yang et al., 2023; Choi et al., 2025b)	M:5, F:2	deploy:3, cost:2, guar.:1, artifact:1
I2	reasoning	(Touretzky & Minton, 1985; Barden, 1989; Mooney et al., 1989; de Penning et al., 2011; Besold et al., 2017; Cohen et al., 2017; Xiao et al., 2017; Yang et al., 2017; Evans & Grefenstette, 2018; Xu et al., 2018; Dong et al., 2019; Riegel et al., 2020; Yang et al., 2020; Tsamoura et al., 2021; Aakur & Sarkar, 2023; Chen et al., 2023c,a; Liu et al., 2023; Schick et al., 2023; Jana, 2024; Oltramari, 2024; Feng et al., 2025a; Hu et al., 2025; Zhou et al., 2025)	M:21, C:2, F:1	cost:7, artifact:4, guar.:2
I3	perception	(Winters et al., 2022; Oltramari, 2024)	M:2	risk:1
I3	planning / control	(Fabiano et al., 2023; Saxena et al., 2025a)	M:2	cost:2, risk:1, artifact:1
I3	reasoning	(Besold et al., 2017; Yi et al., 2018; Amizadeh et al., 2020; Yang et al., 2020; Winters et al., 2022; Eiter et al., 2023; Li et al., 2023b; Pan et al., 2023; Oltramari, 2024; Hazra et al., 2025; Hu et al., 2025; Jahangard et al., 2025; Kabir et al., 2025; Perrier, 2025)	M:11	cost:3, guar.:1, artifact:1
I4	planning / control	(Alshiekh et al., 2018)	M:1	cost:1
I4	reasoning	(Banerjee et al., 2025)	M:1	cost:1, guar.:1
I5	reasoning	(Elboher et al., 2020; Choi et al., 2025a)	M:2	cost:2
I6	knowledge / kr	(Demir & Ngomo, 2023)	M:1	cost:1

Continued on next page

Table 5 – continued from previous page

Code	Function role	Representative references	Evidence tags	Limitations
16	perception	(Mao et al., 2019b; Chen et al., 2021)	M:2	cost:1
16	planning / control	(Silver et al., 2016; Kirk & Laird, 2019; Mitchener et al., 2022)	M:3	cost:3, artifact:2, deploy:2
16	reasoning	(Rocktäschel & Riedel, 2016, 2017; Manhaeve et al., 2018; Arabshahi et al., 2021; Kalyanpur et al., 2022; Morris, 2022; Hsu et al., 2023; Weir et al., 2024)	M:8, F:3, C:1	guar.:1, cost:1, deploy:1, artifact:1
17	knowledge / kr	(Arabshahi et al., 2021)	M:1, F:1	
17	planning / control	(Yang et al., 2018; Cao et al., 2023; Fabiano et al., 2023; Saha et al., 2024; Hao et al., 2025; Liang et al., 2025)	M:3	cost:3, guar.:2, artifact:1, deploy:1
17	reasoning	(Qu & Tang, 2019; Cunnington et al., 2023; Liu et al., 2023; Pan et al., 2023; Trinh et al., 2024; Li et al., 2025b; Lin et al., 2025; Liu et al., 2025a; Su et al., 2026)	M:5	cost:1

Architectural Paradigms for Efficiency and Scalability We cite a small set of neural architectures as *context* for the neural architectures that hybrid interfaces attach to; these are not treated as neurosymbolic evidence by themselves. Examples include distributed and contextualized representations for language (Mikolov et al., 2013; Peters et al., 2018), attention-based sequence transduction (Bahdanau et al., 2014; Shaw et al., 2018; Vaswani et al., 2023), and long-context sequence models (Dai et al., 2019). We also include representative sequence-to-sequence pretraining and recurrent encoders as common base models that hybrid systems build on (Graves & Schmidhuber, 2005; Lewis et al., 2020a). For relational inputs, graph attention networks are a commonly used neural architecture (Veličković et al., 2018). Scaling discussions and emergent abilities in large language models provide important context for why tool grounding and verifier-in-the-loop designs are increasingly used as *interfaces* in practice, even when they do not imply correctness guarantees (Wei et al., 2022). Graph Transformers generalize attention to arbitrary graphs via connectivity-aware attention and spectral

positional encodings, and are reported to improve generalization on relational inputs in the evaluated settings (Dwivedi & Bresson, 2020). Surveys of GNNs within neural-symbolic computing synthesize applications in combinatorial optimization, constraint satisfaction, and relational reasoning, and discuss GNNs as common neural architectures for hybrid systems (Lamb et al., 2020). Domain-specific foundation representations, such as geospatial embedding fields, illustrate how compact, reusable embeddings can ground downstream mapping and analysis at scale (Brown et al., 2025).

Representative hybrid paradigms integrating neural and symbolic components include Logic Tensor Networks and related differentiable semantics (Donadello et al., 2017; Yang et al., 2017), probabilistic logic programming approaches such as DeepProbLog (Manhaeve et al., 2018), and neural logic machines and differentiable rule learning (Dong et al., 2019). Early knowledge-injection and embedding-based integration frameworks provide additional coupling patterns (Hu et al., 2016; Kolb et al., 2018; Chen et al., 2019, 2023b).

A comprehensive integration framework harmonizes symbolic constraints and domain knowledge with deep learning components to improve reasoning, generalization, and transfer (Himabindu et al., 2023).

Compositional integration treats neural and symbolic modules as black boxes with deduction, abduction, and induction interfaces, enabling modular coupling without assuming internal semantics (Tsamoura et al., 2021).

Recent workload characterizations of neurosymbolic systems (runtime profiling across representative operators and hardware) highlight the compute bottlenecks and parallelism profiles that differentiate symbolic reasoning from neural components, informing design trade-offs for scalable hybrid pipelines (Susskind et al., 2021).

On extreme-edge platforms, hardware-aware neurosymbolic architecture search reports joint optimization of symbolic and neural operators under tight memory and latency budgets, generating microcontroller-ready code for multiple NeSy model families in the evaluated settings (Saha et al., 2024).

Neurosymbolic logic programming frameworks based on stochastic derivations, such as DeepStochLog, offer improved scaling for inference and learning compared to neural probabilistic logic programs while retaining end-to-end trainability (Winters et al., 2022). Automated architecture innovation moves beyond classical NAS toward autonomous hypothesis generation and empirical evaluation for model design, suggesting new pathways for scaling hybrid systems (Liu et al., 2025b).

Efficient reasoning can be further supported by program-guided perception and learned prioritization of proof paths, which reduce search overhead while retaining interpretability (Mao et al., 2019b; Morris, 2022). Differentiable logic compilation and declarative neurosymbolic languages streamline training and inference by leveraging deep-learning backends for logical queries (Cohen et al., 2017; Yang et al., 2020; Li et al., 2023b). Modular couplings with cognitive architectures can orchestrate hybrid components efficiently at system level, improving throughput and latency via division of labor and tool-use (West et al., 2023; Joshi & Ustun, 2024; Liu et al., 2024; Romero et al., 2024; Thomson & Bastian, 2024; Roy et al., 2025). Self-supervised representation learning (e.g., I-JEPA) provides perceptual base models that can be paired with symbolic interfaces (Assran et al., 2023).

Tool grounding and structured artifacts for factuality and task success Retrieval-augmented generation and tool-augmented inference are *reported* to improve factuality and task success on specific benchmarks and workloads, often at the cost of additional latency, compute, and tool calls (Mialon et al., 2023; Zhao et al., 2023c; Gao et al., 2024; Annepaka & Pakray, 2025; Li et al., 2025a). In line with our evidence protocol (Section 2.6), we treat tool grounding as an interface pattern rather than a guarantee: tool grounding can reduce error rates but does not, by itself, certify correctness. Under our scope boundary, tool grounding becomes neurosymbolic *evidence* only when it is coupled to explicit symbolic artifacts and operators - for example, when a model emits a typed/executable query or program that is executed and checked by a KG/reasoner, constraint system, or verifier. Retrieval and tool-use provide mechanisms for connecting models to external sources and computations (Lewis et al., 2020b; Mialon et al., 2023; Schick et al., 2023; El-Kishky et al., 2024). For this survey, the key dividing line is whether the interface produces an *explicit, checkable artifact*. When the model emits typed/executable structures (e.g., logical queries/programs) and these are executed/validated by symbolic operators (KG query engines, reasoners, constraint systems, verifiers), the coupling can convert tool grounding into an operator-level neurosymbolic interface (Chen et al., 2021; Li et al., 2022; Tammet et al., 2024; Weir et al., 2024). When such checking is absent, we treat tool grounding as adjacent context and avoid interpreting it as a correctness mechanism (Gao et al., 2024; Sahoo et al., 2024; Huang et al., 2025). Table 6 summarises the boundary cases this distinction produces. Knowledge-intensive pipelines also leverage graph-structured corpora and link structure (document graphs, KG-derived training signals) as *interfaces* that shape retrieval and attribution behavior, with gains and limitations reported in the evaluated

settings (Da et al., 2021; Yasunaga et al., 2022). Within NLP, neuro-symbolic reasoning is often framed as bridging neural language models with explicit logic, latent structures, or knowledge bases; applied overviews and reviews provide context on representative integration patterns (Aithal et al., 2022; Liu et al., 2023; Keber et al., 2024). Popular commentary sometimes frames neurosymbolic AI as a remedy for hallucination (Garcez, 2025); in this survey we treat that framing as motivation rather than as technical evidence unless operator-level coupling and scoped evaluations are reported. Practical toolkits and resources support commonsense inference and persona- or task-specific knowledge acquisition that can feed neurosymbolic interfaces (Gao et al., 2023; Ismayilzada & Bosselut, 2023). Solver-in-the-loop training and symbolic feedback loops have been proposed as a way to improve reasoning in math and software engineering tasks without relying solely on scale; such approaches are evaluated and should be interpreted in the scope of their feedback signals and benchmarks (Jana, 2024). In knowledge-intensive QA, coupling LMs to explicit KB/KG artifacts and symbolic teachers has been reported to improve generalization and robustness in the evaluated settings, while introducing additional failure modes and overhead (Oltamari et al., 2021; Aakur & Sarkar, 2023).

Table 6. Boundary cases for “tool grounding” in performance-oriented pipelines. Rows distinguish adjacent tool augmentation from operator-level neurosymbolic coupling under the scope boundary in Section 1.

Code	Pattern	Artifact / operator	What is often reduced (scoped)	What is not guaranteed + typical costs
10	Tool grounding (adjacent context)	retrieval/tool calls; no executable symbolic artifact	factuality errors in reported settings (Lewis et al., 2020b; Gao et al., 2024)	does not certify correctness; costs include tool-call latency and additional context handling (Gao et al., 2024; Huang et al., 2025)
11 / 13	Typed artifacts + execution/checking (NeSy evidence)	typed query/program + KG/reasoner/constraint execution	invalid-output rates; some factuality failures when the checker is sound for the artifact class (Chen et al., 2021; Weir et al., 2024)	well-formed-but-wrong artifacts remain possible; costs include execution and checking overhead
15	Verifier-in-the-loop (NeSy evidence)	explicit verifier / constraints that accept/reject/repair outputs	constraint violations and some unsafe/invalid behaviors under stated assumptions (Katz et al., 2017a; Alshiekh et al., 2018)	guarantees are property- and assumption-scoped; costs include solver/verifier overhead and potential rejection loops

Planning, Control, and Reinforcement Learning Planning and control integrations leverage symbolic models and cognitive frameworks for improved efficiency and decision quality (Clark et al., 2016; Yang et al., 2018). Earlier neurosymbolic planning/control architectures and distributed cognitive robotics systems provide

additional coupling patterns (Mastrogiovanni et al., 2007; Belle & Lakemeyer, 2011; de Penning et al., 2011). A neurosymbolic planning architecture, Plan-SOFAI, instantiates dual-process fast/slow reasoning to combine planners across classical scenarios, illustrating modular integration patterns for deliberative control (Fabiano et al., 2023). Structure-of-thought prompting strategies, including chains, trees, and graphs of thought, provide flexible scaffolds for decomposition, search, and evaluation in reasoning and planning with language models; these scaffolds are not treated as symbolic evidence unless intermediate artifacts are typed and executed/checked by explicit operators (Besta et al., 2024).

Neurosymbolic pipelines improve sample efficiency and generalization by inducing symbolic abstractions and models for classical planners (Asai & Muise, 2020; Shah, 2023). Symbolic controllers and differentiable planners elevate decision quality and long-horizon optimization (Zhang & Hannaford, 2020; Jeong et al., 2021; Chatterjee et al., 2023). Language-model interfaces to planning and control include translating domains to plans and shaping RL with structured signals (Karia & Srivastava, 2022; Mitchener et al., 2022; Pallagani et al., 2023). Related approaches couple language models to symbolic planning or control abstractions for decision-making (Kimura et al., 2021; McDonald et al., 2024). Surveys benchmark hybrid methods and outline open challenges for sequential decision-making (Núñez-Molina, 2022; Núñez-Molina et al., 2024; Valmeekam et al., 2024). Explainable AI planning perspectives further contextualize requirements for transparent decision-making in planners (Chakraborti et al., 2020). Classical TD-network formulations characterize predictive representations that are useful for control and planning (Sutton & Tanner, 2004). Evaluations of large reasoning models on combinatorial tasks reveal current limitations and the need for symbolic planners and reasoners in the loop (Hazra et al., 2025).

Evaluation and Measures Benchmarking considerations for knowledge-intensive tasks and QA datasets are synthesized in (Rogers et al., 2023), including classic open-book settings that stress retrieval and multi-hop reasoning requirements (Mihaylov et al., 2018). Cost-effectiveness measures for neural models, such as TALES, quantify resource–accuracy trade-offs using FLOPs, parameter counts, and predicted latency to guide model selection on constrained platforms (Zhao et al., 2023b). System-level workload studies categorize NeSy algorithms and profile runtime, memory, sparsity, and operator mixes across CPUs, GPUs, and edge SoCs, informing architecture-aware evaluation (Wan et al., 2024b). A systems perspective extends this profiling toward joint hardware–software design (co-design) for NeSy acceleration (Wan et al., 2024a).

General-purpose evaluators and exam-style test suites facilitate comparable assessment of generation quality and task success (Zhong et al., 2022; He et al., 2024; Zhong et al., 2024). Reflections on benchmark validity and historical use (Orr & Kang, 2024) caution against reading reported gains as evidence of progress without explicit task, dataset, and measure scoping.

Theme takeaway (interface patterns and trade-offs). Reading Table 5 along the interface-pattern axis, three regularities recur. First, the largest measured-gain cluster is training-time coupling (I2): symbolic constraints, rules, KGs, or ontologies that shape learning produce the most consistently measured improvements, but at recurring cost overhead and artifact-validity risk (mis-specified or stale knowledge propagating into learned representations). Second, inference-time coupling via typed artifacts (I1/I3) is where artifact-validity risk and cost dominate the limitation columns: gains depend on whether the learned artifact is actually well-formed and whether the symbolic operator has the coverage to consume it. Third, solver-orchestrated coupling (I6) and bidirectional loops (I7) deliver some of the strongest formal-and-measured rows in the reasoning and planning/control function roles, but bring the highest cost overhead and the most explicit guarantee-scope limitations. Across all three families, tool augmentation alone (I0) is not treated as performance evidence; only when tool augmentation is paired with a typed artifact and an explicit operator (becoming I1 or I3) does it appear in the evidence rows.

3.2 *Understandable AI: Opening the Black Box*

This theme covers 20 evidenced (interface pattern, function role) rows from the paper-level coding. Table 7 presents those rows for this theme; the rest of this subsection narrates the table along three families that recur in the rows: (a) **KR-anchored explanation** (I1/KR, I2/KR, I6/KR) — KGs, ontologies, rules, and concept spaces give explanations stable semantics and inspectable artifacts; (b) **intrinsic transparency via typed artifacts** (I1 reasoning, I3 reasoning, I6 reasoning) — programs, proofs, queries, or rule traces produced by the system and consumed or checked by symbolic operators; and (c) **concept and oversight bottlenecks** (I2/perception, I8/oversight) — intermediate human-meaningful variables and revision workflows that make the model editable rather than only inspectable. Across all three families we keep the same two guardrails: *plausibility is not faithfulness* — where *faithfulness* is the property that the explanation actually reflects the computation the model performed, rather than merely sounding plausible to a human reader — so a coherent narrative may not match the

actual decision process; and *artifact validity is not task correctness*, so a well-formed query, rule, or trace can still support a wrong conclusion. We do not treat post-hoc natural-language rationales as symbolic explanation evidence unless they are typed and executed/checked by an explicit operator (Section 2.6).

Table 7. Per-theme evidence table: *understandable* theme. Rows are evidenced (interface pattern, function role) combinations. Tag codes: M=measured, F=formal / scoped, C=claimed, NE=not evaluated, A=annotated coding note. Limitation codes: cost=cost overhead, guar.=guarantee scope, artifact=artifact validity risk, deploy=deployment / governance risk, risk=risk noted. Each cell lists every paper coded under the row's (interface pattern, function role) combination; per the citation-role vocabulary defined in Section 2.6, a cited paper may appear either as an evidence reference (tagged M / F / C / NE / A in the evidence column) or as a pattern-exemplar reference (no evidence tag; the paper instantiates the row's interface-pattern coupling without itself supporting a measured, formal, claimed, or not-evaluated evaluative statement at the row's grain). The evidence and limitation columns aggregate counts only over the evidence-tagged subset.

Code	Function role	Representative references	Evidence tags	Limitations
I1	knowledge / kr	(Rosa & Franeozo, 1999; Minato et al., 2007; de Penning et al., 2011; Daniele et al., 2023; Glauer et al., 2023; Järv et al., 2023; Kant et al., 2024; Vakharia et al., 2024; Sunny & Sivan-Sevilla, 2026)	M:4, C:4	deploy:2, artifact:1
I1	oversight	(Craven & Shavlik, 1995; Siyaev et al., 2023; Leung et al., 2025)	M:3, C:2, NE:1	artifact:1, deploy:1
I1	perception	(Stammer et al., 2021; Smirnov et al., 2024)	M:1	
I1	planning / control	(Kimura et al., 2021; Liang et al., 2025)	M:1, C:1, NE:1	
I1	reasoning	(Yang et al., 2017; Evans & Grefenstette, 2018; Shih et al., 2018; Cambria et al., 2022; Murali et al., 2022; Chanin & Hunter, 2023; Hsu et al., 2023; Järv et al., 2023; Liu et al., 2023; Ganguly et al., 2024; Lin et al., 2025; Perrier, 2025; Sha et al., 2025; Su et al., 2026)	M:10, C:3, F:2	artifact:4, guar.:2, risk:1, cost:1
I2	knowledge / kr	(Kirk & Laird, 2019; Crochepierre et al., 2022; Jain et al., 2025)	M:2, C:2	artifact:3, cost:2, guar.:1, deploy:1

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Table 7 – continued from previous page

Code	Function role	Representative references	Evidence tags	Limitations
I2	oversight	(Sengupta & Rekik, 2025)	C:1	
I2	perception	(Qu & Tang, 2019; Koh et al., 2020)	M:1	
I2	reasoning	(Riegel et al., 2020; Aakur & Sarkar, 2023)	M:2, C:1	
I3	knowledge / kr	(Wickramarachchi et al., 2024; Kabir et al., 2025)	C:1	
I3	oversight	(Vakharia et al., 2024; van Hurne et al., 2026)	C:2	artifact:1
I3	reasoning	(Yi et al., 2018; Mao et al., 2019a; Amizadeh et al., 2020; Eiter et al., 2023; Li et al., 2023b; Smirnov et al., 2024; Feng et al., 2025a; Jahangard et al., 2025; Murtas et al., 2025)	M:8, C:3	artifact:4, cost:1, guar.:1
I5	oversight	(Kirk & Laird, 2019; Xie et al., 2022)	M:1, C:1	artifact:2
I6	knowledge / kr	(Demir & Ngomo, 2023)	M:1	
I6	perception	(Mao et al., 2019b)	C:1, NE:1	
I6	planning / control	(Kirk & Laird, 2019; Mitchener et al., 2022)	C:2, NE:1	artifact:2
I6	reasoning	(Rocktäschel & Riedel, 2016, 2017; Arabshahi et al., 2021; Kalyanpur et al., 2022; Weir et al., 2024)	C:3, M:3, F:3, NE:2	deploy:1
I7	knowledge / kr	(Cunnington et al., 2023; Bonfanti et al., 2025)	M:1, C:1	artifact:1, deploy:1, guar.:1
I7	reasoning	(Trinh et al., 2024; Li et al., 2025b)	F:1	
I8	oversight	(Qu & Tang, 2019; Kim et al., 2020; Koh et al., 2020; Stammer et al., 2021)	M:3, C:1, NE:1	guar.:1, artifact:1, deploy:1

Knowledge Representation as a Foundation Structured KR provides the semantics that make explanations and audits interpretable: it defines *what counts* as an entity,

relation, rule, or constraint, and which operators are valid for querying and inference. We therefore treat KR choices as a first-order design decision for understandability. Foundational work and surveys motivate how symbols are represented and queried and why semantics matter for explanation (Brachman et al., 1985; Miller, 1995; Ding, 2007; Donadello et al., 2017; Dumančić et al., 2019; Kramer, 2020; Raedt et al., 2020; Jaeger, 2023; Marra et al., 2024; Marra, 2024).

KGs/ontologies and queryable semantics. When knowledge is stored as a KG or ontology, explanations can be grounded in explicit relations and retrieved via typed queries; provenance can be attached to edges, documents, and entailment steps. This supports explanation artifacts such as query traces, retrieved subgraphs, and entailment chains, but it also introduces maintenance risks (coverage gaps, stale knowledge, inconsistent schemas) that should be reported and versioned. Representative resources and surveys discuss how KGs/ontologies can support human-aligned concepts and interpretable inference across domains (Lecue, 2020; Hogan et al., 2022; Ji et al., 2022; Kau, 2024; Rajabi & Etmnani, 2024).

Rules/programs and executable structure. Rule- and program-based representations (logic programs, ASP, ILP, Datalog-style rules) support *executable* explanations: the explanation is the program/rule trace that leads from inputs to outputs. Such artifacts are inspectable and editable, but the central validity question becomes whether the neuro→symbolic mapping is faithful and whether the program semantics match the intended domain assumptions. Representative mechanisms include coupling neural predictions to symbolic constraints, inducing programs/rules under constraints, and using declarative languages that expose provenance (Yang et al., 2020; Ciatto et al., 2021; Cropper & Morel, 2021; Li et al., 2023b). Learning and transferring symbolic representations, and using symbolic priors as soft guides to neural semantic parsing, provide additional context on how executable structure can improve sample efficiency and interpretability in the evaluated settings (Xiao et al., 2017; James, 2018).

Probabilistic and differentiable semantics. When uncertainty is central, probabilistic-symbolic or differentiable semantics can provide explanation artifacts that encode both structure and uncertainty (e.g., weighted rules, probabilistic programs, differentiable query provenance). These can improve interpretability by making uncertainty explicit, but they also complicate evaluation because explanation faithfulness depends on both the symbolic structure and the learned scoring/inference dynamics (Sato & Kameya, 1997; Minato et al., 2007; Serafini & Garcez, 2016; Cohen et al.,

2017; Serafini et al., 2017; Qu & Tang, 2019; Badreddine et al., 2022). Grammar-based symbolic structure and refined nonterminals illustrate a classical symbolic representation where learnable components yield explicit, inspectable structure, while retaining strong empirical performance in the evaluated settings (Shindo et al., 2013).

Further reading (KR assets and construction at scale). The works in this paragraph are context citations rather than evidence-table rows: they describe the KR assets and construction methods on which the section’s evidenced systems build, but do not themselves contribute artifact-plus-operator evidence at the bar required for promotion into Table 7. Human-interpretable KR assets and large ontologies provide reusable concept spaces for explanation (e.g., commonsense and biomedical ontologies), while knowledge construction and integration work addresses coverage and consistency in deployed pipelines (Robinson et al., 2008; Bordes et al., 2013; Han et al., 2018; Speer et al., 2018; Bosselut et al., 2019; Hitzler et al., 2020; Mostafazadeh et al., 2020; Fang et al., 2021; Hwang et al., 2021; Schockaert et al., 2021; Järv et al., 2022; Odense & Garcez, 2022; Järv et al., 2023; Smirnov et al., 2024; Werner, 2024; Jain et al., 2025; Wang et al., 2025a). Formal argumentation further contextualizes symbolic reasoning artifacts (e.g., non-monotonic logics, inconsistency handling, and argumentative traces) that can support auditable reasoning (Ulbricht, 2024).

Intrinsic Explainability and Transparent Decision-Making Intrinsic transparency via rule extraction and differentiable/provable reasoning is exemplified by early rule extraction and neural-symbolic approaches (Craven & Shavlik, 1995; d’Avila Garcez et al., 2002a,b), as well as later differentiable and end-to-end formulations (Rocktäschel & Riedel, 2016, 2017). Program-guided perception and manipulation induce symbolic structure from images, enabling extrapolation and regularity editing within the proposed framework (Mao et al., 2019b). Adaptive proof-path selection policies improve tractability in neural theorem proving by learning to prioritize likely derivations, retaining interpretability while scaling reasoning (Morris, 2022).

Logical reasoners and hybrid provers provide verifiable traces and coherent explanation graphs for domain tasks and QA (Kalyanpur et al., 2022; Tammet et al., 2023; Vakharia et al., 2024; Weir et al., 2024). Symbol-aware pipelines disentangle perception from logic to expose step-by-step reasoning and support contrastive explanations (Yi et al., 2018; Amizadeh et al., 2020; Eiter et al., 2023). Interpretable model classes and compilation to tractable forms support minimal feature-based and rule-level explanations (Shih et al., 2018; Riegel et al., 2020; Ignatiev et al., 2021). Related approaches connect explanation to program induction and end-to-end neurosymbolic

learning (Rocktäschel & Riedel, 2017; Evans & Grefenstette, 2018). Domain pipelines (e.g., sentiment) illustrate that conversion to symbolic representations can make decision paths more transparent by exposing explicit intermediate structure (Cambria et al., 2022).

Concept-Based Models for Interpretable Bottlenecks Concept bottlenecks are a class of architectures in which the network is forced to predict a small set of human-understandable concepts before producing its final output; the concept layer becomes a narrow “bottleneck” through which all task-relevant information must pass, improving transparency and controllability because the intermediate concept predictions can be inspected and edited (Koh et al., 2020). Neurosymbolic concept learners ground visual and relational concepts in language or structured supervision, enabling programmatic reasoning over explicit symbols (Mao et al., 2019a). End-to-end integrations learn latent concepts alongside symbolic rules or ASP programs to support decision pipelines with checkable intermediate structure (Murali et al., 2022; Cunnington et al., 2023). Domain adaptations leverage ontologies to define concept spaces that strengthen interpretability and performance in specialized settings (Glauer et al., 2023). Learning strategies invent new interpretable relational concepts and efficient search heuristics to scale symbolic learning (Daniele et al., 2023; Demir & Ngomo, 2023; Sha et al., 2025).

Visual reasoning beyond VQA. Visual reasoning is broader than question answering alone. *Scene graph generation* (extracting object–relation–object triples from an image), *multimodal event representations* (typed records linking visual and textual events), image captioning, retrieval, and generation can all expose typed visual relations that downstream symbolic operators can query, enrich, or check. Recent visual reasoning surveys emphasize scene graphs and *commonsense knowledge graphs* (KGs of everyday-world facts such as ConceptNet or ATOMIC) as explicit representations for objects, relations, attributes, and external knowledge, covering downstream tasks beyond VQA while retaining VQA as a major benchmark family (Khan et al., 2025). Representative systems in this survey therefore treat VQA as one important test case: program-guided perception, differentiable first-order logic for visual reasoning, salient scene-graph generation, and structured intermediate representations illustrate how visual perception can be coupled to executable or inspectable artifacts (Mao et al., 2019b; Amizadeh et al., 2020; Chen & Yang, 2021; Benetatos et al., 2023). The post-2023 evidence rows extend this coverage across four perception sub-areas.

Indoor and outdoor 3D scene understanding couples LLM-built spatial ontologies and 3D scene graphs to logic-tensor or modal-logic operators (Hsu et al., 2023; Strader et al., 2024; Murtas et al., 2025; Saucedo et al., 2025).

Autonomous-driving perception couples driving-scene knowledge graphs, scenic-program scene representations, and conformal perception bounds to SPARQL extractors, simulator semantics, and downstream verifiers (Hallyburton & Pajic, 2025; Leung et al., 2025; Waite et al., 2025; Zhou et al., 2025).

Spatio-temporal scene-graph generation and multimodal grounding couples weakly supervised STSG generators to differentiable symbolic reasoners and graph-search executors (Huang et al., 2024; Jahangard et al., 2025; Kabir et al., 2025; Sha et al., 2025).

Domain-specific perception couples GNN-based pipelines to fuzzy-rule and ontology operators for medical imaging and wireless sensing (Savazzi et al., 2025; Sengupta & Rekik, 2025).

Reading the four sub-areas together, the perception evidence is no longer anchored on VQA: it now covers indoor and outdoor 3D scenes, on-road driving scenes, spatio-temporal video events, and scientific-imaging modalities, each with a typed artifact and an explicit symbolic operator.

Evaluation and Measures Evaluation of explainability combines quantitative and qualitative criteria to assess usefulness, faithfulness, and human factors (Islam et al., 2024). Interactive interpretability leverages language models to generate or critique explanations, requiring human-centered protocols for validation (Singh et al., 2024). Post-hoc natural language explanations and task-specific settings (e.g., education, grading) illustrate measurement of explanation quality in practice (Tornqvist et al., 2023). Task addresses high-level understanding (e.g., humor comprehension) expose current gaps and help benchmark progress beyond surface correlations (Hessel et al., 2023). Symbolic domains such as music highlight discrete-generation evaluation measures and evaluation needs (Plasser et al., 2023). Multilingual KGQA benchmarks support fairer accessibility in grounded QA evaluation (Perevalov et al., 2022). Comprehensive surveys of XAI and explainability taxonomies inform evaluation protocols for hybrid systems (Zhang & Sheng, 2024; Ullah et al., 2025). Evaluation implications extend to domain-specific symbolic generation tasks, including symbolic music rearrangement (Zhao et al., 2023a).

Theme takeaway (interface patterns and trade-offs). Reading Table 7 along the interface-pattern axis, three regularities recur. First, the strongest measured rows for

understandability are intrinsic-artifact rows in reasoning and KR (I1 and I3): rules, programs, queries, and proofs that the system actually emits and that a symbolic operator consumes or checks. These rows are also where artifact-validity risk dominates, because a well-formed artifact can still be wrong if the upstream mapping or knowledge base is incomplete. Second, concept bottlenecks (I2/perception) and human-revision workflows (I8/oversight) extend understandability from inspection to editability, but with cost-overhead, artifact-validity, and deployment-risk limitations. Third, solver-orchestrated reasoning (I6) gives the deepest formal/measured rows — proof artifacts and refinement traces — with deployment risk as the recurring limitation. Across all three, post-hoc natural-language rationales do not enter the table at all; only typed artifacts checked by explicit operators meet the evidence bar.

From plausibility to faithfulness. The plausibility-vs-faithfulness guardrail above is a constraint on what counts as evidence; faithfulness in this survey’s sense is the property that an explanation actually reflects the computation the model performed. For practitioners who want to operationalise the guardrail in their own pipeline, the per-theme rows for I1/reasoning and I3/reasoning suggest four steps that map onto the (artifact, assumption, dataset, progress measure) template used elsewhere in this paper. (1) Pin the *explanation artifact* (e.g., the typed query, program, or proof trace the system emits) and the *symbolic operator* that consumes or checks it, rather than scoring free-text rationales; this gives the explanation a stable referent that downstream tests can target, and is what the per-theme evidence rows for I1 and I3 actually count as evidence. (2) Run *counterfactual-style intervention tests* that perturb inputs, intermediate concepts, or knowledge-base entries and verify that the artifact and the predicted answer co-vary in the way the symbolic operator’s semantics predict; concept-bottleneck architectures supply the canonical neurosymbolic instantiation of this test (Koh et al., 2020). (3) Score *provenance and grounding* on the cited sources or extracted facts: with neurosymbolic context-gathering and KB-validation modules in place, the artifact-and-operator pair can be queried for which knowledge-base entries supported each output and whether removing them breaks the answer (Vakharia et al., 2024). (4) Close the loop with *user-evaluated usefulness* on at least one tagged task — error detection, error correction, or trust calibration — to verify that the artifact-and-operator pair is not only technically faithful but also actionable for the intended audience. Together these four steps let a deployer report a faithfulness claim with the same scope discipline (task, dataset, measure) that the rest of the per-theme evidence tables use; survey-level reviews of

explainable-AI evaluation provide complementary checklists and protocol catalogues that can be reused alongside this recipe (Islam et al., 2024; Ullah et al., 2025).

3.3 *Reliable AI: Robustness and Verifiability*

This theme covers 20 evidenced (interface pattern, function role) rows from the paper-level coding. Table 8 presents those rows for this theme; the rest of this subsection narrates the table along three families: (a) **certified checking and formal scoping** (I5/reasoning, I5/planning-control, I3/reasoning) — specifications, SMT-checked properties, and proof certificates, evaluated as property- and assumption-scoped; (b) **constraints-in-loss for robustness** (I2 across all function roles) — symbolic constraints embedded in training objectives that bound learned representations; and (c) **inference-time enforcement and orchestration** (I4 across function roles, I6 reasoning, I7 planning-control) — shields, filters, controllers, and solver-orchestrated loops that bound or repair outputs at deployment. Throughout, we apply a guarantee-scope checklist before accepting any formal claim: (i) *what is specified* (property class and formalization), (ii) *what is modeled* (environment and threat-model assumptions), (iii) *what is covered* (which pipeline components are verified or constrained), and (iv) *what method limits apply* (solver completeness, abstractions, approximations, uncertified heuristics). Guarantees in the table are reported as scoped to the verified object and stated assumptions.

Table 8. Per-theme evidence table: *reliable* theme. Rows are evidenced (interface pattern, function role) combinations. Tag codes: M=measured, F=formal / scoped, C=claimed, NE=not evaluated, A=annotated coding note. Limitation codes: cost=cost overhead, guar.=guarantee scope, artifact=artifact validity risk, deploy=deployment / governance risk, risk=risk noted. Each cell lists every paper coded under the row’s (interface pattern, function role) combination; per the citation-role vocabulary defined in Section 2.6, a cited paper may appear either as an evidence reference (tagged M / F / C / NE / A in the evidence column) or as a pattern-exemplar reference (no evidence tag; the paper instantiates the row’s interface-pattern coupling without itself supporting a measured, formal, claimed, or not-evaluated evaluative statement at the row’s grain). The evidence and limitation columns aggregate counts only over the evidence-tagged subset.

Code	Function role	Representative references	Evidence tags	Limitations
I1	knowledge / kr	(Järv et al., 2022)	M:1, F:1, C:1	guar.:1, risk:1

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Table 8 – continued from previous page

Code	Function role	Representative references	Evidence tags	Limitations
I1	perception	(Hallyburton & Pajic, 2025)	C:1	artifact:1, cost:1
I1	planning / control	(Shah, 2023; Siyaev et al., 2023)	M:1, F:1	artifact:1, guar.:1
I1	reasoning	(Järv et al., 2022; Kant et al., 2024)	M:1, F:1, C:1	artifact:1, deploy:1, cost:1, guar.:1
I2	knowledge / kr	(Huang et al., 2024; Strader et al., 2024)	M:2	artifact:1, guar.:1
I2	perception	(Hu et al., 2016; Donadello et al., 2017; Qu & Tang, 2019; Koh et al., 2020; Stammer et al., 2021; Saha et al., 2024)	M:4, F:1	guar.:3, artifact:1
I2	planning / control	(Achiam et al., 2017)	M:1, F:1	cost:1, guar.:1, deploy:1
I2	reasoning	(Touretzky & Minton, 1985; Mooney et al., 1989; Evans & Grefenstette, 2018; Xu et al., 2018; Dong et al., 2019; Yang et al., 2020; Oltramari et al., 2021; Badreddine et al., 2022; Aakur & Sarkar, 2023; Ahmed et al., 2023; Chen et al., 2023c; Schick et al., 2023)	M:9, F:3	guar.:6, cost:2, artifact:2
I3	knowledge / kr	(Glauer et al., 2023; Bougzime et al., 2025)	F:1, C:1	guar.:1, artifact:1
I3	oversight	(Amizadeh et al., 2020; Eiter et al., 2023)	M:1, F:1	guar.:1, deploy:1, cost:1
I3	perception	(Ding, 2007; Yang et al., 2020; Hallyburton & Pajic, 2025)	M:2, F:1, C:1	artifact:2, guar.:2, deploy:1

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Table 8 – continued from previous page

Code	Function role	Representative references	Evidence tags	Limitations
I3	planning / control	(Fabiano et al., 2023; Pallagani et al., 2023; Hao et al., 2025)	M:3, C:1	guar.:2, risk:1, cost:1
I3	reasoning	(Yi et al., 2018; Riegel et al., 2020; Pan et al., 2023; Ganguly et al., 2024; Oltramari, 2024; Vakharia et al., 2024; Weir et al., 2024; Feng et al., 2025a; Hu et al., 2025; Perrier, 2025; Yang et al., 2026)	M:9, C:1, F:1	guar.:7, artifact:3, cost:3, risk:2
I4	perception	(Elia et al., 2024)	M:1, F:1	cost:1, guar.:1, artifact:1
I4	planning / control	(Alshiekh et al., 2018; Liu et al., 2023; Yang et al., 2023; Court et al., 2025; Feng et al., 2025b; van Hurne et al., 2026)	M:4, F:3, C:1	guar.:5, artifact:3, cost:3, deploy:2
I4	reasoning	(Xiao et al., 2017; Chen et al., 2023c; Schick et al., 2023; Banerjee et al., 2025)	M:3, F:1	guar.:2, artifact:1, cost:1
I5	planning / control	(Kouvaros, 2023; Kouvaros et al., 2024; Ahn et al., 2025; Waite et al., 2025)	M:4, F:3	guar.:4, cost:3, artifact:3, deploy:1
I5	reasoning	(Katz et al., 2017b,a; Kirk & Laird, 2019; Qu & Tang, 2019; Elboher et al., 2020; Murali et al., 2022; Xie et al., 2022; Trinh et al., 2024; Choi et al., 2025a; Feng et al., 2025b; Liu et al., 2025a; Su et al., 2026; Sunny & Sivan-Sevilla, 2026)	F:7, M:5	guar.:9, cost:5, artifact:5
I6	reasoning	(Manhaeve et al., 2018; Chen et al., 2021)	F:2	guar.:2
I7	planning / control	(Yang et al., 2018; Kambhampati et al., 2024; Ahn et al., 2025)	M:3	artifact:3, cost:2, guar.:1

Formal Verification and Safety Guarantees Formal guarantees in hybrid/multi-agent contexts are explored in (Kouvaros et al., 2018). Neural SAT solvers illustrate learned

propositional reasoning capabilities that can support verification and analysis tasks within hybrid pipelines (Selsam et al., 2018).

Verification of neural components has progressed via SMT-based solvers, abstraction techniques, and neurosymbolic specifications, expanding the space of certifiable properties (Katz et al., 2017a,b; Elboher et al., 2020; Xie et al., 2022). Additional formulations and implementations of Reluplex further characterize the feasibility and limitations of DNN property checking (Katz et al., 2017a). Methodologies and surveys outline processes for certifiable AI in safety-critical domains and for multi-agent settings (Elia et al., 2024; Kouvaros et al., 2024; Renkhoff et al., 2024). These works emphasize testability, evidence-backed assurance cases, and the role of formal safety arguments in deployment (Kouvaros, 2023; Lenat & Marcus, 2023; Lu et al., 2024). Neuro-symbolic theorem proving provides a complementary reliability pattern: neural guidance can prioritize proof search while a symbolic deduction engine produces checkable (and often human-readable) proofs (Trinh et al., 2024).

Robustness to Adversarial and Distributional Shifts Symbolic constraints embedded in objectives improve robustness by enforcing invariants during learning (Xu et al., 2018; Ahmed et al., 2023; Chen et al., 2023c). Encoding contextual knowledge into model parameters and deconfounding strategies mitigate distractors and shifts (Chen et al., 2023d; Wang et al., 2024). Evaluation requires systematic tests across domains and shift conditions to characterize reliability boundaries. Reasoning under uncertainty via probabilistic logics (e.g., Logical Credal Networks) provides calibrated inference with imprecise probabilities, supporting reliability in open settings (Qian et al., 2022). Constraint-guided fine-tuning of generative models has been proposed as another route to reduce forbidden outputs under specified constraint classes, but its reliability should be interpreted as constraint- and evaluation-scoped (Yin et al., 2024).

Constraint Satisfaction and Safe Reinforcement Learning Classical symbolic solvers illustrate constraint handling and approximate reasoning under uncertainty, informing safety mechanisms in hybrid controllers (Sacks, 1989).

Constrained optimization and temporal-logic shields are used to enforce or encourage safety specifications during exploration and execution, within the scope of the stated constraints and environment assumptions (Achiam et al., 2017; Alshiekh et al., 2018; Yang et al., 2023). Neurosymbolic controllers leverage logical constraints to guide policies and (in some settings) enforce checkable safety properties during learning and deployment.

Evaluation and Measures Foundational theories and empirical studies on assessment, progress quantification, and reproducibility include (Gundersen & Kjensmo, 2018; Liu et al., 2018; Rezazadegan et al., 2024). Measurement models and testing frameworks support standardized reliability evaluation for commercial and research systems (Zhang et al., 2022; Li et al., 2023a).

Theme takeaway (interface patterns and trade-offs). Reading Table 8 along the interface-pattern axis, three regularities recur. First, formal/certified rows (I5/reasoning, I5/planning-control, I3 across roles) are where guarantee-scope is most concentrated and where cost overhead is highest: SMT-checked properties, proof certificates, and shield/spec pairs are evaluated under explicit assumptions and apply to specific pipeline components rather than to end-to-end systems. Second, constraints-in-loss (I2) is the largest measured cluster: symbolic invariants encoded in objectives improve robustness across reasoning, perception, and planning, with guarantee-scope as the dominant limitation in the table. Third, inference-time enforcement (I4) and hybrid loops (I7) provide bounded mitigation rather than guarantees, and the table records this as cost+guarantee+deploy limitations. The synthesis risk we keep explicit is conflating mitigation with guarantees: when a row reads M-only without F, we describe the system as bounded or hardened.

3.4 Ethical AI: Value Alignment and Accountability

The ethics theme is the narrowest in the synthesis: **two evidenced (interface pattern, function role) rows** meet the bar that requires both an explicit ethics-relevant theme tag and an artifact-and-operator coupling (Table 9). The two rows are training-time injection of normative constraints for planning/control (I2, (Ahmed et al., 2023)) and governance/oversight workflows over policy/audit artifacts (I8, (Elia et al., 2024; Bonfanti et al., 2025; Sunny & Sivan-Sevilla, 2026; van Hurne et al., 2026)). The I8/oversight row consolidates four ethics-relevant systems across the 2024–2026 window: a structured accountability assessment for autonomous driving (Elia et al., 2024), a knowledge-graph-driven oversight pipeline that revises agent behaviour on demand (Bonfanti et al., 2025), a neuro-symbolic agent architecture with explicit traceability and reflexive verification of agent decisions (Sunny & Sivan-Sevilla, 2026), and an ontological foundation that lifts accountability assignment from prose to a queryable artifact (van Hurne et al., 2026). This count still reflects a methodological choice rather than a coverage gap in the broader bibliography: only the papers that

simultaneously (i) make an evidenced neurosymbolic-method contribution and (ii) couple that contribution to an explicit accountability artifact (norm / policy / audit / revision-trace) operated on by an explicit workflow are promoted to evidenced rows. The rest of this subsection complements those two rows with the broader ethics-relevant literature in three deliberately separated categories: (a) executable normative artifacts (rules, constraints, policies that a reasoner can check); (b) governance workflows (oversight roles, audit trails, escalation mechanisms); and (c) trustworthy-AI reviews (evaluation criteria that can be mapped onto accountability interfaces but are not themselves evidence that a specific system enforces an ethical constraint (McCormack & Bendechache, 2024; Michel-Deletie & Sarker, 2025)). Table 10 characterises each of the three families by artifact + operator + workflow + cited literature for deployers in regulated domains, who should treat the prose patterns and named candidate systems as the primary entry point and Table 9 as the coarser map back to the evidence-table vocabulary.

Table 9. Per-theme evidence table: *ethical* theme. Rows are evidenced (interface pattern, function role) combinations. Tag codes: M=measured, F=formal / scoped, C=claimed, NE=not evaluated, A=annotated coding note. Limitation codes: cost=cost overhead, guar.=guarantee scope, artifact=artifact validity risk, deploy=deployment / governance risk, risk=risk noted. Each cell lists every paper coded under the row's (interface pattern, function role) combination; per the citation-role vocabulary defined in Section 2.6, a cited paper may appear either as an evidence reference (tagged M / F / C / NE / A in the evidence column) or as a pattern-exemplar reference (no evidence tag; the paper instantiates the row's interface-pattern coupling without itself supporting a measured, formal, claimed, or not-evaluated evaluative statement at the row's grain). The evidence and limitation columns aggregate counts only over the evidence-tagged subset.

Code	Function role	Representative references	Evidence tags	Limitations
12	planning / control	(Ahmed et al., 2023)	M:1	artifact:1, deploy:1
18	oversight	(Elia et al., 2024; Bonfanti et al., 2025; Sunny & Sivan-Sevilla, 2026; van Hurne et al., 2026)	C:3, M:2, F:1	deploy:4, guar.:2, cost:1, artifact:1

Value Alignment and Encoding Ethical Principles Human-compatible AI principles and preference-uncertainty arguments are articulated in (Russell, 2019).

Encoding norms into symbolic components supports auditable reasoning about duties, rights, and constraints. In interface-pattern terms, the key questions are: what is the

executable norm artifact (rules, constraints, policies); what operator checks or enforces it (reasoner, constraint solver, verifier); and where does that operator act (training-time objective, inference-time check, or governance workflow)? Neurosymbolic pipelines can translate legal or policy text into logical code for transparent compliance, producing inspectable artifacts that can be reviewed, tested, and updated (Chanin & Hunter, 2023; Kant et al., 2024; School, 2024). Expressivity limits of standard reward formulations motivate explicitly structured objectives for alignment, with implications for how alignment specifications are written and audited (Abel et al., 2021). Comprehensive assessment frameworks guide ethical integration and evaluation in domain settings such as education (Kılınç, 2024).

Algorithmic Fairness and Bias Mitigation Auditing for dataset and model biases requires culturally aware diagnostics and targeted mitigations; surveys highlight Western-centric biases as a persistent risk (Abbas, 2025). A concrete failure mode that motivates the neurosymbolic framing here is the case where a model behaves correctly on aggregate accuracy but exhibits disparate outcomes across protected subgroups (for example a clinical decision-support system whose recommended treatment differs systematically by demographic group despite the same input findings); a purely neural pipeline gives no inspectable artifact that says which attributes are being read or how they propagate, whereas a coupling with explicit constraints, an attribute schema, and an audit trail can be queried directly. From a neurosymbolic perspective, the contribution is to make these fairness-related assumptions *explicit and testable* as constraints, documentation artifacts, and audit procedures rather than implicit behavior. Symbolic knowledge and constraints can support debiasing and accountability by (i) exposing which attributes/relations are used, (ii) enabling constraint-based checks (for example, a constraint that the recommended treatment must be invariant under perturbation of a protected attribute), and (iii) providing versioned artifacts that support rollback and redress.

Human-in-the-Loop Learning for Collaborative Refinement Interactive frameworks allow users to correct concepts, rules, and reasoning traces, improving both performance and trust (Kim et al., 2020; Stammer et al., 2021; Crochepierre et al., 2022). Complementary conversational and iterative learning setups emphasize user-driven correction loops and structured feedback signals (Kirk & Laird, 2019; Arabshahi et al., 2021). Interactive reward and policy learning with human feedback complements symbolic refinement pathways for safer, aligned behavior (MacGlashan et al., 2017). For accountability, HIL protocols should capture rationale, provenance, and rollback: which

artifact was changed (concept, rule, policy), why it was changed (human justification), and how the system behaved before/after the change under a fixed evaluation protocol.

Governance and Oversight National strategies such as Estonia’s Kratt Strategy document concrete policy instruments for accountable AI deployment in public services (Ministry of Economic Affairs and Communications, 2022). Strategic and programmatic drivers for explainable and third-wave AI are summarized in (Daws, 2018; Gunning et al., 2021).

Oversight structures for agent-based AI specify roles, audit trails, and escalation protocols in public organizations (Schmitz et al., 2025). Operational governance typically requires logging of data access, tool-use, and explanations to enable audits and redress.

Interface-coded ethics patterns. Across the reviewed work, the most concrete ethical interfaces are (i) *norms as executable constraints*, where policies, rights, or domain rules are translated into logic or code; (ii) *audit trails*, where data access, tool use, intermediate artifacts, and interventions are logged for later inspection; and (iii) *human revision loops*, where domain experts can correct concepts, rules, or policies and rerun a fixed evaluation protocol. These patterns are technically meaningful because they specify both the artifact being governed and the operator or workflow that checks it. Table 10 characterises each family by the kind of artifact, the operator that checks or enforces it, and the surrounding governance workflow, drawing on the broader ethics-relevant literature that does not rise to evidenced-row promotion in Table 9 but is concrete enough for a regulated-domain deployer to use as a starter kit. The main limitation of all three families is shared: a system can be auditable with respect to the encoded norms while still missing harms not represented in the knowledge base, policy set, or evaluation protocol.

Evaluation and Measures Ethics-focused evaluation spans fairness measures, participatory audits, and governance checklists; documentation of assumptions and failure modes is essential. Systematic reviews of evaluation criteria for trustworthy AI provide broader taxonomies that can be mapped onto neurosymbolic accountability interfaces (McCormack & Bendecheche, 2024).

Theme takeaway (interface patterns and trade-offs). Across the two evidenced rows in Table 9 and the broader literature narrated above, ethical NeSy concentrates on two interface families: (i) **normative constraints as I2-style training-time injection** — policies, rights, or rules encoded as constraints/regularizers that shape learned representations; and (ii) **accountability workflows as I8-style oversight** — explicit

Table 10. Ethics interface families discussed in Section 3.4 beyond the two evidenced rows in Table 9. Columns name the kind of artifact that carries the accountability claim, the operator that checks or enforces it, and the surrounding workflow that produces or revises it. Inclusion in this table is not equivalent to evidenced-row promotion in Table 9: the cited literature characterises the family but does not always supply the artifact-plus-operator-plus-workflow triple at the bar required for evidence-row promotion.

Family	Artifact	Operator	Workflow	Cited literature
Executable normative artifacts	Policy / right / domain rule translated into logic or code (compliance specification)	Symbolic reasoner, constraint solver, or compliance checker	Domain-expert authoring; versioned release; training-time injection (I2) or inference-time check (I3) of the specification	(Ahmed et al., 2023; Chanin & Hunter, 2023; Kant et al., 2024; School, 2024)
Governance workflows over audit artifacts	Data-access log, tool-use log, intermediate-artifact log, intervention log, audit trail	Audit procedure, escalation protocol, oversight role with defined authority	Runtime logging; periodic audit; escalation to oversight role; published oversight report; revision of upstream specification when audit identifies a gap (I8)	(Ministry of Economic Affairs and Communications, 2022; Elia et al., 2024; Ilves, 2025; Schmitz et al., 2025)
Human revision loops	Concept, rule, or policy artifact under human control; rationale and provenance record attached to each revision	Domain-expert correction; before/after re-run of a fixed evaluation protocol	Interactive review session; rationale capture; before/after evaluation; rollback path if evaluation degrades; revision-trace record retained for later audit	(MacGlashan et al., 2017; Kirk & Laird, 2019; Kim et al., 2020; Stammer et al., 2021; Crochepierre et al., 2022)

policy/audit/revision artifacts handled by a defined governance workflow. A central trade-off in both families is between flexibility (updating norms) and assurance (demonstrating compliance under deployment conditions). The thin evidence base is itself a finding: the field has many *principles* papers and many *governance/trustworthiness* reviews, but relatively few systems that simultaneously implement an evidenced neurosymbolic coupling and bind it to an explicit accountability artifact and workflow. Closing that gap — the kind of evidence we would record as additional ethical rows — is the most concrete progress signal for this theme.

4 Discussion

This section positions our synthesis relative to prior surveys and theories, clarifies scope and novelty, and discusses broader implications for human-compatible AI. We first compare with related works and taxonomies, then consider impacts, risks, and policy considerations that inform practical deployment and governance.

To make cross-paper synthesis defensible, we keep three anti-patterns out of the per-theme evidence tables. First, each paper is described by one or more (theme, interface pattern, function role) rows (Section 2.4, Table 2). Second, tool-augmentation rows (I0) appear in the tables only as adjacent context, and become NeSy evidence only when paired with typed artifacts and an explicit operator (becoming I1 or I3) (Davis, 2023). Third, every comparative cell carries an evidence tag, every limitation is a column-level annotation, and every comparison is scoped to a task/dataset/measure (Section 2.6).

4.1 Comparison with Previous Works and Theories

Table 11 summarizes how this survey differs from recent complementary surveys and systematic reviews. We use these works as navigation aids for the reader (rather than as evidence categories), and we avoid implying that one taxonomy or survey scope is universally superior; instead, we make explicit which comparison dimensions (interfaces, guarantees, and costs) we emphasize.

This synthesis complements prior reviews by organizing the field around human-compatibility goals (themes) rather than methods alone, while mapping to system functions and evaluation practices. For NLP and knowledge-graph reasoning, structured reviews and surveys provide domain-specific taxonomies and evaluation emphases that we use for triangulation (Hamilton et al., 2024; DeLong et al., 2025). Trustworthy-AI lenses and governance perspectives supply adjacent evaluation criteria and deployment considerations (Acharya et al., 2024). Systems/workload perspectives motivate cost-aware comparisons that complement algorithm-centric summaries (Wan et al., 2024a). Surveys on RL/planning and cross-domain applications provide additional entry points where neurosymbolic interfaces are instantiated in sequential decision-making and applied domains (Zhang et al., 2021; Yu et al., 2023; Cheng et al., 2024). Meta-analyses and mappings aggregate the literature into architecture- or application-oriented taxonomies; we use these primarily as navigational aids rather than as evidence categories (Bouneffouf & Aggarwal, 2022; Gibaut et al., 2023; Colelough & Regli, 2024; Feldstein et al., 2024; Colelough & Regli, 2025). Compendia and broad surveys

Table 11. Comparison with representative recent surveys and systematic reviews. Columns summarize each work’s primary organizing lens and whether it explicitly separates evidence from context (e.g., measured vs. claimed), treats costs/guarantees as first-class dimensions, and distinguishes tool grounding from symbolic-operator coupling. This table is illustrative (not exhaustive).

Work (representative)	Primary organizing lens	Evidence separation	Costs / guarantees	Tool grounding vs. symbolic coupling
(Bhuyan et al., 2024) (broad survey)	broad taxonomy (representation, learning, reasoning, decision-making)	mostly narrative synthesis	discussed, but not a central comparison axis	may cover both; boundary varies by subtopic
(Renkhoff et al., 2024) (V&V)	verification/validation/testing taxonomy	explicit evaluation framing for V&V settings	central (assurance arguments, testability); guarantee scope emphasized	focuses on assurance; tool grounding treated case-by-case
(DeLong et al., 2025) (KG reasoning)	KG reasoning tasks and method families	task- and benchmark-oriented survey framing	costs/guarantees typically task-scoped	focuses on symbolic structure in KG pipelines; tool-use is peripheral
(Michel-Deletie & Sarker, 2025) (trustworthy NeSy)	systematic review lens focused on interpretability/trustworthiness	systematic review methodology; categorization dimensions	trustworthiness dimensions emphasized; costs variable	emphasizes symbolic structures; boundary depends on inclusion criteria
(Colelough & Regli, 2025) (systematic mapping)	mapping / taxonomy of NeSy research areas	systematic review-style aggregation	costs/guarantees typically not the primary axis	boundary depends on mapping categories
This survey	themes (performance, understandability, reliability, ethics) + interface patterns	explicit citation roles + evidence tags (Measured/Claimed/Not evaluated)	first-class comparison dimensions (cost profiles + guarantee scope)	strict boundary: tool grounding is context unless paired with typed artifacts + explicit operators

provide additional breadth and terminology alignment across subcommunities (Hitzler & Sarker, 2022; Hitzler et al., 2023; Wang et al., 2025b). Finally, surveys and position papers on neurosymbolic agents and system-level integration motivate how the same interface patterns recur in agentic pipelines (Yu et al., 2021; Kishor, 2022; Silver & Mitchell, 2023; Belle et al., 2024; Bhuyan et al., 2024; Bougzime et al., 2025). Related works in neural architecture optimization provide useful contrasts to hybrid approaches (Wang et al., 2021). Domain and scope-specific reviews situate advances in healthcare and visual reasoning (Frisoni et al., 2021; Hossain & Chen, 2025; Khan et al., 2025). Robotics and embodied settings add distinct integration constraints and evaluation practices (Basumatari, 2025; Ugur et al., 2025). Foundational and historical perspectives anchor the trajectory of neural-symbolic computing up to the present (Garcez et al.,

2015; Besold et al., 2017; Garcez & Lamb, 2023). Complementary reviews emphasize the evolution of architectures, datasets, and evaluation practices (Sarker et al., 2022).

Systematic reviews of trustworthy neurosymbolic AI foreground interpretability-focused taxonomies and open questions (Michel-Deletie & Sarker, 2025).

4.2 Implications for Human-Compatible AI

Framing progress by themes emphasizes co-design of performance, understandability, reliability, and ethics for deployable systems. Policy-driven and principled approaches highlight value alignment, oversight structures, and operational accountability (Russell, 2019; Schmitz et al., 2025). National and sector programs illustrate governance requirements for agent-based AI in practice (Ministry of Economic Affairs and Communications, 2022; Ilves, 2025). Evaluation against structured levels of capability and autonomy facilitates clearer communication of risk and fitness for purpose (Morris et al., 2024). Beyond applications, AI is transforming the scientific process itself, with implications for governance, reproducibility, and collaboration (Roded & Slattery, 2025).

4.3 Limitations and Deferred Extensions

This synthesis has bounded scope. The boundaries below describe the survey’s interpretive frame so that a reader can place the per-theme evidence tables and the per-theme analyses correctly, rather than to qualify the contribution claims of Sections 1.3 and 1.4.

Perception evidence is anchored on visual question answering. The I1/perception rows in Tables 5 and 7 are dominated by VQA exemplars. Section 3.2 (the “Visual reasoning beyond VQA” paragraph) extends the perception evidence to four further sub-areas (indoor and outdoor 3D scene understanding; autonomous-driving perception; spatio-temporal scene-graph generation and multimodal grounding; domain-specific perception); each sub-area is named and grounded in evidenced rows, but the row density is lower than for the textual reasoning and knowledge-graph families. Pushing density up across these four sub-areas is the largest content extension we plan for the next revision.

Evidenced ethics rows are sparse by methodological choice. Table 9 contains only the (interface pattern, function role) combinations where the cited system supplies an explicit accountability artifact plus an explicit operator plus an explicit workflow. As a consequence the ethics-theme prose in Section 3.4 carries more weight than the per-theme table, and readers in regulated domains should treat the three prose categories

(executable normative artifacts, governance workflows, trustworthy-AI reviews) as the primary entry point.

The synthesis reflects a paper-level coding protocol. The 65 grouped rows that populate the per-theme evidence tables were produced by applying the per-paper coding protocol described in Section 2.3 against the documented dimensions, retaining multiple rows per paper when the evidence is multi-dimensional. The full codebook is deferred to a methods supplement; the responsibility for the interpretive frame the rows carry rests with the authors.

Temporal scope is 2020 to mid-2026. Earlier foundational work appears only as anchors for historical context. The synthesis is restricted to the 2020 to mid-2026 window; the corpus was assembled from the source-specific queries logged in Appendix A. Publications that surfaced after the mid-2026 cutoff are tracked for the next revision rather than being added late and unevenly.

5 Future Directions and Open Challenges

Drawing from the preceding analysis, we propose concrete directions for advancing neurosymbolic AI. We group open problems into four areas: scalability and deeper integration; comprehensive trustworthiness and meta-cognition; research-to-engineering design principles; and meaningful evaluation. For each area, the intended contribution is a testable setup: what artifact is coupled, what assumption or guarantee is claimed, which dataset/workload/stress condition is used, and which cost, correctness, or human-centered measure would count as progress.

5.1 Scalability and Deep Integration of Hybrid Architectures

Scalable NeSy systems require workload-aware acceleration (optimizing for the actual runtime/operator mix), memory-efficient KR integration, and differentiable reasoning backends (Susskind et al., 2021; Wan et al., 2024b,a). Promising directions include hardware-aware architecture search, stochastic logic programming, and declarative differentiable languages (Winters et al., 2022; Li et al., 2023b; Saha et al., 2024). Long-term visions for modular systems motivate deeper fusion of perception, KR, planning, and self-supervised objectives (LeCun, 2022).

Testable setup.

- *Artifact*: a typed differentiable reasoning kernel (probabilistic logic program, differentiable solver, declarative differentiable language) compiled into the training graph.
- *Assumption / guarantee*: forward and backward passes preserve the operator semantics; runtime and memory cost are bounded relative to a pure-neural baseline.
- *Dataset / workload*: reasoning workloads with mixed operator types (logic + arithmetic + retrieval) at scale beyond unit-test domains, with the operator mix recorded per item.
- *Progress measure*: end-to-end accuracy at fixed compute budget, plus operator-mix sensitivity (accuracy versus the symbolic-to-neural operation ratio).

5.2 Advancing Towards Comprehensive Trustworthiness and Meta-Cognition

Reliability at scale will combine formal verification of neural components with symbolic specifications and constraint-aware training objectives (Katz et al., 2017a; Elboher et al., 2020; Xie et al., 2022). Meta-cognitive strategies (self-monitoring that chooses among reasoning modes) can arbitrate between reasoning modes via conflict detection and self-monitoring, improving adaptation in novel contexts (Raja et al., 2024; Hu et al., 2025). Stress-testing for hallucination, compositional complexity, and shift remains essential to validate claims (Huang et al., 2025; Saxena et al., 2025b; Shojaee et al., 2025).

Testable setup.

- *Artifact*: a verified neural component paired with an explicit specification (safety property, monotonicity, constraint) that the verifier checks, plus a meta-cognitive monitor that issues deferral signals.
- *Assumption / guarantee*: the specification is faithful to the deployment context; the verifier is sound on the chosen network class; the monitor’s confidence calibration is empirically validated on a held-out tail.
- *Dataset / workload*: out-of-distribution and adversarial stress conditions plus a normal-traffic baseline, with adversary budget specified.

- *Progress measure*: certified accuracy and certified abstention rate at fixed adversary budget; the rate at which the meta-cognitive monitor correctly defers on items that lie outside the verified envelope.

5.3 From Research to Engineering: Design Principles

Methodological guidance should cover dataset governance, KR curation, tool-use auditing, and end-to-end testability. A research-to-engineering bridge for neurosymbolic systems can be structured around four design elements that lift the per-theme evidence tables into a deployer playbook.

First, the *pipeline shape*. A deployable system typically decomposes into a chain of boundaries (perception, KR, reasoning, planning/control, oversight), and each boundary should be assigned an interface-pattern code (I0–I8 per Section 2.4) so that the engineering trade-offs recorded in the per-theme evidence tables (Tables 5–9) are inherited rather than rediscovered when a new boundary instance is added.

Second, an *ablation set* per release. At minimum: a remove-one-component variant at each boundary, a stale-knowledge probe that holds an older KR snapshot constant while inputs vary, and a constraint-violation probe that intentionally feeds inputs which should trigger deferral or rejection. These three probes attribute behaviour to the coupling structure, to the KR contents, and to the oversight workflow respectively.

Third, an *audit log schema*. At minimum: the input fingerprint, the typed artifact handed across each boundary (with hash), the operator outcome, and the deferral reason where applicable. These fields are the minimum needed to reproduce a deployment-time decision after the fact, and they are the natural per-row record that an oversight workflow (I8 in Section 2.4) consumes.

Fourth, a *versioning cadence* for KR assets and rule sets that is decoupled from the model release cadence. A KR refresh should be a first-class release event with its own ablation pass against the unchanged model, so that KR drift can be distinguished from model drift in post-deployment incident review.

Standardized testing and measurement models complement these design elements by improving comparability and deployment readiness (Gundersen & Kjensmo, 2018; Zhang et al., 2022; Li et al., 2023a).

Testable setup.

- *Artifact*: a versioned coupling spec naming the per-boundary interface-pattern codes (I0–I8), the typed artifacts transmitted between boundaries, the KR assets

and rule sets the pipeline depends on, and the audit-log schema recorded at runtime.

- *Assumption / guarantee*: each boundary’s interface-pattern code maps to one of the patterns characterised in Section 2.4, so trade-offs and the recommended ablations are inherited from the per-theme evidence tables.
- *Dataset / workload*: a paired evaluation set that exercises the nominal pipeline, the remove-one-component ablation at each boundary, the stale-knowledge probe, and the constraint-violation probe.
- *Progress measure*: per-boundary accuracy delta from each ablation, monotonicity of accuracy under KR refresh, and oversight precision/recall on the constraint-violation probe.

5.4 The Challenge of Meaningful Evaluation and Benchmarking

Evaluation must move beyond benchmark chasing to measure reasoning, tool grounding (retrieval/citations/tool use), and robustness with higher-quality datasets and protocols (Davis, 2023; Rogers et al., 2023; Orr & Kang, 2024). Multi-dimensional evaluators and exam-style test suites offer practical instruments for comparable assessment (Zhong et al., 2022; He et al., 2024; Zhong et al., 2024).

Testable setup.

- *Artifact*: a multi-dimensional test suite with explicit role tags (capability, robustness, calibration, tool-grounding, oversight) and a documented item-to-tag map.
- *Assumption / guarantee*: items in each role tag are non-redundant with the training distribution and are stable under minor perturbation; the tag taxonomy is fixed before scoring.
- *Dataset / workload*: an exam-style suite mixing held-out reasoning problems, retrieval-grounded items with verifiable provenance, and oversight items with adjudicated ground truth.
- *Progress measure*: role-tagged accuracy with a held-out tail, plus tool-grounding precision/recall (cited claim versus underlying document) and oversight calibration (deferral-when-uncertain rate).

6 Conclusion

Across the 2020 to mid-2026 literature surveyed here, neurosymbolic AI is most usefully characterized by the goal its coupling is meant to serve, the operator that actually enforces the coupling, and the evidence that supports the claim. The four theme recaps below summarize what the per-theme evidence tables (Tables 5, 7, 8, 9) record under this lens; the closing paragraph then names the engineering and evaluation problems that remain when those interface claims are made precise.

Performance-oriented neurosymbolic AI balances capability with efficiency. Progress stems from architecture and compiler choices, workload-aware design, and the strategic use of tool grounding, tools, and structured knowledge that is *reported* to improve factuality and task success in specific settings, while increasing measurable costs (latency, compute, tool calls). The per-theme evidence frames these gains as scoped improvements under reported workloads and benchmarks rather than universal superiority claims; the per-row evidence tags (M/F/C/NE per Section 2.6) and limitation columns make that scope directly inspectable for any cited system.

Understandable neurosymbolic AI puts knowledge representations and explicit reasoning at the center of explanation. KR-centric pipelines, intrinsic proof traces, and concept bottlenecks make model behavior inspectable and editable, enabling human oversight and targeted error analysis. However, evaluation must move beyond plausibility to measure faithfulness and usefulness with human-centered protocols, provenance, and versioned assets; natural-language rationales or valid-looking artifacts should not be treated as faithful explanations without such evidence.

Reliable neurosymbolic AI combines formal specifications, verifiable components, and robustness objectives to maintain integrity under shift and attack. Constraint satisfaction, shields, and differentiable planners can provide enforceable guarantees for specified properties under stated assumptions, while uncertainty-aware reasoning offers calibrated behavior in open settings. Reliability claims in this theme are most useful when paired with their guarantee scope — specified property, modelled assumptions, covered inputs, and method limits (Section 3.3) — so that a local check travels with the conditions under which it holds and a deployer can read it as a verified property over a stated envelope rather than as a global safety claim.

Ethical neurosymbolic AI encodes values, rights, and duties into explicit structures that can be audited and refined. Human-in-the-loop protocols enable correction of concepts, rules, and policies; fairness assessments and mitigation plans should be integrated into the development lifecycle. Operational governance (roles, logging, and escalation)

turns principles into accountable practice, especially for public-sector and high-stakes deployments. These mechanisms are only as complete as the norms, data, and evaluation protocols they encode, so documentation of limitations and routes to redress remains essential.

The resulting trajectory is deeper but more accountable integration: scalable differentiable reasoning and KR backends, platform-aware co-design, meta-cognitive control that arbitrates among reasoning modes, and open assets that make evidence claims inspectable. By co-designing performance, interpretability, reliability, and ethics around concrete system functions and evaluation levers, the field can move toward neurosymbolic systems whose benefits and limits are stated clearly enough to be tested, compared, and improved.

A Search Strategy and Information Sources

We queried leading AI venues and digital libraries covering learning, knowledge representation, reasoning, and systems between 2020 and mid-2026. Sources included prominent conference proceedings and journals, publisher portals, and indexing services. Representative query terms combined neurosymbolic and theme-specific keywords (e.g., logic, ILP, differentiable reasoning; KGs, symbol grounding, tool grounding, retrieval/tool use; planning/control, safe RL; verification, SMT; explainability, bottlenecks; governance). Searches were oriented toward identifying systems with an explicit symbolic representation and operator-level coupling, consistent with our categorization system and evidence protocol (Sections 2.4–2.6).

Keyword summary (representative). Table 12 lists the keyword sets actually combined per source, the typical filters applied on top, and the date the queries were last run. The exact boolean expressions and operator syntax differ from platform to platform; the keyword columns capture the substantive search vocabulary so the table stays comparable across sources.

Screening workflow. Records from multiple sources were consolidated and screened with AI-aided assistance using ASReview (Van De Schoot et al., 2021) to prioritize likely-relevant items, with final inclusion decisions made by the authors.

Notes. Dates are month-level to indicate when queries were last run.

Table 12. Representative keyword sets per information source used during evidence collection, with typical filters and the approximate date last searched. This table is a reporting aid; the platform-specific boolean operators and quoting conventions are not reproduced here.

Source	Keywords (combined per source)	Typical filters	Date
Semantic Scholar / OpenAlex	neurosymbolic; neural symbolic; logic; knowledge graph; differentiable reasoning; ASP; ILP; SMT	2020–mid-2026; CS / AI; English	2026-05
arXiv	neurosymbolic; neural symbolic; neural-symbolic; logic; knowledge graph; ILP; ASP; SMT; verifier; constrained decoding	2020–mid-2026; cs.AI; cs.CL; cs.LG	2026-05
ACL Anthology	neurosymbolic; reasoning; knowledge graph; tool use; retrieval; verification	2020–mid-2026; ACL; EMNLP; NAACL; Findings	2026-05
IEEE Xplore	neuro symbolic; neurosymbolic; verification; safety; formal methods; constraint; SMT	2020–mid-2026; journals; conferences	2026-05
ACM Digital Library	neurosymbolic; survey; review; evaluation; explainability; governance	2020–mid-2026; surveys; journals	2026-05
SpringerLink / IOS Press portals	neurosymbolic; knowledge representation; ontology; semantic web; explainability	2020–mid-2026; AI; KR venues	2026-05

B Study Selection Flow and Counts

Screening and selection followed the standard identification → screening → eligibility → inclusion stages over a consolidated candidate pool of **968** records aggregated across sources. AI-aided prioritisation (ASReview) (Van De Schoot et al., 2021) was used to triage the candidate set, with title/abstract decisions taken iteratively. Table 13 reports the aggregate stage counts. **Total studies included in synthesis: 375.** These stages mirror those used in systematic reviews but were conducted iteratively rather than under a single pre-registered protocol; formal protocol registration, dual independent screening, and reporting-checklist conformance are deferred to a future protocol-driven update.

Notes. The full-text-eligibility stage acted as scope-confirmation rather than scope-filtering: papers that survived title/abstract screening were retained on full-text inspection and, where appropriate, downgraded to comparator-survey or context status (used to anchor framing) rather than excluded outright. Of the 375 included studies, 152 contributed the 313 accepted evidence rows reported in Section 2.3; the remaining 223 are retained as bibliographic context (comparator surveys, position papers, foundational anchors, or entries where the neurosymbolic coupling did not meet the evidence-row promotion criteria).

Table 13. Record screening and inclusion counts used for this survey. Stages reflect a typical identification → screening → eligibility workflow, applied iteratively rather than as a single pre-registered protocol.

Stage	Records (n)
Records identified (all sources)	968
Records excluded at title/abstract screening	593
Reports assessed for eligibility (full text)	375
Studies included in synthesis	375
<i>of which: contributed evidence rows in Tables 5–9</i>	152
<i>of which: retained as bibliographic context</i>	223

C Data Extraction Dimensions and Materials

For each included study we extracted, per paper-level coding row: (i) the theme(s) addressed (Table 1); (ii) the interface pattern code(s) (Table 2); (iii) the function role(s) (Table 3); (iv) the artifact and operator that realize the coupling; (v) the evidence tag (Table 4) and explicit scope (task/domain, dataset/benchmark) for each comparative cell; (vi) the dominant trade-off or limitation (cost overhead, guarantee scope, artifact validity risk, deployment/governance risk); (vii) code/data availability when reported. Each included paper was coded against these dimensions, with reread / clarification notes recorded for rows whose coupling required further review before promotion; the resulting accepted rows were aggregated into the per-theme evidence tables (Tables 5–9). The aggregated row counts (accepted rows, distinct contributing papers, evidenced combinations) are reported in Section 2.3; the full codebook is deferred to a methods supplement.

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Declaration of conflicting interests

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