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Metadata and Vocabulary for Knowledge Representation Learning

Paola Di Maio[1,*], Qin Jian[2]

[1] W3C AI KR CG and Igdore.org, GB
[2] Syracuse University, Syracuse, USA

Abstract

Artificial Intelligence (AI) is advancing rapidly, introducing both opportunities and risks. A critical gap exists in the explicit use of Knowledge Representation (KR) within AI standards and practice. This paper presents an initial, alphabetically sorted vocabulary of terms for KRL (Knowledge Representation Learning), justifies the approach, evaluates outcomes, and sets the stage for future refinement in the context of vocabulary standardization for AI. The work aims to bridge semantic gaps, enhance explainability, and support trustworthy AI by standardizing the terminology to be used of AI resource description. This work is presented to the metadata and vocabulary research community to foster discussions and collaboration.

Keywords

Knowledge representation, Artificial intelligence, Vocabulary, Metadata

1. Introduction

Knowledge Representation (KR) is foundational to AI, enabling machines to encode, store, and reason about information in ways that support complex tasks like reasoning, decision-making, and problem-solving [3, 18]. KR consists of countless methods and tools, from logical formalisms to ontologies, that structure knowledge for intelligent systems design and operation. One of the important KR artifacts are vocabularies (Figure 1), which standardize the choice of terms and sometimes their formal definitions. They are used to declare explicit existential descriptors of components and data used by automated intelligent systems and processes, and one of their main functions in resource description as in metadata. Explicit, shared and standardized Knowledge Representation in AI is a mechanism for creating human-readable, explainable, and auditable data models [5]. Despite its centrality, explicit and shared KR is rarely used to design modern AI systems, particularly machine learning (ML). This omission can lead to increased risks as the lack of resource description limits the transparency and auditability needed for trustworthy AI [19].

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*Corresponding author.
paola.dimaio@gmail.com (P. D. Maio); jqin@syr.edu (Q. Jian)
0000-0003-0770-3713 (P. D. Maio); 0000-0002-7094-2867 (Q. Jian)

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Term	Focus	Includes Definitions?	Scope	Structured?
Glossary	Definitions of terms	✅ Yes	Specific document/topic	Alphabetical
Thesaurus	Synonyms & concept grouping	❌ or partial	Synonyms/concepts	Thematic or hierarchical
Vocabulary	Word set (known/used)	❌ (not always)	General or domain-specific	Varies (can be controlled)
Lexicon	Entire word set with detail	✅ Usually	Language-wide or domain	Often structured

Figure 1: Types of vocabularies

2. Background and Approaches

KR methods have evolved from symbolic logic and expert systems to ontologies and knowledge graphs. Key approaches where vocabularies can be useful include:

- **Logical Representation:** Uses formal languages to encode facts and rules, enabling inference [3]. = *vocabulary of formal language*
- **Semantic Networks:** Graph-based models of concepts and relationships [18]. = *vocabulary defining concepts and relationship*
- **Frames:** Structures for organizing stereotypical situations or objects [5]. = *vocabulary naming structures*
- **Ontologies:** Formal specifications of domain concepts and relations, supporting interoperability [11]. = *vocabularies as part of the ontology*

KR languages include logic-based languages (e.g., Description Logics), frame-based representations, semantic networks, production rules, ontologies (e.g., OWL), conceptual graphs, and structured natural language [1, 20]. All of these languages use vocabularies, specially controlled vocabularies and metadata to codify the use of terms.

KR is essential for enabling AI to reason and interact with the world, underpinning advances in expert systems, the Semantic Web, and modern AI applications [13]. However, a disconnect remains between traditional KR and its application in ML-driven AI.

3. The Role of KR in Explicit and Trustworthy AI

Explicit KR is crucial for mitigating AI risks by encoding knowledge in human-readable formats, enabling audit, analysis, and evaluation by diverse stakeholders [8]. It provides a “source of truth” accessible to developers, domain experts, and end-users, making AI outcomes more interpretable. Integrating KR with ML can enhance risk identification and mitigation by combining expert knowledge with data-driven analytics [12]. Structured KR also supports governance and compliance by documenting policies, ethics, and regulatory requirements.

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4. Constructing Core Vocabularies

Developing a KR vocabulary involves domain analysis, modeling, and ontology engineering. Semantic modeling platforms leverage NLP, formal concept analysis, and entity extraction to create robust vocabularies that support reasoning and interoperability [1]. Creating domain-specific vocabularies and metadata sets requires collaboration with experts, analysis of domain needs, and computational knowledge extraction [16]. A core set of terms and definitions that covers the entire AI KR domain in all its facets is going to result of ongoing refinement and scoping based from knowledge of facets and co-occurring terms.

Metadata sets—also known as metadata schemas, element sets, or standards—play a critical role in knowledge representation by providing a structured way to describe, classify, and relate data. Their primary function is to enable semantic clarity, interoperability, and discoverability across systems, particularly in digital information environments, linked data, and the semantic web. Metadata sets define a consistent model for how knowledge about resources is described and organized, usually using elements (e.g., title, creator, subject, date). "Metadata provides the structured description of information objects, making it possible to retrieve and reuse them effectively." [10] They allow diverse systems to understand and interpret data the same way by using a shared vocabulary and structure. "A key function of metadata is to support semantic interoperability among heterogeneous systems." [15]

When metadata sets are aligned with ontologies (e.g., in RDF/OWL), they support automated reasoning, enabling machines to infer new knowledge from existing metadata. Metadata sets help express relationships among resources, making them integral to intelligent reasoning on the web. A subset of the intended outcome (vocabulary for KRL together with a proposed approach for its evaluation) is presented in this paper, however it does not, nor it is intended to be exhaustive of all possible outcomes.

Metadata uses terms from **vocabularies** to express knowledge within a formal **knowledge representation** framework.

As such, vocabularies that describe AI-based inputs, processes and outcomes, can be used to support the development of metadata, as well as providing standard mechanisms to describe the resources associated with AI.

5. Gaps in AI Standards

During a routine search for terminology in the current standards for AI database,[1] a key concept from the KR domain such as "truth preservation" [9] is missing, not to be found in any of the AI standards in development. These focus on technical definitions, risk management, and compliance but omit critical system safety functions. Influential standards (ISO/IEC JTC 1/SC 42, IEEE, NIST, CEN/CENELEC) lack sufficient KR provisions to minimize AI risks. Further review confirms that concepts like "truth maintenance" are not formalized in current standards, despite their foundational role in classical AI [9, 6]. In this paper this omission is flagged as potentially leading to critical AI systems failures and sets out to search for other critical gaps.

[1] AI Standards Hub, Alan Turing Institute UK

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6. Consequences of KR Omissions

In ML, belief propagation and probabilistic inference replace classical truth maintenance, but do not provide explicit consistency management or traceability [17, 18]. The lack of TMS-like mechanisms leads to:

- Inconsistent knowledge management
- Reduced explainability
- Difficulty handling contradictions
- Limited dynamic updates

These limitations need to be understood and addressed to mitigate AI risks. Addressing these shortfalls and gaps requires importing concepts from reliable knowledge systems and reliability engineering which is work in hand at the W3C AI KR CG [7].

7. Scoping the Vocabulary

An initial flat list of KR terms, aligned with the W3C AI Knowledge Representation Community Group's goals, is being compiled and is being discussed elsewhere. The creation of unique definitions for each term is remanded at a further stage.

The vocabulary aims to first identify core concepts that are required to represent knowledge in machine learning, and will be used as a benchmark to identify gaps between KR and other domains (such as for example AI safety). Eventually a set of unique definitions is going to be associated with each term and content, addressing at least in part the semantic gap in AI standards. The first subset of the vocabulary presented here is scoped through domain facet identification and use case analysis. It is not intended to cover application-specific or domain-specific terms but to capture some aspects of foundational KR concepts essential to query, explain and evaluate machine learning processes. This is deemed essential to attempt auditable trustworthy and human-readable assessments necessary to identify AI risks. Creating a domain vocabulary for knowledge representation and a metadata set tailored to specific KR tasks and targeted subdomains involves systematic processes to ensure representativeness, interoperability, and support for data management, discovery, and reuse. Common methods adopted in the development of the vocabulary under development include:

Domain-Specific Metadata Scheme Development: Collaborate with domain experts to design a metadata scheme that captures all necessary concepts without overburdening users [16].

Domain Analysis and Metadata Element Identification: Study the domain to define the scope, resource types, and user needs, identifying relevant metadata elements [16].

Semantic Knowledge Extraction and Knowledge Discovery: Use computational methods to extract and formalize domain knowledge [13].

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```
+----------------------------+
|   Knowledge Representation |
|  (e.g., RDF, OWL, graphs)   |
+----------------------------+
              ↑
Uses structure & logic to organize meaning
              ↑
+----------------------------+
|         Vocabularies        |
| (controlled terms, ontologies) |
+----------------------------+
              ↑
Supplies terms for describing resources
              ↑
+----------------------------+
|          Metadata           |
| (resource descriptions using |
|    vocabularies in KR)       |
+----------------------------+
```

Figure 2: Conceptual Graph of the relation between artefacts

Component	Definition	Role in Knowledge Representation	Examples
Knowledge Representation	Formal modeling of concepts and their relationships for use by machines.	Provides the structural and logical framework for expressing knowledge.	RDF, OWL, logic-based models, knowledge graphs
Vocabulary	A structured set of terms used consistently to describe concepts.	Supplies the semantic building blocks used in KR and metadata.	Dublin Core, SKOS, schema.org, FOAF
Metadata	Structured data about resources, using vocabulary terms.	Concrete instantiation of knowledge; describes resources in machine-readable ways.	`<doc1> dc:title "Report"` `<doc1> dc:creator "Jane Doe"`

Figure 3: Table version of Figure 2

8. Challenges

KR is vast and interdisciplinary, with overlapping terminology across mathematics, logic, computer science, and engineering [3]. The lack of a standardized KR lexicon complicates communication and hinders explainability, transparency, and trustworthiness in AI. A major challenge is defining the core body of knowledge and identifying essential co-occurring terms within KR's many facets, as well as to handle the vast and heterogeneous datasets (Figure 4). This paper discusses the challenge by scoping the work tightly and by limiting focus on presenting a subset of terms for evaluation and discussion (See Appendices).

9. Methods

This vocabulary development presented here is carried out by using a combination of methods:

- **Domain Scoping:** Defining the KR body of knowledge and selecting authoritative sources

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[3]

- **Facet Identification:** Analyzing domain facets and use cases to select representative terms.
- **Expert Collaboration:** Engaging with domain experts and standards organizations.

Future iterations will refine the vocabulary subset, populate a master list of global terms that capture the extended AI KR domain and will provide formal definitions that can be used in learning for the purpose of disambiguation, teaching and professional development.

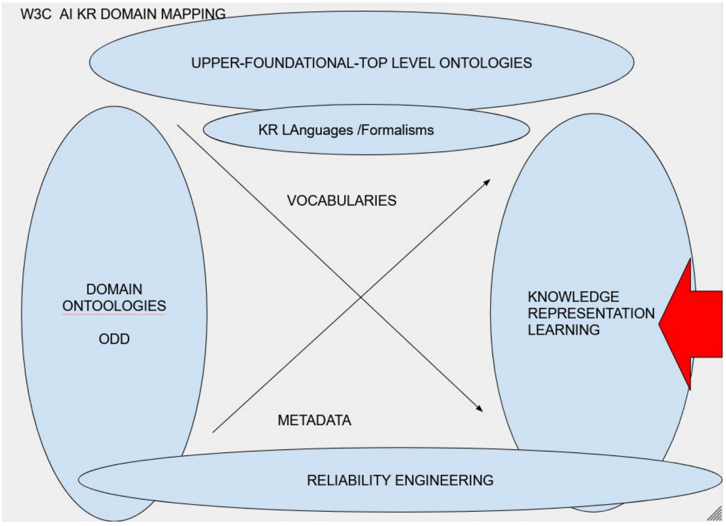

Figure 4: Scoping the many Facets of the AI KR Vocabulary

10. Sample Vocabulary from KRL

A wide and disparate range of knowledge sources from AI KR, from classic textbooks which laid the foundations of this foundational epistemic field of knowledge from its beginnings, to the most contemporary uses in machine learning, is an extensive list of terms, numbering in the thousands.

The terms, once compiled in a long masterlist, cover most of the AI KR in use in literature. However there are variations in definitions of these terms in each knowledge source, and each term can point to concepts that can have either a very generic meaning applicable to diverse disciplines, including say, the broader aspects of computer science and information systems, to very specific interpretations and uses that can be narrowed down to answering the explainability questions:

What data and knowledge are used by the algorithm? In what way? Following what processes? With what outcomes?

This work focuses on the latter goal, to list terms and concepts that can help to answer the explainability questions. To facilitate the human readability aspect and cognification of a long

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flat lists of terms, a first layer of abstraction aims to identify categories and metatags that can be used to categorize the terms, as in Figure 5.

Category	Metatags
Functional Categories	Representation, Reasoning, Formal (Mathematical) Knowledge
Representation Systems	Semantic Networks, Frames, Logic, Conceptual Dependencies, Scripts, Rule-Based Systems
Ontological/Taxonomical	Classes, Objects, Events, Processes, Mental Objects
Specialized Subcategories	Argument Mapping, Belief Revision, Ontologies, Scientific Models, Thesauri
Scientific/Descriptive Types	Logical, Formal, Mathematical, Grammatical, Theoretical, Historical

Figure 5: Categories and Meta Tags for KRL

Secondly, each facet is used to shape a subset of the terms in use (remember that the master list is very long), that is a set of separate vocabularies of terms that although have common uses in multiple domains and facets, are presented to characterize a specific context.

For example, as in the case presented in Appendix A, a vocabulary representing the domain KRL (Knowledge Representation Learning). Knowledge Representation Learning bridges symbolic AI (structured knowledge) and statistical AI (machine learning) by embedding symbolic structures into vectors. It enables more effective reasoning, inference, and generalization across a wide range of AI applications.

In our work, KRL vocabulary lists terms in use in ML tagged with corresponding concepts in symbolic AI (Appendices B, C).

11. Evaluation

A number of use cases extracted from literature are being adopted to verify the validity and usefulness of the outcomes in terms of adequacy of coverage, with these specific questions in mind:

> In attempting to answer the evaluation questions for each use case (what does the AI system do, what data/knowledge does it use, which processes does it follow): Are there key terms in the use cases that are missing from the vocabulary? Can the candidate terms in the proposed draft vocabulary adequately describe what the AI system does and how?
>
> Is the coverage of the terms identified adequate to represent the knowledge representation in the AI (noting that domain knowledge is not in scope of the vocabularies being developed)?

Sample Use Cases used for the evaluation include:

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1. Medical Expert Systems: Low Back Pain Management (Santra et al., 2018)
2. Manufacturing Decision Support: Actionable Cognitive Twins (Rožanec et al., 2021)
3. Intelligent Personal Assistants: CALO Project (Cheyer, 2005)
4. Ontology-Based Explanation in Clinical AI (Chari et al., 2020)
5. Biomedical knowledge analysis and recommender system
6. Legal decision support

12. Conclusion and Future Work

The usefulness of standardizing the terminologies of knowledge representation in AI, to support the explicit and shared description of associated resources and processes, thus facilitating their explainability and trustworthiness, is consistently proven and part and parcel of information technology. The preliminary outcome of the KRL vocabulary definition confirm the importance and role of such practices.

Explicit, standardized KR is essential for explainable, trustworthy, and auditable AI. Current AI standards lack critical KR concepts, increasing system risks. This paper's initial vocabulary is an example of work being undertaken toward bridging the semantic gap and supporting the development of reliable AI systems.

Future work includes identifying further terms (from ongoing evaluations), attempting to produce unique meaningful definitions, and derive further levels of abstraction as meta tags pointing to higher order categories of logic and process definition.

See also Appendices A, B, C.

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A. Appendix A: KRL Vocabulary Terms

- architecture reformulation
- bag-of-words
- begin-inside-outside
- bidirectional
- bidirectional long short-term memory
- big model systems for large-scale representation learning
- chain-of-thought
- complexity of an algorithm
- compositional semantics
- computer vision
- concatenate a list of vectors/tensors
- conditional random field
- continuous bag-of-words
- convolution operator
- convolutional neural network
- cosine similarity
- cross-lingual representation learning
- cross-modal representation
- deep convolutional generative adversarial networks
- deep high-resolution representation learning
- distillation
- domain adaptation
- domain transfer
- element-wise multiplication
- encoder representations
- expectation-maximization algorithm
- exponential function
- feed-forward network in transformers
- feed-forward neural network
- gated recurrent unit
- generative pre-trained model
- gradient of a function
- graph convolutional network
- graph processing unit
- graph representation learning
- hidden markov model
- hidden representation
- high-to-low resolution subnetworks
- hyperbolic tangent function
- information extraction

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- information maximizing generative adversarial nets
- input augmentation
- interpretable representation learning
- inverse document frequency
- knowledge base
- knowledge graph
- knowledge-guided NLP
- kronecker product of two matrices
- language model
- latent dirichlet allocation
- layer norm layer in transformers
- limitation
- logical
- loss function
- LSTM long short-term memory
- machine translation
- mask language modeling
- mixture-of-experts
- momentum contrast for unsupervised visual representation learning
- momentum contrastive learning
- multi-layer perceptron
- multi-resolution subnetworks in parallel
- multilayer perceptron
- named entity recognition
- natural language inference
- natural language processing
- neural discrete representation learning
- neural probabilistic language model
- norm of a vector
- normal distribution
- objective regularization
- ordinary differential equations
- parallel distributed processing
- parameter transfer
- part-of-speech
- partial derivative of a function
- pointwise mutual information
- pre-trained language model
- pre-trained model
- proportional
- pruning
- quantization
- rectified linear unit activation function
- recurrent neural network
- relation extraction
- representation learning
- retrosynthetic prediction
- robust representation
- self-attention layer
- sememe-based lexical knowledge representation
- sequence tagging
- sigmoid function
- similarity
- single-model networks
- singular value decomposition
- size of a set
- softmax function
- support vector machine
- tagging
- term frequency-inverse document frequency
- transformers
- transpose
- unsupervised representation learning
- visual question answering

B. Appendix B: KRL Terms Mapped to Symbolic AI

architecture reformulation When referring to the redesign or restructuring of symbolic knowledge systems, rule sets, or reasoning frameworks.

chain-of-thought As it emulates explicit, step-by-step reasoning akin to symbolic inference processes.

complexity of an algorithm Fundamental for analyzing the performance of symbolic algorithms like search, planning, or logical inference.

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compositional semantics A core principle in symbolic NLP and formal linguistics, where the meaning of a complex expression is built from the meanings of its parts and their structure.

domain adaptation Relevant when adapting symbolic rules, ontologies, or knowledge bases to new problem domains.

domain transfer Concerned with transferring symbolic knowledge, rules, or learned structures from one domain to another.

expectation-maximization algorithm Can be used in contexts that overlap with symbolic AI, such as learning parameters for Hidden Markov Models or probabilistic grammars which have symbolic interpretations.

graph representation learning When focused on learning or reasoning with symbolic graph structures like semantic networks or knowledge graphs, rather than just learning embeddings.

hidden markov model A probabilistic model often used in early NLP for tasks like part-of-speech tagging, having interpretations as finite automata which are symbolic structures.

information extraction A task frequently addressed by Symbolic AI using rule-based systems, pattern matching, and ontologies.

interpretable representation learning A primary goal of Symbolic AI, as its representations—such as logic, rules, and ontologies—are inherently designed to be human-understandable.

knowledge base A foundational component of most Symbolic AI systems, used to store facts, rules, and ontologies.

knowledge graph A structured representation of knowledge, central to Symbolic AI, capturing entities and their relationships symbolically.

knowledge-guided NLP Natural language processing approaches that explicitly incorporate symbolic knowledge from knowledge bases or ontologies.

language model While modern LMs are predominantly neural, early n-gram models and probabilistic context-free grammars have symbolic underpinnings or were used in conjunction with symbolic systems.

limitation In Symbolic AI, this refers to analyzing the inherent limitations of formal systems, such as the expressiveness, decidability, or completeness of a logic.

logical Refers to logic itself—such as predicate calculus, propositional logic—which is a cornerstone of Symbolic AI for representation and reasoning.

loss function In a more abstract sense, can correspond to objective functions or heuristics used in symbolic search, planning, or optimization of symbolic structures.

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machine translation Early and historically significant approaches to MT were heavily reliant on symbolic, rule-based systems.

named entity recognition An NLP task that can be effectively performed using symbolic approaches like rule-based systems, gazetteers, and regular expressions.

natural language inference A task that can be tackled using symbolic methods involving logical reasoning, theorem proving, and semantic analysis based on symbolic representations.

natural language processing Symbolic AI was the dominant paradigm in early NLP, contributing foundational concepts like formal grammars, parsers, and symbolic semantic representations.

part-of-speech A fundamental linguistic concept heavily used in symbolic NLP, forming the basis for grammars and parsing rules.

pruning A critical technique in Symbolic AI search algorithms like alpha-beta pruning in game playing, and also in machine learning for simplifying rule sets or decision trees.

quantization The process of converting continuous data into discrete symbols or categories, often a necessary step for processing by symbolic systems.

relation extraction An information extraction task focused on identifying semantic relationships between entities, often implemented using symbolic patterns, rules, or ontological reasoning.

representation learning When the goal is to learn or discover symbolic representations, such as inducing rules, concepts, or logical theories from data.

retrosynthetic prediction In chemistry, this problem often utilizes symbolic AI techniques, including rule-based systems, planning, and graph transformations to find synthesis pathways.

robust representation A desirable characteristic for symbolic representations, enabling them to be less brittle and handle variations or noise in input.

sememe-based lexical knowledge representation A symbolic approach to lexical semantics, representing word meanings using minimal semantic units called sememes.

sequence tagging A class of NLP tasks, including part-of-speech tagging and named entity recognition, which can be addressed by symbolic models like Hidden Markov Models or rule-based systems.

similarity In Symbolic AI, defining and computing similarity between symbolic structures, concepts, or descriptions is often crucial, e.g., in case-based reasoning or analogical reasoning.

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size of a set A basic mathematical concept from set theory, fundamental to formalizing and reasoning about collections of symbols, objects, or properties in symbolic systems.

support vector machine While a statistical learning method, SVMs can be used with features derived from symbolic representations, thus acting as a component in hybrid systems.

tagging A general term in NLP that encompasses processes like part-of-speech tagging or semantic tagging, which have strong traditions in symbolic AI.

unsupervised representation learning In a symbolic context, this can refer to methods like conceptual clustering, automated discovery of symbolic patterns, or induction of rules from unlabeled data.

update the value of left-hand side value with right-hand side value Represents the fundamental concept of assignment, crucial in algorithmic execution and knowledge manipulation within symbolic systems, such as updating facts in a knowledge base or variable bindings in logical deduction.

C. Appendix C: Possible Other Tags

Formal Logic: Model, Proof, QBF, SAT

KR: Default Logic, Frame, Model, Schema

Logical: Clause, Contradiction, Ground, Inference, Negation, Nonmonotonic, Predicate, Skolemization, Variable

Nonmonotonic: Default Logic

Person: Reiter

Programming: Function

Reasoning: Backtracking, Inference, Nonmonotonic, Resolution, Suppression Task

Structure: Frame, Schema

Syntax: Clause, Function, Ground, P(c,x) (predicate example), Predicate, Skolemization, Variable

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