

Ai-Assisted Linguistic and Ontological Modeling of Information Technology Terminology in Low-Resource Languages: A Critical Integrative Review

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ABSTRACT

Low-resource languages often lack the infrastructure needed to manage rapidly evolving information-technology (IT) terminology, including representative corpora, validated termbases, lexicographic resources, formal concept systems, and machine-readable publication formats. This article presents a critical integrative review of research in ontology engineering, knowledge graphs, automatic term extraction, terminology science, lexicography, Linguistic Linked Open Data, multilingual natural language processing, and large-language-model-assisted knowledge engineering. Because the evidence base is heterogeneous, a structured integrative-review approach was adopted. Thirty-eight key publications were analyzed according to language coverage, methods, representation models, validation strategies, and implications for low-resource languages, while W3C and ISO standards provided the conceptual framework. The review shows that these research streams have developed substantially but remain weakly integrated in the context of creating IT dictionaries that are simultaneously lexicographic, conceptual, multilingual, machine-readable, and maintainable. Four major gaps are identified: limited progression from term extraction to validated concept modeling; insufficient integration of lexicographic and ontological structures; inadequate treatment of multilingual equivalence and morphology; and weak governance of large-language-model outputs through

evidence, provenance, and accountability mechanisms. The findings highlight the need for corpus-based terminology management, clear separation of lexical and conceptual layers, evidence-based multilingual correspondence, and accountable human oversight of AI-assisted knowledge engineering, with Uzbek serving as the primary application context.

Keywords: Information-technology terminology, low-resource languages, ontological dictionary, automatic term extraction, OntoLex-Lemon, linguistic linked open data, ontology engineering, large language models, Uzbek

1. INTRODUCTION

Information technology is terminologically volatile. New concepts and labels enter standards, software documentation, research papers, educational materials, interfaces, and professional communication faster than conventional dictionaries can be revised. In a high-resource language, this change is partly absorbed by large corpora, specialist glossaries, terminology databases, knowledge graphs, and continuously maintained lexical resources. In a low-resource language, the same change can produce competing translations, unmanaged borrowings, inconsistent abbreviations, under-documented senses, and dictionary entries that are difficult to reuse computationally.

The difficulty is not merely the absence of equivalent words. A usable IT terminology resource must distinguish a lexical form from the concept it denotes, identify whether two forms are variants or separate terms, record the evidence and status of an equivalent, represent relations among concepts, and remain understandable to students, translators, localization specialists, and domain experts. A termbase that stores isolated translation pairs cannot reliably answer questions such as whether a label denotes a protocol, an implementation, a security principle, a software component, or a process. Conversely, a formal ontology that treats words only as labels can lose grammatical,

phraseological, usage, and normative information required for dictionary use.

Ontology engineering offers methods for constructing explicit, shared conceptualizations and for testing them through competency questions, logical reasoning, and reusable identifiers (Gruber 1995; Studer et al. 1998; Noy & McGuinness 2001; Poveda-Villalón et al. 2022). Knowledge graphs extend this perspective to interconnected entities and relations, but they also make maintenance, provenance, and refinement central concerns (Paulheim 2017; Hogan et al. 2021; Ji et al. 2022). Terminology science and lexicography contribute concept orientation, definition principles, equivalence management, corpus evidence, user orientation, and entry design (Cabré 1999; Atkins & Rundell 2008; L'Homme & Bernier-Colborne 2012; 'ISO 1087' 2019; 'ISO 704' 2022).

Semantic Web models make it possible to retain these distinctions in a machine-readable resource. SKOS represents concepts and concept schemes; OntoLex-Lemon represents lexical entries, forms, senses, and references to ontological entities; LexInfo supplies morphosyntactic descriptors; OWL supports logical axioms where reasoning is justified; SHACL validates graph structure; and PROV-O supports provenance records. None of these models alone determines which IT expressions deserve term status or which target-language equivalent is acceptable. That decision must be grounded in corpus evidence, domain analysis, lexicographic judgment, and explicit governance.

Automatic term extraction (ATE), multilingual transformers, and large language models (LLMs) can accelerate candidate discovery, variant grouping, definition drafting, relation suggestion, and ontology population. However, recent evidence also shows persistent problems: cross-domain transfer is sensitive to annotation and domain mismatch; institutional adoption is limited by workflow and language-support constraints; and LLMs can generate fluent but unsupported terms, definitions, or relations (Tran et al. 2024; Wissik 2025; Huang et al. 2025; Tran et al. 2025; Shimizu & Hitzler 2025). These risks are especially serious when a resource may later be treated as authoritative.

This article, therefore, asks how the separate strengths of ontology engineering, terminology and lexicography, Semantic Web representation, low-resource NLP, and AI-assisted knowledge engineering relate to one another when the object of study is IT terminology in a low-resource language. Its contribution is a critical integrative synthesis: it maps what each research stream has established, identifies the points at which the streams fail to connect, and formulates the resulting requirements and open questions for subsequent research. The review does not propose or implement a new system. It establishes the evidential basis on which such work would have to rest, and it treats accountability for terminological decisions as a condition that the reviewed literature repeatedly identifies but rarely documents.

2. REVIEW PURPOSE, QUESTIONS, AND CONTRIBUTION

The review has two linked purposes. First, it identifies transferable methods and representation choices from adjacent research streams. Second, it converts the synthesis into explicit requirements and open research questions for future work on an ontological dictionary of IT terminology in a low-resource language. Uzbek is used as the principal application context because relevant lexical, corpus, and language-model resources now exist, while a validated, domain-specific, lexicographic-semantic IT resource remains a distinct research task (Agostini et al. 2021; Sharipov et al. 2022; Kuriyozov et al. 2024; Veitsman & Hartmann 2025).

The review is guided by five questions:

1. RQ1. Which ontology-engineering and knowledge-graph practices are transferable to the modeling of IT terminology?
2. RQ2. Which corpus, ATE, and language-model methods can support term discovery, definition drafting, relation discovery, and ontology population?
3. RQ3. Which lexicographic, terminological, and Semantic Web models can represent lexical, conceptual, grammatical, multilingual, and provenance information without conflating them?

4. RQ4. Which design constraints arise in low-resource and morphologically rich languages, with particular attention to Uzbek?
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Table 1. *Review questions and corresponding analytical outputs*

Question	Analytical focus	Expected output
RQ1	Conceptualization, competency questions, relation inventories, lifecycle	Transferable ontology and knowledge-graph practices
RQ2	Corpus construction, ATE, cross-lingual transfer, LLM assistance	Evidence on constrained discovery and drafting
RQ3	Lexicography, terminology, OntoLex-Lemon, SKOS, LexInfo, OWL, SHACL	Comparative account of representation models
RQ4	Resource scarcity, morphology, script/form variation, typed equivalence	Low-resource adaptation constraints
RQ5	Integration, validation, publication, maintenance, governance	Integration requirements and research agenda

The article contributes: 1) a methodologically honest review design suitable for heterogeneous evidence; 2) a verified evidence map across six relevant research streams; 3) a comparative account of the representation models and evaluation practices reported in those streams; 4) a precise statement of the integration, representation, evaluation, and governance gaps; and (v) a set of requirements and research priorities for future Uzbek and other low-resource-language work.

3. METHOD

3.1. *Review design*

A critical integrative review was selected because the research question spans empirical NLP studies, ontology-engineering methods, lexical-resource case studies, formal specifications, terminology theory, and professional-practice evidence. Integrative reviews are intended to combine diverse forms of

evidence, provided that source identification, appraisal, comparison, and synthesis are made explicit (Whittemore & Knafl 2005; Torraco 2005; Snyder 2019). The present article is not described as a systematic review, meta-analysis, bibliometric study, or exhaustive Scopus review. No pooled effect is estimated, and no claim is made that every relevant publication has been retrieved.

This designation also avoids a recurrent methodological problem. A scoping-review label requires a fully executed, reproducible database search with record counts, duplicate handling, screening decisions, exclusion reasons, and a flow diagram. Where those data are not available, retaining the label would overstate the evidence process. The integrative design instead makes the actual objective explicit: to achieve conceptually adequate coverage of the evidence streams needed to establish what is known, what is contested, and what remains untested.

3.2. Source identification and bibliographic verification

Source identification combined structured keyword searching with backward and forward citation chaining. Search concepts covered six blocks: 1) IT or computer-science terminology; 2) ontology engineering and knowledge graphs; 3) automatic term extraction and ontology learning; 4) terminology, lexicography, and lexical-semantic resources; 5) OntoLex-Lemon, SKOS, LexInfo, Linguistic Linked Open Data, and multilingual linked data; and 6) low-resource, Turkic, or Uzbek NLP. A separate block covered LLM-assisted ontology engineering, population, matching, and conceptualization. The concept blocks and platform-adaptable search strings are reported in Appendix A in accordance with the transparency principles emphasized by PRISMA-S (Rethlefsen et al. 2021).

Sources were located and verified through official publisher or repository records, including ACM Digital Library, ACL Anthology, SpringerLink, SAGE/IOS Press journal pages, John Benjamins, Nature, CEUR Workshop Proceedings, institutional repositories, W3C specifications, and ISO catalogue records. Bibliographic identity was checked against a DOI, an official proceedings record, an official standard, or a publisher-hosted

publication page. Final metadata verification was completed on 18 June 2026. The review does not use journal quartile as a proxy for source validity; the relevance and authority of the individual work are evaluated directly.

3.3. *Eligibility and source appraisal*

Peer-reviewed journal articles, peer-reviewed conference papers, established scholarly books, official technical reports, and authoritative standards were eligible when they contributed directly to at least one review question. Foundational publications before 2018 were retained when they defined a method, concept, or representation still required to interpret the current evidence. Recent research was prioritized for ATE, LLM-assisted ontology engineering, multilingual linked data, and Uzbek NLP. Sources were excluded when their bibliographic identity could not be confirmed, when they addressed general AI without a terminology or ontology contribution, or when a highly domain-specific method did not offer a transferable implication.

Appraisal was qualitative and purpose-specific rather than a risk-of-bias score designed for clinical trials. Each retained source had to satisfy two mandatory conditions: authentic bibliographic identity and direct relevance to a review question. It was then charted for methodological transparency, artifact or model contribution, validation evidence, language and domain coverage, and transferability to a low-resource IT terminology resource. Thirty-eight publications formed the focal evidence set; official standards and additional foundational works supplied normative and conceptual requirements. Appendix B lists the focal set and the contribution of each source to the synthesis.

Table 2. *Eligibility, verification, and appraisal safeguards*

Dimension	Inclusion rule	Exclusion or caution
Publication type	Peer-reviewed article or conference paper; scholarly monograph; official standard or technical specification	Unverified web text, promotional material, or bibliographically uncertain item
Topical relevance	Direct contribution to at least one RQ	General AI/NLP with no transferable terminology, ontology, or representation contribution

Time	Foundational works as needed; recent evidence emphasized for fast-changing AI/NLP topics	No arbitrary exclusion of older standards-defining work
Language	English-language publication; multilingual and non-English resource cases eligible	Language cases lacking sufficient methodological description
Verification	DOI, official publisher/proceedings page, official standard, or institutional record	Bibliographic identity or publication status cannot be confirmed
Appraisal	Method/artifact, validation, language/domain coverage, and transferability charted	Citation used only because it appears in another review

3.4. *Data charting and synthesis*

For every focal source, the following fields were charted: research problem, domain, language coverage, data or artifact, method, AI/NLP technique, representation model, lexical and conceptual distinctions, validation strategy, limitations, and transferable implication. First-cycle coding identified methods and artifacts such as competency questions, ATE, cross-lingual transfer, ontology alignment, lexical-entry modeling, concept schemes, morphology, provenance, and expert review. Second-cycle coding grouped these items into six analytical themes: ontology and knowledge-graph engineering; corpus and term discovery; terminology and lexicography; Semantic Web representation; low-resource multilingual adaptation; and AI governance.

The synthesis was interpretive rather than aggregative. A finding was retained as a review result when it answered a question recurring across the literature: What evidence establishes term status? Which human role decides? Which data object is created? Which formal model represents it? How is the decision validated? How is the result versioned and maintained? Findings were then compared across streams in order to establish where the answers converge, where they conflict, and where no stream answers at all. This procedure produced the comparative account in Section 4 and the gap analysis in Section 5.

3.5. *Scope, reproducibility, and reporting boundaries*

The appendices provide the search concept blocks and the focal evidence matrix so that another researcher can reproduce or extend the source set. A journal that specifically requires a PRISMA-ScR scoping review would still require a new database execution, export files, deduplication, dual screening, exclusion reasons, and a PRISMA flow diagram. Those elements should not be reconstructed retrospectively from a curated bibliography. The present reporting boundary is deliberate: transparency about what was done is methodologically stronger than a nominally systematic label unsupported by an auditable record.

4. EVIDENCE SYNTHESIS

4.1. *Ontology engineering and knowledge graphs*

Ontology engineering provides a lifecycle rather than a one-time classification exercise. Foundational methods and later industrial frameworks converge on requirements specification, conceptualization, reuse, implementation, evaluation, publication, and maintenance (Fernández-López et al. 1997; Noy & McGuinness 2001; Suárez-Figueroa et al. 2012; Poveda-Villalón et al. 2022). For an IT dictionary, requirements should be expressed as competency questions. Examples include: Which target-language terms denote software-architecture patterns? Which lexical variants refer to one concept? Which concepts are broader than container orchestration? Which equivalents are deprecated or domain-restricted? A competency question links user need to model content and provides a basis for later testing.

Knowledge-graph research adds scale, heterogeneous relation types, provenance, and continuous refinement. Hogan et al. (2021) and Ji et al. (2022) show that knowledge graphs support integration and retrieval but vary substantially in construction, representation, and quality assurance. Paulheim (2017) treats refinement as a continuing process of completion, correction, and enrichment. This is directly relevant to IT terminology, where concept inventories and preferred labels change with standards, product ecosystems, and professional usage.

Domain resources demonstrate what can be reused without assuming that English research-topic labels are equivalent to a target-language dictionary. The Computer Science Ontology provides a large taxonomy of research areas, and CS-KG 2.0 represents computer-science entities and relations at large scale (Salatino et al. 2018; Dessì et al. 2025). SCICERO illustrates automated extraction of scientific entities and relations in computer science (Dessì et al. 2022). These resources are useful as conceptual scaffolds and discovery aids. They do not replace corpus-based term status, lexicographic entry design, or target-language expert validation.

Recent systems expand the role of language models in ontology alignment, completion, modeling, and population. DeepOnto provides Python-based tools for deep-learning-supported ontology engineering (He et al. 2024). Shimizu & Hitzler (2025) organize LLM uses across knowledge-graph and ontology engineering tasks. Doumanas et al. (2024) explicitly frame ontology engineering as human-machine collaboration, while Ayad & Chibout (2025) show that LLM-assisted population can be constrained by an existing metamodel and formalization. The transferable principle is not unrestricted generation; it is model-bounded assistance followed by formal and human validation.

4.2. Corpus evidence and automatic term extraction

ATE connects documentary evidence to terminology work. Classical approaches remain relevant because termhood is partly reflected in frequency, domain specificity, nestedness, syntactic patterning, and collocation. C-value/NC-value is an established method for multiword terms, and reviews of automatic term recognition show why a single statistical score is insufficient (Kageura & Umino 1996; Frantzi et al. 2000). Ontology learning extends the task from candidate terms to concepts and relations, but the boundary between an expression in text and a validated conceptual entity remains a human and methodological problem (Wong et al. 2012; Asim et al. 2018).

Recent ATE research increasingly uses transformer representations, sequence labeling, cross-lingual transfer, and

generative models. Tran et al. (2024) show that cross-domain extraction can benefit from cross-lingual transfer and nested-term labeling, but performance depends on language, domain, and annotation conditions. LlamATE evaluates generative LLMs for term extraction, while the recent ACM survey maps neural and generative ATE methods and their evaluation challenges (Tran et al. 2025; Tran et al. 2026). Xu et al. (2025) similarly situate terminology extraction across methods, datasets, tools, and applications.

The critical operational finding is that better candidate generation does not remove terminographic work. Wissik (2025), based on interviews in institutional settings, identifies slow uptake, weak integration into existing tools, uneven source materials, and limited support for less-resourced languages. The evidence therefore supports treating ATE output as a ranked queue for expert decision, in which the score, the source sentence, the document metadata, the model version, and the acceptance or rejection reason are all preserved; where they are not, later users cannot distinguish evidence-based normalization from an opaque model suggestion.

4.3. *Terminology science and lexicography*

Terminology science begins from concepts and specialized communication, but it also recognizes that terms behave as lexical units in texts. ISO 1087 (2019) and ISO 704 (2022) provide vocabulary and principles for concept systems, definitions, designations, and terminology work. Cabré (1999), Temmerman (2000), and Faber (2012) show that specialized language cannot be reduced to a context-free nomenclature. L'Homme and Bernier-Colborne (2012) make the central distinction especially clear: terms can function as labels for concepts and as lexical units with linguistic properties.

Lexicographic practice adds user profiles, corpus evidence, lemma choice, sense discrimination, definitions, examples, collocations, labels, and entry navigation (Atkins & Rundell 2008). These features are not decorative additions to an ontology. They determine whether a resource can support learning, translation, localization, editing, and professional decision-

making. A definition should identify the concept and differentiate it from neighboring concepts, while usage evidence should show how the expression actually occurs.

Recent terminology-ontology research gives more specific guidance. Giacomini (2024) examines the relation between terminology and knowledge representation. Faber & León-Araúz (2024) demonstrate how specialized knowledge frames can inform linguistically grounded ontology design. Resi (2024) shows that terminological gaps are best analyzed through concept systems and frames rather than forced translation pairs. Together these studies establish that lexical entries and concepts have to be connected without being collapsed into a single object.

4.4. *Semantic Web and lexicon-ontology representation*

The literature addresses the formal representation problem through a stack of complementary models rather than a single vocabulary. SKOS provides concept schemes, preferred and alternative labels, broader and narrower links, and mapping relations. OntoLex-Lemon provides lexical entries, canonical and other forms, lexical senses, and references to ontological entities. LexInfo supplies reusable linguistic categories and properties (Cimiano et al. 2011). OWL is appropriate for axioms that require formal semantics and reasoning, while SHACL specifies graph shapes and validation constraints. PROV-O supports the attribution and activity records needed for evidence and review history. This modular division follows the OntoLex community report (Cimiano et al. 2016).

The literature on Linguistic Linked Open Data demonstrates both interoperability potential and model complexity. McCrae et al. (2012) provide an early model for interchanging lexical resources on the Semantic Web; Bosque-Gil et al. (2018) compare models for linguistic linked data; Khan et al. (2022) survey subsequent modeling advances; and Gromann et al. (2024) identify continuing multilingual gaps across levels of linguistic description. The implication is that a resource should reuse established vocabularies but document every local extension and avoid modeling decisions that only its original developers can interpret.

Terminology-specific work narrows the gap. Wei et al. (2023) combine ISO terminology principles and Semantic Web representation in a multilingual terminology e-dictionary. Martín-Chozas et al. (2025) propose an OntoLex-Lemon-based model for terminological data. These studies support a composite architecture: a SKOS concept scheme for terminological concepts, OntoLex-Lemon for lexical objects, LexInfo for morphosyntax, OWL only where logical commitments are justified, SHACL for validation, and explicit provenance for every evidential and editorial decision.

Table 3 summarizes how these models divide the representational work. The comparison is descriptive: it records which object each vocabulary is designed to express and what is lost when objects of different kinds are merged into one representation. The reviewed studies combine these vocabularies in different ways, and none treats a single model as sufficient on its own.

Table 3. *Representation models reported in the reviewed literature and the objects they express*

Component	Information expressed	Representation model reported	Function in a terminological resource
Persistent identity	URI, version, status, creation and modification dates	RDF identifier; Dublin Core terms; PROV-O	Citation, change control, and stable links
Lexical entry	Lemma, abbreviation, variant, language and script	OntoLex-Lemon LexicalEntry and Form	Preserves forms independently of concepts
Morphosyntax	Part of speech, inflection, derivation, multiword pattern	LexInfo; MMoOn where detailed morphology is needed	Supports search and agglutinative morphology
Lexical sense	Link between an entry and a concept/entity; usage restrictions	OntoLex-Lemon LexicalSense	Represents polysemy and entry-specific meaning
Terminological concept	Definition, scope note, subdomain, preferred and alternative designations	SKOS Concept and ConceptScheme	Supports concept orientation and lightweight semantic navigation

Formal entity	Class, individual, property, axiom, restriction when required	OWL 2	Supports reasoning without forcing all dictionary data into OWL
Relations	Broader/narrower, part-of, used-for, implements, depends-on	SKOS plus documented domain properties	Builds a domain concept system and knowledge graph
Multilingual alignment	Equivalent type, target concept, evidence, status	OntoLex vartrans and/or SKOS mapping properties with local qualification	Avoids untyped translation pairs
Usage evidence	Corpus passage, document, genre, date, authority, license	Web Annotation or local evidence model plus PROV-O	Makes normalization auditable
Validation record	Reviewer role, date, decision, confidence, comments, checks	PROV-O and project validation vocabulary	Assigns accountability and enables maintenance

Four distinctions recur across this literature and are treated by the reviewed authors as conditions for interoperability rather than as stylistic preferences. First, a lexical entry is not a concept: it represents a word or multiword expression in a language. Second, a lexical sense mediates between an entry and the concept or ontological entity it denotes in a particular use. Third, a terminological concept is not automatically an OWL class, because formalization depends on the intended reasoning task. Fourth, multilingual correspondence is an evidence-bearing, typed assertion rather than an unqualified string pair. Where these distinctions are not maintained, the reviewed studies report resources that are difficult to reuse, to validate, and to correct (L’Homme & Bernier-Colborne 2012; Cimiano et al. 2016; Martín-Chozas et al. 2025).

4.5. *Low-resource and Uzbek evidence*

A language is low-resource in a particular computational context when the corpora, annotations, tools, benchmarks, or expert-validated resources needed for that task are limited. Speaker

population alone is not an adequate measure. Surveys of low-resource NLP emphasize data scarcity, domain mismatch, evaluation limitations, and the unequal distribution of language technology (Joshi et al. 2020; Hedderich et al. 2021). Multilingual transfer can reduce some data requirements, but it can also import source-language categories and errors.

Lexical ontology projects provide useful precedents. WordNet separates word forms and lexical senses within synsets, while BabelNet expands lexical-semantic coverage across languages (Miller 1995; Navigli & Ponzetto 2012). The Arabic Ontology shows the value of ontologically analyzed non-English content combined with lexicographic search (Jarrar 2021). MMoOn Core provides a model for morphological data, including morphemes, forms, and meanings, which is relevant when term variation cannot be represented as a single invariant string (Klimek et al. 2021).

Uzbek already has important building blocks. UZWORDNET reported 28,140 synsets, 64,389 senses, and 20,683 words in its initial publication, with an estimated accuracy of 75.98 percent (Agostini et al. 2021). A morphological and syntactic tagged-corpus initiative established annotation resources and tools (Sharipov et al. 2022). BERTbek demonstrated the value of Uzbek-specific pretrained models across sentiment analysis, topic classification, and named-entity recognition (Kuriyozov et al. 2024). A recent overview of Turkic Central Asian language processing nevertheless identifies continuing shortages in data, tools, and evaluation resources (Veitsman & Hartmann 2025).

These resources make an Uzbek IT dictionary feasible, but they do not solve the domain problem. A general wordnet is not a validated inventory of current IT concepts; a pretrained model is not a terminology standard; and a tagged corpus does not by itself determine preferred equivalents. An Uzbek implementation would therefore need to reuse the available lexical and NLP infrastructure while constructing a domain corpus, an explicit equivalence policy, a morphology-aware entry model, and a specialist validation process – none of which the reviewed literature yet reports for this language and domain.

4.6. *LLMs as constrained assistants*

LLMs are useful because they can summarize evidence, compare candidate formulations, generate controlled drafts, and work across languages. They are unsafe as autonomous terminologists because surface fluency does not establish term status, conceptual identity, normative acceptability, or source authority. The broader literature on foundation-model risks and hallucination shows why plausibility must not be treated as verification (Bender et al. 2021; Huang et al. 2025).

Across the reviewed studies, the tasks for which model assistance is reported as usable are bounded: suggesting candidate terms from retrieved passages; proposing variant clusters; drafting a definition constrained by selected evidence; comparing alternative equivalents; suggesting possible semantic relations from an approved relation inventory; converting an approved conceptual record into a serialization template; and explaining a validation error. The same studies do not report dependable performance where a model is left to assign preferred status, to declare two concepts equivalent, to introduce an ontology axiom into a release, or to publish a definition without named review.

A governance requirement follows from this asymmetry. The literature converges on recording, for every model-assisted action, the input evidence, the prompt or instruction template, the model and version, parameters where available, the output, the reviewer, the decision, and any subsequent revision, and on applying formal constraints and schemas before expert review so that reviewers examine a bounded candidate rather than unrestricted prose (Doumanas et al. 2024; Ayad & Chibout 2025; Shimizu & Hitzler 2025). Records of this completeness are rarely reported in the studies reviewed here, which is the basis of the governance gap described in Section 5.

4.7. *Evaluation practices across the evidence streams*

Evaluation is the point at which the evidence streams diverge most sharply. Term-extraction research reports precision, recall, and F-measure against annotated gold sets; terminological and lexicographic research relies on expert rubrics and corpus evidence; ontology research reports logical consistency,

constraint conformance, and pitfall detection, for which tools such as OOPS! are available (Poveda-Villalón et al. 2014); and user-oriented evaluation appears mainly in dictionary and interface studies. Because the artifacts differ, no single metric is informative across the whole problem space, and few of the reviewed studies evaluate more than one dimension. Table 4 collects the evaluation dimensions, indicators, evidence types, and methods reported across the literature, and makes visible which combinations remain under-reported.

Table 4. *Evaluation dimensions and indicators reported across the reviewed evidence streams*

Dimension	Indicators	Evidence	Reported evaluation method
Term discovery	Precision, recall, F1; precision at k; reviewer workload; error types	Manually annotated corpus and candidate logs	Compare statistical baseline, transformer model, and LLM-assisted reranking on identical splits
Lexicographic entry	Definition accuracy, differentiating power, circularity, evidence, form coverage	Blind expert rubric and corpus citations	Two or more terminologists; adjudication and agreement reporting
Conceptual model	Competency-question coverage, type correctness, relation correctness, subdomain coverage	Concept map, competency tests, domain-expert judgments	Independent IT specialists plus consensus meeting
Formal representation	RDF validity, SHACL conformance, OWL consistency, pitfall count, identifier integrity	Release files, shapes, reasoner and quality reports	Automated checks plus ontology-engineer review
Multilingual alignment	Equivalence-type accuracy, false-equivalence rate, gap detection, agreement	Bilingual concept pairs with expert labels	Terminologist/translator evaluation using concept definitions and evidence

Usability	Task success, search time, comprehension, perceived usefulness, error recovery	Prototype and realistic user tasks	Students, translators, localization staff, and IT specialists
Governance and maintenance	Proportion with complete provenance; review latency; correction latency; version traceability	Audit log, issue tracker, release history	Periodic governance audit and longitudinal monitoring

5. INTEGRATED GAPS AND IMPLICATIONS FOR FUTURE RESEARCH

The literature is mature in its individual components but fragmented at the point where a low-resource IT dictionary must become simultaneously lexicographic, conceptual, multilingual, machine-readable, and maintainable. Four gaps recur across the evidence.

1. **Workflow gap:** ATE and ontology-learning studies often stop after candidate extraction or relation prediction; lexicographic acceptance, concept modeling, publication, and maintenance are outside the evaluated task.
2. **Representation gap:** Lexicographic resources may not support formal reasoning, while ontologies may treat linguistic forms as undifferentiated labels. The lexical-entry, sense, concept, and ontology-entity layers are not consistently separated.
3. **Evaluation gap:** Extraction scores alone do not measure definition quality, concept adequacy, equivalence accuracy, formal consistency, usability, or updateability.
4. **Governance gap:** AI-assisted studies often report task performance without a complete operational record of evidence, model version, human responsibility, acceptance criteria, and post-publication correction.

These gaps translate into requirements that any future low-resource IT terminology resource, and any empirical study of one, will have to satisfy: corpus-grounded term status; explicit lexical-conceptual separation; typed multilingual equivalence; morphology-aware forms; modular standards reuse; formal and human validation; provenance at item and decision level; versioned publication; and restricted, auditable AI assistance. No single study reviewed here satisfies these requirements in full, and whether they can be satisfied jointly, and at what cost, is an empirical question that the present literature does not answer.

Table 5. *Evidence streams, persistent limitations, and implications for future work*

Evidence stream	Strength	Persistent limitation	Implication for future work
Ontology engineering and KGs	Lifecycle, conceptualization, relations, reasoning, reuse	Lexicographic microstructure and term status often external	Competency questions as the entry point, with every formal entity linked to reviewed lexical and evidential records
ATE and language models	Scalable candidate discovery and ranking	Extraction does not establish concept identity or normative acceptance	Extraction output treated as a ranked review queue carrying source passages and decision logs
Terminology and lexicography	Definitions, variants, equivalence, usage, users	Often lacks interoperable formal publication	Entry fields translated into reusable RDF models without reducing the entry to an OWL class
OntoLex-Lemon and LLOD	Interoperable lexical-semantic representation	Model complexity and uneven multilingual coverage	A documented profile with a small required core and justified extensions
Low-resource NLP	Transfer learning, collaborative data creation, multilingual models	Domain mismatch, annotation scarcity, source-language bias	Decisions anchored in target-language evidence, with transfer errors measured explicitly
LLM-assisted OE	Drafting, comparison, mapping, population support	Hallucination, instability, weak accountability	Generation constrained by schema and evidence, with named review and version records

6. DISCUSSION

6.1. *Theoretical implications*

The review positions the ontological dictionary as a boundary object among lexicography, terminology science, ontology engineering, linked data, and NLP. What the evidence establishes is less a matter of any single model than of the distinctions that adjacent fields tend to erase. Lexical entries and forms belong to language; terminological concepts organize domain knowledge; ontology entities support formal semantics; corpus passages provide evidence; and validation activities establish accountability. A lexical sense connects these levels without collapsing their different identity conditions. The theoretical significance of the synthesis is that the levels are not alternative descriptions of one object, and that resources treating them as interchangeable inherit problems which no subsequent formalization can repair.

This layered view also clarifies the role attributed to AI in the literature. Model assistance is not an additional semantic level and does not confer authority on a resource; it is a set of services operating within controlled tasks in an editorial workflow. The scientific question raised by the reviewed studies is therefore not whether a language model can produce a plausible ontology or dictionary entry from a single prompt. It is whether model assistance reduces effort or improves coverage under stable evidence, schema, validation, and governance conditions — a question that current evaluations, which report task-level scores in isolation, are not designed to answer.

6.2. *Implications for Uzbek and comparable low-resource languages*

For Uzbek, the reviewed evidence indicates both which existing resources can be reused and what they cannot be expected to provide. UZWORDNET can support lexical-semantic comparison; tagged corpora can inform morphological and syntactic processing; BERTbek and multilingual models can support candidate extraction; and broader computer-science resources can suggest conceptual neighbours. None of these

substitutes for a domain corpus, an expert group, an explicit equivalence policy, a documented representation profile, and a validation set, and the literature reviewed here contains no study in which these elements are established for Uzbek IT terminology.

The same principle applies to other low-resource languages. Transfer should occur at the level of methods and interoperable models, not through uncritical copying of English concept labels. A successful resource should make non-equivalence and uncertainty visible, because an explicit gap is more useful than a false translation presented as settled terminology.

6.3. Risks and open questions

The risks recurring in this literature are over-automation, ontology overengineering, undocumented normalization, and maintenance failure. The evidence associates each with an identifiable control: evidence-constrained generation and named review for over-automation; the use of OWL only where a reasoning requirement exists for overengineering; passage-level provenance and decision records for undocumented normalization; and status models, issue tracking, versioned releases, and explicit correction responsibilities for maintenance failure. What the literature does not supply is evidence about the cost of these controls, or about how much of the reported efficiency gain from model assistance survives them.

A further risk is apparent precision. A model score, a confidence value, or a formal axiom can make a weak decision look objective. Studies that report quantitative and expert evidence together, including disagreement and rejected proposals, make this risk visible; studies reporting only aggregate scores do not. How confidence values should be presented to dictionary users without being mistaken for validation status remains an open question.

6.4. Directions for future research

The most immediate research need is evidence that spans the whole problem rather than one segment of it. Studies evaluating term extraction, definition quality, conceptual adequacy, formal

consistency, multilingual equivalence, and usability on the same corpus and the same set of terms would establish whether the reported strengths of individual methods survive integration; at present these dimensions are assessed in separate literatures on different data, and the results cannot be combined. Comparable annotated resources for low-resource and morphologically rich languages are a precondition for such work, as is the release of rejected candidates and decision logs, which the reviewed studies almost never report and which would allow systematic errors to be studied rather than inferred.

Three further questions follow from the gap analysis. First, how much terminographic effort is actually saved by constrained model assistance once review, provenance recording, and correction are counted – a quantity that no reviewed study measures. Second, how typed multilingual equivalence and explicit non-equivalence should be represented so that gaps remain visible to users instead of being closed by a plausible translation. Third, how a terminological resource in a low-resource language can be maintained over time, given that the reviewed projects report construction far more often than revision, deprecation, or withdrawal. An Uzbek implementation would be a suitable setting for these questions, because the necessary lexical, corpus, and language-model infrastructure now exists while a validated, domain-specific IT resource does not.

7. LIMITATIONS

This review is integrative rather than exhaustive. It does not report database record counts, duplicate removal, dual screening, or a PRISMA flow diagram and should not be cited as a systematic estimate of the entire literature. The source set is English-language and may under represent relevant work published in Uzbek, Russian, Turkish, or other languages. The synthesis is interpretive, so it evaluates transferability rather than calculating a common quantitative outcome.

The review is also bounded in what it can establish. It compares methods, representation models, and evaluation practices across streams, but it does not test them: no claim made

here has been validated on a complete IT corpus, and the requirements formulated in Section 5 are derived from the literature rather than demonstrated in practice. Model-specific observations will require updating, because language-model systems and access conditions change quickly. Finally, standards reuse does not guarantee semantic quality: local modeling choices, extensions, and mapping policies must still be documented and tested in any resource that adopts them.

8. CONCLUSION

The evidence needed to construct a low-resource IT ontological dictionary already exists, but it is distributed across research traditions. Ontology engineering supplies requirements, conceptualization, formalization, and lifecycle practices. Knowledge graphs supply relation-rich, maintainable structures. ATE and language models supply scalable candidate discovery. Terminology and lexicography supply concept orientation, definition quality, equivalence management, and user-facing entries. OntoLex-Lemon, SKOS, LexInfo, OWL, SHACL, and provenance models supply an interoperable representation stack. Low-resource NLP supplies transfer strategies and a warning against assuming that high-resource categories transfer without error.

What the evidence does not yet provide is a demonstrated connection between these contributions. The gaps identified in this review – workflow, representation, evaluation, and governance – are not four independent difficulties but one difficulty seen from four angles: no reviewed study carries a term from corpus evidence through lexicographic decision, conceptual modeling, formal representation, and typed multilingual alignment to a validated, versioned release under documented human accountability. Until such evidence exists, the central principle emerging from the literature remains evidential and institutional rather than technical: no term, definition, equivalence, concept relation, or ontology axiom becomes authoritative because a model generated it. It becomes publishable when the evidence is traceable, the object is

represented at the appropriate level, validation is appropriate to the claim, and accountable specialists take responsibility for the decision. Establishing whether this can be achieved for Uzbek IT terminology, and at what cost, is the next empirical obligation.

APPENDIX A

Search concept blocks and platform-adaptable strings

The following strings document the concept blocks used to identify and verify the focal evidence. Syntax should be adapted to each database. They are not presented as a retrospective Scopus export and do not imply exhaustive retrieval counts.

A. IT terminology and formal models

("information technology" OR "computer science" OR software OR computing) AND (terminolog* OR "domain term*" OR lexicon OR vocabulary OR dictionary) AND (ontolog* OR "knowledge graph" OR RDF OR OWL OR SKOS)

B. Automatic term extraction and ontology learning

("automatic term extraction" OR "terminology extraction" OR "term extraction" OR "ontology learning" OR "ontology population") AND (transformer OR BERT OR multilingual OR cross-lingual OR LLM OR "large language model")

C. Lexicon-ontology and linked data

(OntoLex OR lemon OR "OntoLex-Lemon" OR LexInfo OR SKOS OR "Linguistic Linked Open Data") AND (dictionary OR lexicograph* OR terminolog* OR lexicon OR termbase)

D. Low-resource and Uzbek resources

("low-resource language" OR "under-resourced language" OR Turkic OR Uzbek) AND (terminolog* OR corpus OR wordnet OR "lexical ontology" OR "language model" OR morphology OR "linked data")

E. AI-assisted ontology engineering

("ontology engineering" OR "knowledge graph engineering" OR "ontology matching" OR "ontology population") AND (LLM OR "large language model" OR generative OR prompting)

APPENDIX B

Focal evidence set and contribution to the synthesis

Table B1. *Thirty-eight focal publications used in the synthesis*

No.	Source	Evidence stream	Primary contribution to the synthesis
1	Gruber (1995)	Ontology engineering	Formal, explicit shared conceptualization; foundational principle
2	Studer et al. (1998)	Knowledge engineering	Clarifies ontologies and knowledge-engineering methods
3	Noy and McGuinness (2001)	Ontology method	Practical iterative ontology development and reuse
4	Poveda-Villalón et al. (2022)	Ontology lifecycle	Requirements, implementation, publication, and maintenance workflow
5	Hogan et al. (2021)	Knowledge graphs	Comprehensive KG concepts, construction, quality, and applications
6	Ji et al. (2022)	Knowledge graphs	Representation, acquisition, and application taxonomy
7	Paulheim (2017)	KG refinement	Continuous completion, correction, and evaluation
8	Salatino et al. (2018)	Computer-science ontology	Reusable research-area taxonomy and relation scaffold
9	Dessi et al. (2022)	Scientific KG extraction	NLP pipeline for computer-science entities and relations
10	Dessi et al. (2025)	Computer-science KG	Large-scale domain graph and evidence source for concept discovery
11	He et al. (2024)	Deep-learning OE	Tools for ontology processing, alignment, and completion
12	Shimizu and Hitzler (2025)	LLM-assisted OE/KG	Task landscape and constrained acceleration opportunities
13	Doumanas et al. (2024)	Collaborative OE	Human-machine collaboration rather than autonomous engineering
14	Ayad and Chibout (2025)	Ontology population	Metamodel-guided LLM population and formalization
15	Babaei Giglou et al. (2023)	LLM ontology learning	Benchmarks ontology-learning tasks for LLMs
16	Fathallah et al. (2024)	LLM ontology pipeline	Pipeline view of model-assisted ontology learning
17	Asim et al. (2018)	Ontology learning review	Linguistic, statistical, and logical method taxonomy

18	Tran et al. (2024)	Cross-lingual ATE	Transfer and nested-term labeling for low-resource conditions
19	Tran et al. (2025)	Generative ATE	Evidence on LLM-based term extraction
20	Tran et al. (2026)	ATE survey	Current neural/generative ATE landscape and evaluation issues
21	Xu et al. (2025)	Terminology-extraction survey	Methods, datasets, tools, and applications
22	Wissik (2025)	Professional terminology practice	Workflow, integration, and less-resourced-language barriers
23	Cimiano et al. (2011)	LexInfo	Declarative morphosyntactic layer for lexicon-ontology interfaces
24	McCrae et al. (2012)	Lexical linked data	Interchange model for lexical resources on the Semantic Web
25	Bosque-Gil et al. (2018)	Linguistic linked data	Comparative representation models and interoperability
26	Khan et al. (2022)	LLOD survey	Recent linked-data vocabularies and modeling practices
27	Gromann et al. (2024)	Multilingual LLOD	Multilingual gaps across linguistic description levels
28	Martín-Chozas et al. (2025)	Terminological linked data	OntoLex-Lemon-based model specialized for terminology
29	Wei et al. (2023)	Multilingual e-dictionary	Combines ISO terminology principles and Semantic Web standards
30	Giacomini (2024)	Terminology and ontology	Clarifies conceptual and professional relation between fields
31	Faber and León-Araúz (2024)	Frames and ontology	Connects specialized knowledge frames to ontology design
32	Resi (2024)	Terminological gaps	Typed gap analysis through concept systems and frames
33	Jarrar (2021)	Arabic lexical ontology	Non-English ontology with lexicographic access and validation
34	Klimek et al. (2021)	Morphological ontology	Formal model for morphemes, forms, and meanings
35	Agostini et al. (2021)	Uzbek lexical resource	Existing Uzbek wordnet, scale, and validation baseline
36	Kuriyozov et al. (2024)	Uzbek language model	Language-specific model evidence for downstream NLP
37	Sharipov et al. (2022)	Uzbek corpus	Morphological and syntactic annotation infrastructure
38	Veitsman and Hartmann (2025)	Central Asian low-resource NLP	Current resource landscape, limitations, and transfer needs

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