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REVIEW ARTICLE

Semantic Fidelity for Intelligent 6G Communication: A Taxonomic Deep Dive into Knowledge-Driven Architectures, Benchmarks, and Challenges

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Abstract

Cognitive-semantic communication encodes task-relevant meaning rather than raw bits, improving 6G spectral efficiency and reducing latency, yet evidence remains fragmented across methods, evaluations, and deployments. This PRISMA-based review screens 782 records (2019–2025) from seven databases, retaining 73 studies organized into five method families: neural semantic codecs, KG-based pipelines, LLM-assisted codecs, cross-modal encoders, and semantic relays. We examine how goal-oriented semantics, knowledge graphs, and LLMs shape representation, compression, and task quality under rate and latency constraints across UAVs, NTNs, ISAC, Metaverse, and IoT. Reported gains include bandwidth reductions of 20–60% over conventional baselines, task accuracy improvements of 8–23 percentage points over bit-level systems, and cross-modal alignment scores above 0.80; however, these gains derive predominantly from AWGN simulations, and robustness under realistic fading, mobility, and adversarial conditions remains the most critical open problem. Gaps include narrow datasets, inconsistent metric definitions, and unaddressed security, privacy, and standardization concerns. Recommendations include shared multimodal datasets with channel traces, standardized robustness protocols, unified metric cards pairing task outcomes with resource costs, edge-friendly split designs, and integrity checks with privacy audits.

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1 Introduction

Unlike earlier generations that optimized primarily for throughput and error rates, 6G is being designed around a fundamentally different objective: delivering actionable meaning rather than bit-perfect replicas [1, 2]. In semantic communication, the sender does not attempt to reproduce every symbol at the receiver; instead, it encodes only the information relevant to a specific task, leaving the receiver to reconstruct intent using shared context and local knowledge, and to act on that intent without inspecting every pixel or packet [3, 4]. In practice, semantic systems encode only the task-relevant delta at the sender, which the receiver combines with local knowledge to recover meaning, thereby cutting traffic, reducing latency, and lowering power consumption on edge devices—offering a path to efficient and reliable services under real constraints [1–4]. In 6G, the network becomes AI-native, shifting from raw-data transport toward purpose-focused service delivery for applications such as extended reality, autonomous vehicle coordination, and non-terrestrial links [5, 6]. Large language models and knowledge graphs have become central to realizing this vision, though their contributions are complementary rather than interchangeable [7, 8]. LLMs excel at interpreting loosely specified user intent and generating compact control messages, while knowledge graphs supply a different kind of structure: stable entity definitions and relational constraints that remain consistent across heterogeneous devices and administrative domains, grounding transmitted signals in both user goals and the situational context available at the receiver. Taken together, these components form a closed loop in which the data plane carries compact symbols and references while performance feedback continuously shapes what the encoder transmits next. The practical appeal of this architecture lies in its measurability: bandwidth consumption, time to action, per-task energy, and reliability under fading can each be tracked against a concrete task objective rather than a surrogate signal-quality measure. It is precisely the gap between the promise suggested by early prototype results and the fragmented, often incomparable evidence base in the current literature that motivates a systematic review of cognitive-semantic communication and a careful consolidation of findings across research communities.

Cognitive-semantic communication extends beyond earlier semantic methods. It adds reasoning, context awareness, and structured knowledge to message design and delivery. It aims to send a meaning that helps the task instead of every raw sample. In practice, cognition uses three tools. Knowledge graphs store facts and links between them. Contextual models track the situation, the device limits, and the current goal. Large language models help interpret intent and plan compact messages. Together, these tools adapt each exchange to application needs, radio conditions, and the receiver's state [7–9]. This direction aligns with the vision of AI native 6G. Work already covers UAV control, non-terrestrial networks, immersive metaverse services, and integrated sensing and communication [5, 6]. The building blocks are concrete: semantic encoders at the edge convert sensor data into symbols linked to a shared ontology, while semantic decoders use that ontology and local caches to recover meaning. A control plane sets goals and policies; a data plane carries compact payloads and references. Early results are encouraging, with studies reporting lower required bandwidth for a target task accuracy and improved robustness under resource and channel constraints [7–9]. This paper takes that step with a systematic literature review from 2019 to 2025. It gathers scattered findings. It explains what works and where it fails. It identifies open problems that must be solved to make cognitive-semantic communication practical in 6G.

1.1 Limitations and Research Gaps in Existing Research

Research on semantic communication has advanced, but clear limits remain. Many studies use small or narrow datasets, a limitation that affects even carefully designed proposals: representative single-scenario evaluations—including those for 6G-oriented semantic approaches [10]—reduce external validity for deployments that span diverse tasks, channels, and device populations [2, 6, 11]. Evaluation practice across the field remains uneven. There is no shared set of metrics or test suites: performance definitions vary substantially across works, with individual proposals [10] adopting task-specific criteria that are not directly comparable to those used in adjacent studies, a fragmentation documented across broader surveys of the field [2]. Robustness evaluation presents a related but distinct problem: the majority of experiments assume quasi-static channels and rely almost exclusively on additive white Gaussian noise as the impairment model, leaving non-Gaussian distributions, bursty packet loss, and deliberate adversarial perturbations largely unexamined [12, 13]. This matters because the interference patterns encountered in dense urban or satellite-assisted deployments differ substantially from AWGN, and it is unclear how far published accuracy figures generalize to those conditions. Separately, the term "semantic accuracy" is used inconsistently across the literature—sometimes denoting symbol-level reconstruction fidelity, sometimes downstream task performance, and sometimes a composite of both—making cross-study aggregation impossible without re-examining each paper's definitions individually [11, 14]. Scalability evidence is thin for a more straightforward reason: because most experiments are conducted on small simulation testbeds with homogeneous node populations, it remains unknown whether reported gains survive when node counts, task heterogeneity, and traffic loads increase to realistic 6G scales [6, 13–15]. The integration of knowledge graphs and large language models into semantic frameworks remains in its early stages. Existing work mainly reports prototypes and simulations; practical deployments at the edge remain rare [7, 8, 16]. Edge nodes also face strict limits on latency, memory, and energy budgets [7, 8, 16]. Security, trust, and privacy remain open problems. Recent surveys highlight the lack of common threat models, benchmarks, and defenses for semantic attacks and model inversion [13, 17, 18]. Standards for evaluation and exchange are limited. Open datasets are scarce across many core tasks. Benchmark suites and public leaderboards would help align tasks, metrics, and reporting [15, 19]. Integrating KGs and LLMs raises engineering constraints. Model size and edge delay require compression, pruning, quantization, and distillation, with careful tuning to preserve task accuracy [7, 16]. Beyond single-user settings, extending semantic communication to multi-user scenarios introduces further design challenges around task diversity, modality alignment, and shared encoder architectures [20]. Open questions remain about interpretability and control of these semantic stacks. Interoperability across platforms and vendors is underexplored. Practical 6G deployment will need cooperation at scale across operators, vendors, and standardization bodies [15, 17–19].

The limitations outlined above directly motivate the review design. RQ1 and RQ2 address the need for clearer organization of method families and enabling mechanisms, including knowledge graphs, goal-oriented semantics, and LLM-based approaches. RQ3 examines how these methods are used across the major 6G application domains and what outcomes are reported. RQ4 addresses the remaining gaps in robustness, security, privacy, scalability, and standardization. RQ5 and RQ6 focus on datasets, benchmarks, evaluation metrics, and reporting consistency, where the literature remains fragmented.

1.2 Key Contributions

This review builds on the identified limitations and organizes evidence for cognitive-semantic communication. Earlier surveys address semantic communication in broad terms, with limited methodological depth, across cognitive, knowledge graph, and LLM-based variants [6, 15, 19]. We address these gaps with a systematic organization of methods and results. We summarize key contributions here and provide details in later sections.

- A structured taxonomy of five method families for cognitive and knowledge-driven semantic communication in 6G: neural semantic codecs, knowledge graph-based pipelines, LLM-assisted codecs, cross-modal encoders, and semantic relays, with explicit definitions and boundaries.
- A unified synthesis of datasets, metrics, and evaluation practices that pairs task outcomes with reported rate, latency, energy, and computation where available, and highlights missing reports and inconsistent practices.
- A comparative analysis across UAVs, NTNs, ISAC, Metaverse services, and IoT using a small set of aligned outcome measures, identifying strengths and gaps in the available evidence. These domains were selected for their distinct 6G operating conditions: real-time control, long-delay constrained links, joint sensing and communication, multimodal low-latency interaction, and edge-constrained analytics.
- Practical guidance on robustness, scalability, security, privacy, and standardization, with concrete next steps such as dataset releases with channel traces, integrity checks for semantic components, and edge-friendly designs for knowledge graphs and LLMs.

1.3 Research Questions

Clear, bounded research questions define the review scope and selection rules. They determine what

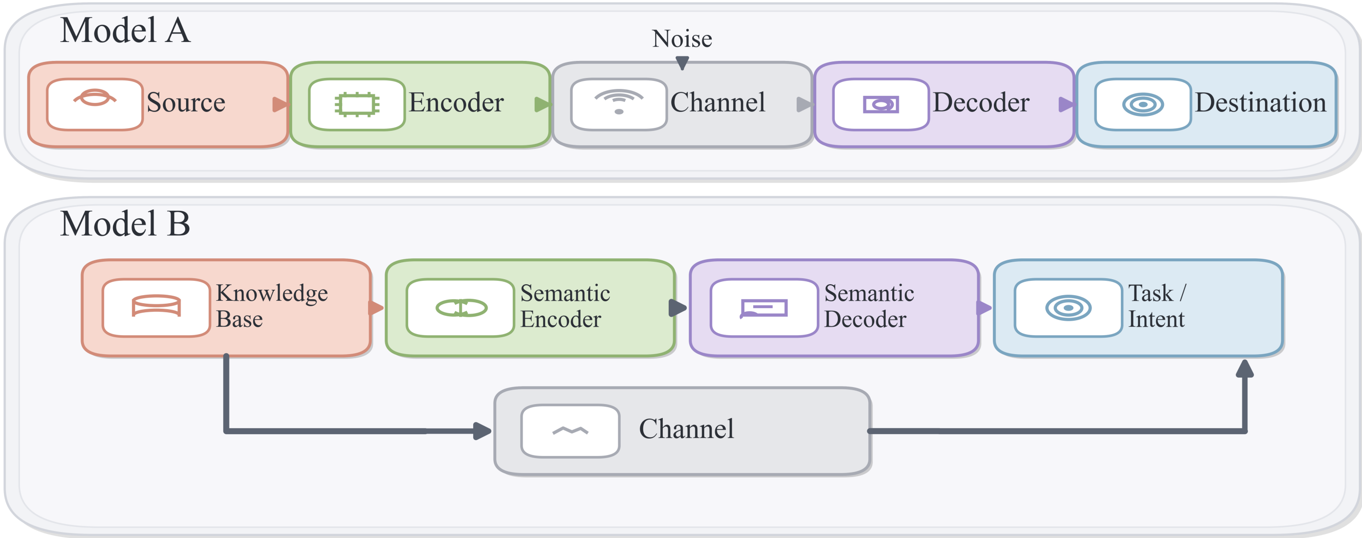

Figure 1. Comparison between Shannon's bit-level (Model A) and a semantic communication (Model B).

to extract, how to screen, and how to synthesize results to preserve traceability. In cognitive-semantic communication, questions target comparisons across models, datasets, metrics, tasks, and domains. The questions below frame screening, extraction, and comparative analysis.

- **RQ1:** Which method families for cognitive and knowledge-driven semantic communication in 6G were proposed from 2019 to 2025, and how are they defined and bounded? See Subsection 4.2.
- **RQ2:** How do knowledge graphs, goal-oriented semantics, and LLM-based codecs change representation, compression, and decision quality under rate and latency limits? See Subsection 4.3.
- **RQ3:** Which 6G application areas, including UAVs, NTNs, ISAC, and Metaverse, use these methods, and what outcomes are reported? See Subsection 4.4.
- **RQ4:** What gaps remain in robustness, security, privacy, scalability, and standardization, and what specific directions follow for future work? See Subsection 4.7
- **RQ5:** Which datasets and benchmarks are used, what properties do they provide, and where are the coverage gaps? See Subsection 4.1.
- **RQ6:** Which evaluation metrics and procedures assess semantic fidelity, task success, system performance, and robustness, and how consistent are they across studies? See Subsection 4.6.

1.4 Study Outline

This paper is organized as follows. Section 2 presents core principles of semantic and cognitive communications. Section 3 describes the PRISMA search, screening, and quality assessment. Section 4 reports datasets, method families, enabling components, application domains, evaluation practices, and open issues. Section 5 summarizes findings and recommendations. The appendices collect full search strings, screening logs, and extraction tables. They support replication of the review and reuse of datasets and settings.

2 Background

Classical information theory focused on transmitting bits reliably over noisy channels through coding, modulation, and error control, without treating meaning or task relevance as design goals [21]. The subsections below trace the evolution from this bit-centric paradigm to cognitive-semantic communication and define the architectural components examined in this review. Semantic communication reframes information as task-relevant content. Semantic encoders extract features required for a given task, and semantic decoders combine received signals with shared knowledge to reconstruct the intended meaning. Feedback supports targeted clarification when the receiver's uncertainty increases. Cognitive extensions add perception, memory, reasoning, planning, and online adaptation around the pipeline. A cognitive controller tracks goals and context, then decides what to send, defer, or request. It adapts bitrate, protection, and scheduling based on

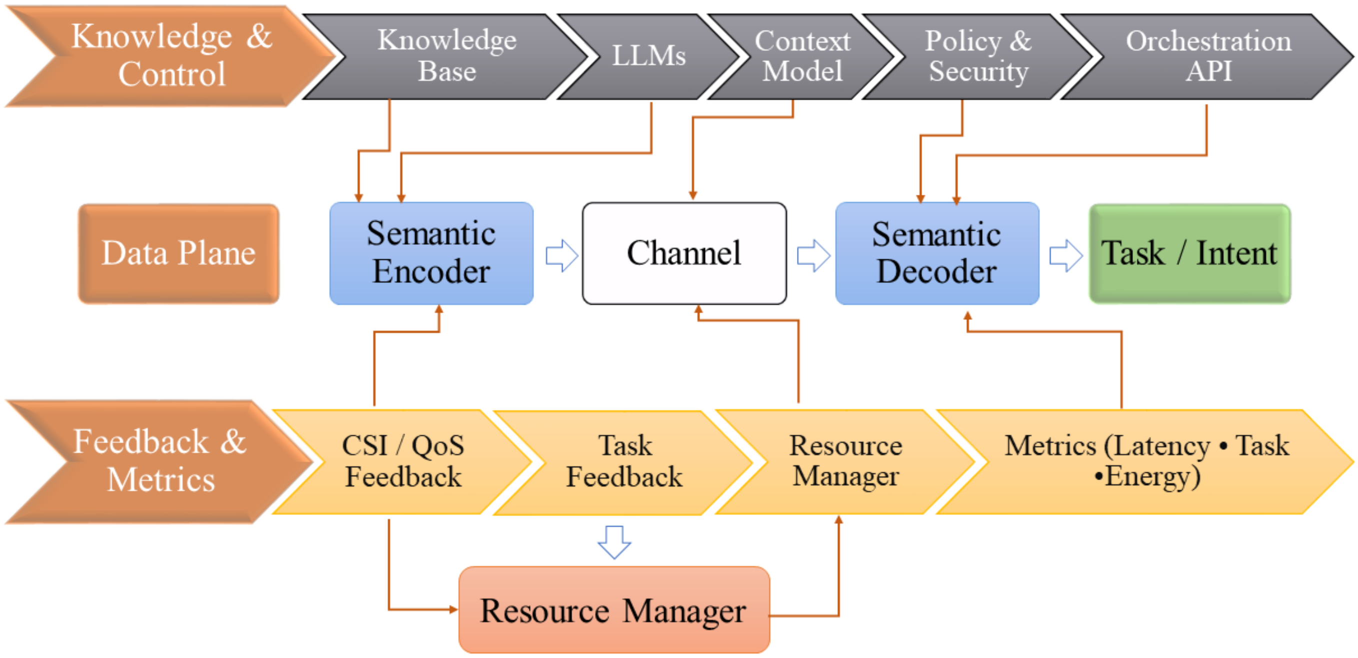

Figure 2. Cognitive-semantic communication: integration of LLMs, knowledge graphs, and context-aware reasoning for adaptive 6G services.

observed performance and risk. Typical constraints include stringent latency requirements, high reliability, and mobility. Knowledge bases align representations to real-world entities and tasks. Task outcomes, rather than bit accuracy alone, measure performance. Figure 1 and Figure 2 illustrate these concepts.

2.1 From Shannon to Semantic Communications

Shannon and Weaver defined communication as the reliable transfer of symbols over noisy channels [21]; recent theoretical work has extended this framework to incorporate semantic fidelity as a first-class design objective [22]. Classical information theory emphasized capacity, coding, and error control, shaping digital systems for decades, but treated meaning as outside the problem. Recent work has challenged this paradigm by incorporating semantics directly into source and channel coding design [23]. Semantic information theory later explored links between symbols and meaning, but remained largely theoretical [24]. Machine learning enabled semantic systems learn end-to-end mappings from inputs to channel-aware representations [25–27]. These systems compress task-relevant content into compact latent representations and transmit fewer symbols while preserving downstream performance [26, 28]. Empirical work reports bandwidth and latency savings in drone coordination, autonomous driving, and immersive services [2, 26–29]. Implementations include neural text, image, and speech encoders trained end-to-end with joint source-channel coding objectives to preserve task-relevant content under channel noise [25, 30, 31]. Figure 1 contrasts the classic pipeline with a semantic pipeline that adds a knowledge base, semantic encoder and decoder, and feedback to align transmission with task intent [32]. Current challenges include domain dependence, distribution shift sensitivity, and sparse benchmarking [33]. Ongoing work targets robust representations, transferable knowledge stores, and standard evaluation protocols to support reproducible comparison and deployment [32].

2.2 Semantic Communication Models, Architectures, and Metrics

Neural models map inputs to compact, task-aware latents for robust transmission [25]. Image and speech codecs apply content-adaptive joint source-channel coding to preserve semantic fidelity under channel noise and bandwidth constraints; quantitative performance figures from the reviewed corpus are reported in Section 4.2, where codec families are compared against conventional JSCC baselines across SNR regimes. Knowledge graphs and shared concept spaces improve alignment between sender and receiver [34, 35]. Hybrid designs combine neural encoders with symbolic reasoning and LLMs to handle more complex tasks and select what to transmit [36, 37]. Semantic relays and forwarding rebuild meaning at intermediate nodes to reduce load and latency

[38]. Cross-modal coding unifies text, image, and audio into shared embeddings for multisensor tasks [39]. Evaluation commonly combines task success, semantic similarity, and conventional performance measures. Representative examples include BiLingual Evaluation Understudy (BLEU), BERTScore, Fréchet Inception Distance (FID), mean average precision (mAP), and F1 score [28, 33, 40–42]. The field lacks standardized benchmarks and protocols, which hinders reproducible comparison [43].

2.3 Cognitive Semantic Communications

Cognitive semantic communication extends semantic exchange beyond message compression by embedding reasoning, adaptivity, and context awareness into the communication loop. It uses knowledge graphs, contextual models, and LLMs to decide what to transmit, when transmission is needed, and what quality level is sufficient for the task. Rather than treating the shared knowledge base as a passive lookup table, cognitive semantic communication integrates it actively into transmission decisions. A context model at the transmitter monitors link quality, device mobility, and the evolving task priority, and uses this information to determine not just what to encode but whether to transmit at all, at what fidelity level, and with what degree of error protection. The knowledge graph underpins this process by supplying stable entity and relational anchors that prevent reference ambiguity from accumulating across retransmissions or handovers—a problem that purely neural approaches handle poorly without explicit symbolic grounding. In UAV networks, for instance, combining semantic encoding with KG-based reasoning has been shown to reduce control signaling volume while preserving task performance under dynamic channel conditions [44, 45]. Similar ideas are used in non-terrestrial and satellite edge networks, where semantic coding and intent-level compression improve efficiency under limited bandwidth and long paths [46]. LLM-based encoders support unified processing of text, image, and audio, which helps integrate sensor data and maintain consistent decisions at the receiver [36, 37]. ISAC settings benefit from the same principle through improved target discrimination and lower false alarm rates under constrained resources [47]. Virtual and mixed reality systems also benefit because semantic transfer of scene changes supports tight delay budgets and stable multi-user interaction, while constrained edge devices gain from transmitting only features relevant to the current task or scene [48, 49]. Taken together, these results reflect a shift from basic semantic coding toward cognitive communication that plans around goals, adapts to context, and allocates resources where they provide the most utility [1, 6].

This shift also introduces practical deployment costs. Richer reasoning can improve task fidelity and semantic consistency, but it also increases model size, memory demand, inference delay, synchronization overhead, and energy use, especially on resource-constrained edge devices. Knowledge graph-based designs require ontology maintenance and reasoning overhead, while LLM-assisted components can impose substantial computational cost when placed close to the endpoint. Figure 2 illustrates how these capabilities connect knowledge access, feedback control, and adaptive scheduling to the semantic encoder and decoder. The Orchestration API coordinates cross-domain task scheduling and resource negotiation between the control plane and external systems, while the Resource Manager dynamically allocates bandwidth, compute, and memory budgets based on CSI feedback and task priority signals issued by the cognitive controller. Within this pipeline, neural semantic codecs mainly realize the encoder and decoder path, knowledge graph-based pipelines strengthen the shared knowledge and reasoning layer, LLM-assisted codecs support intent interpretation and adaptive control, cross-modal encoders learn shared representations across modalities, and semantic relays perform meaning-aware forwarding between intermediate nodes. In practice, deployable systems therefore depend on efficiency-conscious strategies such as pruning, quantization, distillation, lightweight adapters, split execution, caching, and careful placement of reasoning functions across device, edge, and cloud resources [1, 6, 50].

3 Methodology

This review follows a predefined systematic literature review protocol [51] and reports findings using the PRISMA 2020 framework [52]. The subsections below describe the review protocol and search strategy, inclusion and exclusion criteria, data extraction schema, and quality assessment rubric.

3.1 Review Protocol

We followed a pre-registered protocol for English-language records on semantic and cognitive communication. Searches were conducted in IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect (Elsevier), MDPI, Taylor & Francis, and arXiv, using combined keywords for semantic, goal-oriented, and cognitive communications, knowledge graphs, and LLMs. Screening used six stages: title, abstract, full text, methodological scope, domain fit, and quality appraisal. Two reviewers screened in parallel; disagreements were resolved by discussion and recorded adjudication. Extracted fields include channel model, system setup, dataset, evaluation metric, robustness checks, security/privacy notes, and links to code or data. All search strings, run dates, deduplication steps, and screening logs are archived in the appendix to preserve reproducibility and enable audit.

3.2 Inclusion and Exclusion Criteria

The study selection followed a set of written rules defined before the searches began. The aim was topical fit, research merit, and results that others can verify. The focus was on semantic or cognitive communication for 6G during 2019-2025. Language was English, and the full text had to be available. Foundational works on information theory cited in the background section provide context only and are not included in the screened corpus. Each record used the same checklist to ensure consistent decisions. Reviewers recorded a brief rationale for each keep or reject decision. Those notes form an audit trail for later review. Reference lists and citation chains were inspected using the same rules. Records from multiple sources were deduplicated before screening to prevent double-counting. Preprints with a final version were linked to the journal article. The lists below state the exact inclusion and exclusion criteria. Preprints from arXiv were eligible when the contribution was methodologically complete with reproducible experimental details and posted by authors with verifiable institutional affiliations; their peer-review status is noted in the Availability field of the dataset summary to allow readers to assess it independently.

Inclusion

- **Subject relevance:** Empirical or theoretical work on semantic or cognitive communication for 6G or beyond 5G using knowledge graphs, goal-oriented semantics, or large language models.
- **Time window and language:** Published 2019-2025, in English, with full text available.
- **Source indexing:** Retrieved from at least one of the following: IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier ScienceDirect, MDPI, Taylor & Francis, or arXiv; with a stable identifier (DOI or arXiv ID) enabling deduplication.
- **Contribution type:** Method, evaluation, dataset, or system report covering domains such as UAVs,

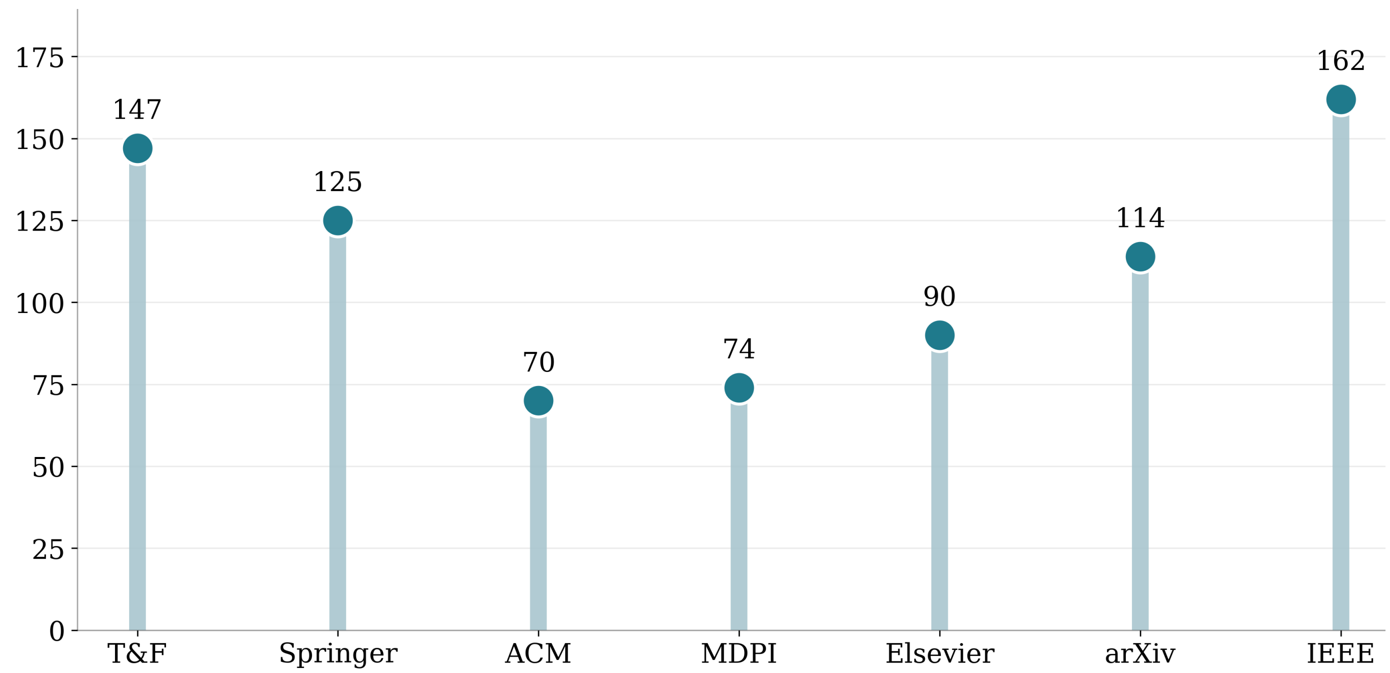

Figure 3. Distribution of selected papers across the searched databases, showing the number of relevant studies retrieved from each source.

NTNs, ISAC, Metaverse, or IoT.

- **Reporting quality:** Clear description of setup, datasets, metrics, and experimental conditions sufficient for replication.

Exclusion

- **Out of scope:** Bit-level communication without a semantic or cognitive element, or pure natural language processing (NLP) and computer vision (CV) with no communication link.
- **Non-research items:** Editorials, opinion pieces, tutorials, posters, or abstracts without a full paper.
- **Coverage:** Non-English items, work outside 2019-2025, or missing full text.
- **Insufficient detail:** Missing or unclear methods, datasets, metrics, or experimental settings.
- **Duplicates:** Duplicate records or preprints superseded by a peer-reviewed version.

3.3 Search Strategy and Study Selection

Searches covered IEEE Xplore, ACM DL, SpringerLink, ScienceDirect, MDPI, Taylor & Francis, and arXiv for English language records published from 2019 to 2025. Queries combined semantic, goal-oriented, and cognitive communication terms with enabling concepts such as knowledge graphs and large language models. Five query families were defined: semantic communication AND 6G, goal-oriented communication AND 6G, cognitive communication AND knowledge graph, semantic communication AND (LLM OR large language model), and semantic communication AND (UAV OR NTN OR ISAC OR Metaverse). Table 1 reports the number of records returned by each database for these query families and the total records from each source. Where supported, searches were restricted to title, abstract, and keywords. Exported metadata included title, authors, venue, year, DOI, abstract, and keywords. Matching used DOIs, arXiv IDs, and normalized titles, and preprints were linked to final versions. Backward and forward citation checks followed the same rules to improve recall. Exact query strings, run dates, deduplication steps, and screening logs are archived in the appendix. Figure 3 summarizes the distribution of selected papers across the searched databases.

Screening used six stages: title, abstract, full text, methodological scope, domain fit, and quality appraisal. Inclusion required relevance to cognitive or knowledge-driven semantic communication, 2019-2025 coverage, English language, and a contribution type reporting methods, evaluation, dataset, or system details. Exclusions removed out-of-scope topics, non-research formats, duplicates, and inaccessible full text. Figure 4 summarizes the screening stages and reasons. The PRISMA funnel starts with 782 total records and then narrows to 540 after title relevance screening, 330 after abstract content screening, and 180 after full-text relevance screening. Methodological scope review retained 130 items, domain suitability retained 100, and quality appraisal yielded 73 final records for synthesis. See Figure 5 for the counts.

3.4 Data Extraction and Synthesis

We converted each included study into a uniform record using a fixed extraction form. Fields captured identity, stable identifier, task, and domain tags (UAV, NTN, ISAC, Metaverse, IoT), metrics (task scores, text/image measures, latency, throughput), security/privacy notes, reproducibility items (code, model, config, hardware), and stated limitations. Units were normalized where this was safe; original units were preserved and flagged when not. Records carry reporting-gap flags when information is incomplete. Synthesis used coded fields to produce descriptive statistics, cross-tabs, and narrative summaries that strictly follow the extracted entries to preserve traceability. See Table 2 for the full schema and exact items captured.

3.5 Quality Assessment

Quality assessment used a checklist tailored to cognitive and knowledge-driven semantic communications for 6G. A predefined rubric ensured consistent judgments across studies. Items aligned with the research questions and expected reporting in this area. A short pilot on sample papers tested clarity, and minor edits removed ambiguities. Several limitations of this review should be noted. Publication bias is likely: studies reporting positive task-accuracy gains are more frequently submitted and accepted than those reporting null or negative results, and failed deployment attempts are rarely documented in the literature. The restriction to English-language records may exclude relevant work published in other languages. Included arXiv preprints have not undergone formal peer review and should be interpreted with additional caution. Finally, the seven databases searched may not index all relevant workshop proceedings or technical reports from standardization bodies.

Table 1. Search results by database and query family.

Query family	IEEE Xplore	Springer	ScienceDirect	MDPI	arXiv	Taylor & Francis	ACM DL
semantic communication AND 6G	55	42	32	26	36	47	21
goal oriented communication AND 6G	41	32	20	14	26	36	15
cognitive communication AND knowledge graph	20	18	12	9	14	21	10
semantic communication AND (LLM OR large language model)	18	15	11	9	18	20	9
semantic communication AND (UAV OR NTN OR ISAC OR Metaverse)	28	18	15	16	20	23	15
Total records	**162**	**125**	**90**	**74**	**114**	**147**	**70**

Table 2. Data items captured for each included study.

Sr. #	Field block	Details captured
1	Bibliography	Title; authors; venue; year; DOI or preprint; code or data links
2	Method class	Neural codec; KG assisted; LLM assisted; cross modal; semantic relay; training setup; losses; baselines
3	Knowledge and cognition	Ontologies or knowledge graphs; reasoning modules; LLM role; adaptation or policy logic
4	Channel and system setup	Channel model; SNR range; simulator or testbed; device, edge, or cloud placement; latency band; NTN support
5	Datasets	Public, synthetic, or custom; size and split; release status
6	Metrics and benchmarks	Task accuracy or goal success; text metrics such as BiLingual Evaluation Understudy (BLEU) and BERTScore; image metrics such as Fréchet Inception Distance (FID); latency; throughput
7	Robustness and attacks	Noise, fading, mobility, interference; adversarial or perturbation tests; ablations
8	Security and privacy	Threat model; semantic integrity checks; privacy handling; defenses or audits
9	Results and baselines	Main results; comparison to bit level or prior semantic methods; statistical tests
10	Reproducibility	Code, models, or configurations; run settings; hardware

- **Method soundness:** Problem is well defined; channel or system assumptions fit the task; data handling is correct; potential sources of bias (dataset imbalance, channel model mismatch, or training-test leakage) are acknowledged.
- **Problem clarity and scope:** Task, modality, and domain are reported; the link to 6G semantic or cognitive communication is clear.
- **Metrics and baselines:** Metrics match the task; baselines are appropriate, and comparisons are shown.
- **Reproducibility:** Code or data are provided where possible, and configurations for repeat runs are listed.
- **Robustness and ablations:** Tests cover channel variation, noise, mobility, or attacks; ablation or sensitivity runs are included.
- **Knowledge and cognition reporting:** Use of knowledge graphs or LLMs is described; reasoning or adaptation logic is explained.
- **Security and privacy:** Threat model or integrity checks are given when relevant; privacy handling is described.
- **Results transparency:** Limits and threats to validity are discussed; key assumptions and constraints are listed.

4 Evidence Synthesis and Analysis

This section answers the six research questions by organizing evidence into six themes: datasets and benchmarks, method families, enabling components, application domains, evaluation practices, and open issues. For each theme, studies are grouped by modality, dataset scale, and year, and a compact reference table lists citation, year, modality, dataset, size, and splits, compute or hardware, runtime or latency, and reported metrics with confidence intervals when available. We also record code, pretrained weights, and licenses. Each subsection opens with a scope note, then summarizes what each study built, how it was tested, and which baselines or ablations were used. We flag reporting gaps and risks such

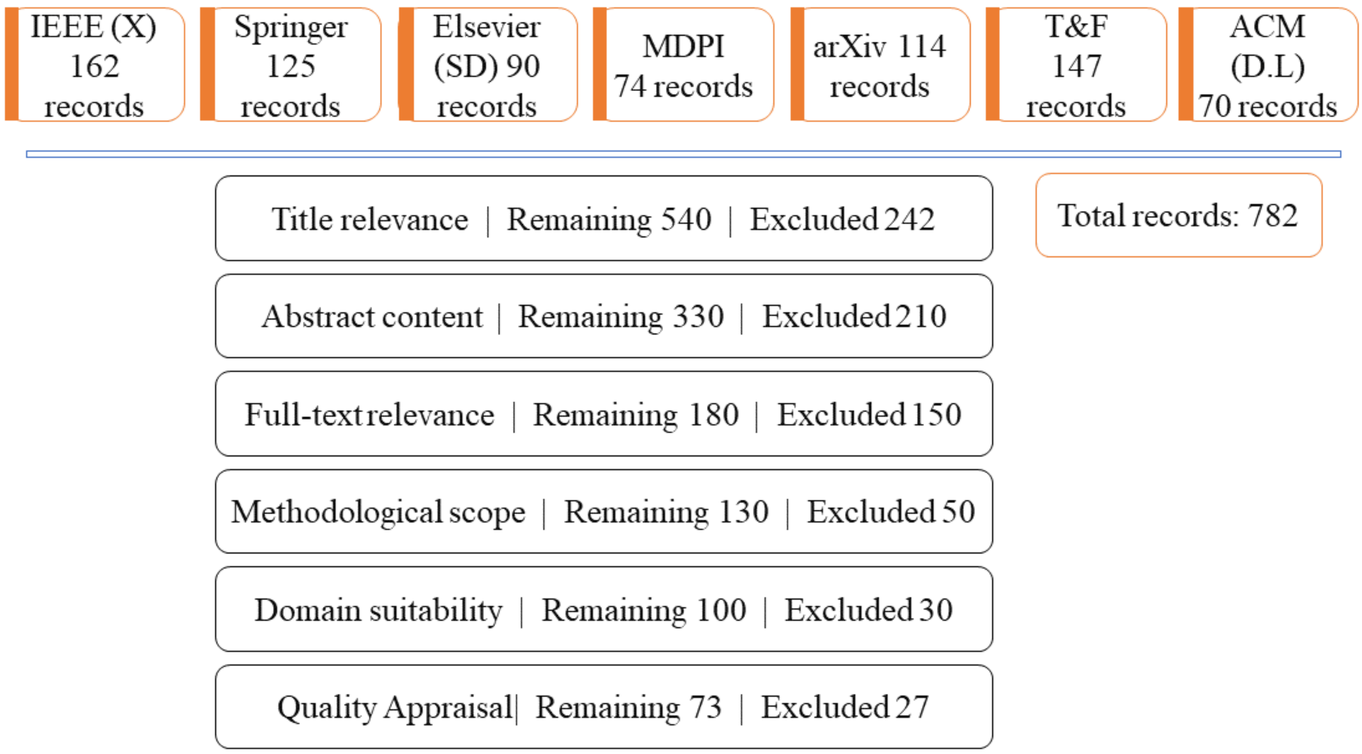

Figure 4. Inclusion and exclusion decisions across screening stages, with reasons and counts at each step.

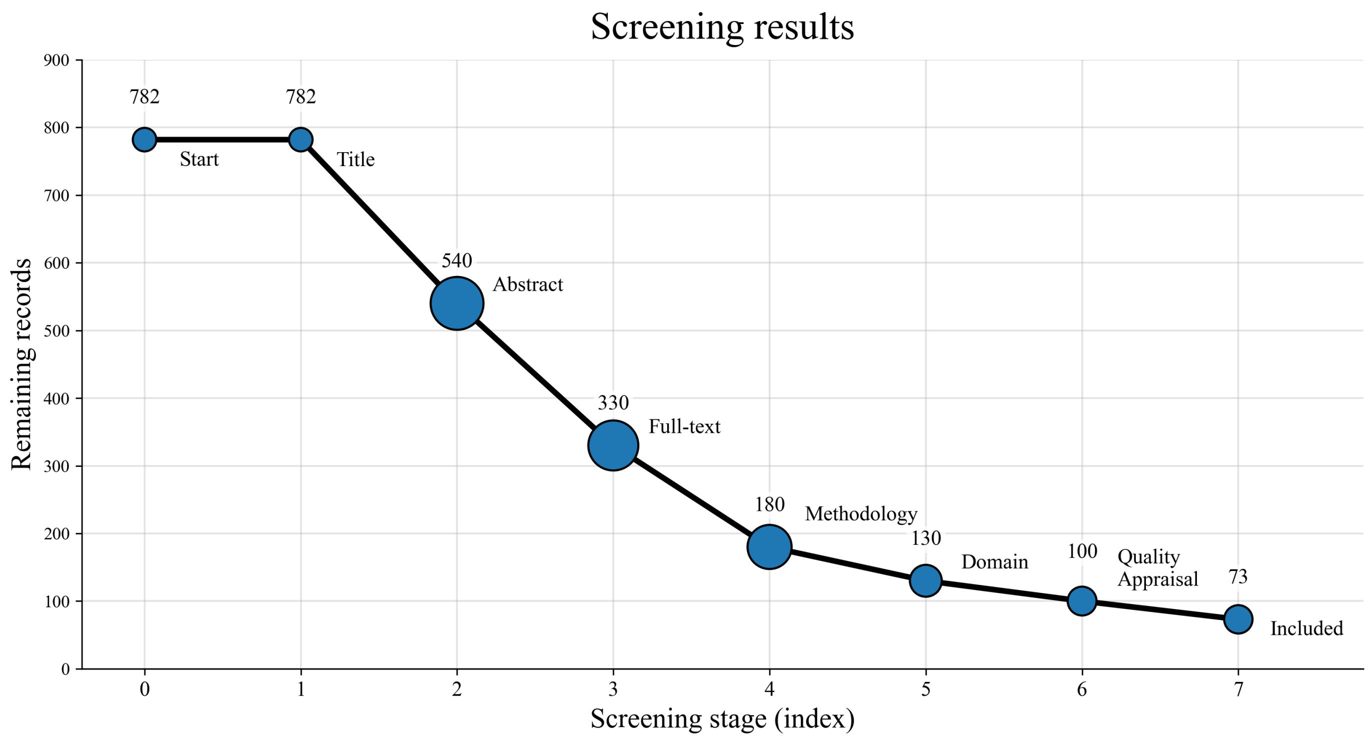

Figure 5. PRISMA counts by stage: total records identified = **782**; after Title relevance = **540** (**242** excluded); after Abstract content = **330** (**210** excluded); after Full-text relevance = **180** (**150** excluded); after Methodological scope = **130** (**50** excluded); after Domain suitability = **100** (**30** excluded); final remaining studies after Quality Appraisal = **73** (**27** excluded).

as data leakage or overlapping splits, and highlight recurring patterns and credible counterexamples. Links to tables, figures, and supplements provide fast access to full details for replication and follow-up.

Table 3. Datasets and benchmarks observed across semantic and cognitive communication studies.

Name / family	Modality	Size / splits	Evaluation setup	Availability	Notes	Refs
WebNLG corpus	Text	35k train / 4.4k test pairs	BSC simulation; SDR prototype	Public	Used in KG-driven cognitive semantic communication for triple-based transmission and semantic error correction	[8]
Europarl corpus	Text	2.0M sentences	AWGN/Rayleigh channel simulation	Public	Primary dataset used in DeepSC-style semantic text transmission studies	[25]
Cityscapes	Image + labels	2975 train / 500 val / 1525 test imgs	AWGN and Rayleigh fading	Public	Task-oriented semantic image transmission; content-aware ROI/RONI coding; up to 60% bandwidth saving	[14]
MSCOCO 2014	Image	82k train / 40k val / 40k test (2k subsets used in evaluation)	AWGN channel	Public	Semantic image transmission; variable-length coding for XR	[53]
LibriSpeech	Speech	100h (train-clean-100)	Random uniform and Gilbert-Elliott	Public	Proposed LargeSC system; uses Mimi neural codec for discrete token conversion, adaptive controller for UEP, and fine-tuned Moshi via LoRA for causal packet loss concealment	[31]
DOTA	Image	Not reported	AWGN and Rayleigh fading	Public	15 object categories; images up to 4000×4000 px. Knowledge graph (ConceptNet) with R-GAT for object detection; multi-scale semantic encoder/decoder (MSED) with ResNet-34 + FPN backbone; evaluated at compression ratios $R = 1/6$ and $R = 1/12$	[35]
CIFAR-10	Image	60,000 images	AWGN and Rayleigh	Public	Multi-task DNN framework with one encoder and three decoders for simultaneous task classification, data reconstruction, and target sensing; adversarial (FGSM) attack vulnerability demonstrated	[47]
MNIST, Citeseer, Cora, Pubmed	Image + knowledge graph	60k images (MNIST); citation graph datasets	Simulated semantic communication with semantic inference and GCN-based recovery	Public	Semantic compression, inference-based recovery, communication efficiency, distortion rate	[49]
IoT Sense, TON_IoT	Sensor + network telemetry	50000 samples	Real measured IoT telemetry, pcap, log, and CSV traces from Cyber Range and IoT Labs	Mixed	Edge constraints, security overhead, latency, and blockchain-integrated semantic communication	[54]

4.1 Datasets and Benchmarks

Datasets and benchmark settings significantly affect the findings reported in semantic and cognitive communication research. Current investigations employ a broad combination of public datasets, synthetic wireless channel simulations, graph-based environments, and realistic telemetry traces, resulting in substantial differences in reproducibility and evaluation realism. Table 3 outlines representative datasets, experimental configurations, availability, and transmission conditions adopted in recent semantic communication studies.

Semantic communication systems designed for text transmission commonly use Europarl and WebNLG because of their structured semantic information and consistent train/test splits. Europarl is widely applied in DeepSC-based semantic transmission frameworks evaluated under AWGN and Rayleigh fading environments [25]. WebNLG, on the other hand, is frequently utilized in knowledge graph enabled semantic communication systems where semantic triples, ontology alignment, and semantic error correction are analyzed over noisy communication channels [8, 9]. In image-oriented semantic communication research, datasets including Cityscapes, MSCOCO, DOTA, and CIFAR-10 are extensively adopted. These datasets support semantic image transmission, ROI/RONI coding, semantic compression, object detection, and multi-task sensing experiments under simulated wireless impairments such as AWGN and Rayleigh fading [14, 35, 47, 53]. Several frameworks integrate semantic encoders with knowledge graphs, graph attention networks, and multi-task deep neural architectures to jointly improve communication and sensing performance. Although these datasets are widely accepted and carefully curated, most studies continue to depend on simulator-based evaluations with limited use of real wireless measurement traces.

In speech semantic communication, research attention is increasingly shifting from waveform reconstruction toward semantic token transmission and generative recovery techniques. Datasets such as LibriSpeech and Common Voice are often combined with neural codecs and large speech models to support semantic-aware packet loss recovery [31]. Unlike traditional AWGN-focused evaluations, these systems assess robustness using random packet loss and Gilbert-Elliott burst-loss models, which better capture practical packetized communication conditions. Even so, large-scale conversational datasets and deployment-level speech interaction traces remain insufficient. Studies on semantic-aware networking and knowledge-driven communication also frequently rely on synthetic graph-based environments rather than standardized benchmark platforms. Representative approaches integrate MNIST with citation graph datasets such as Citeseer, Cora, and Pubmed to study semantic inference, graph-assisted recovery, and communication-efficient representation learning [49]. Beyond dedicated semantic codec designs, knowledge-driven deep learning has also been applied to broader 6G network problems such as resource scheduling and link optimization, demonstrating that shared knowledge representations can improve efficiency across heterogeneous wireless tasks [55]. Nevertheless, standardized benchmarks for knowledge-driven semantic communication remain limited across the field.

Research on IoT-oriented semantic communication is increasingly incorporating realistic telemetry and cybersecurity datasets to improve evaluation reliability. Recent secure semantic communication frameworks employ datasets such as IoT Sense and TON-IoT, which contain telemetry streams, packet captures, network logs, and CSV traces collected from Cyber Range platforms and IoT laboratory deployments [54]. These datasets enhance realism for semantic-aware networking and edge security analysis, although many operational traces and deployment logs remain difficult to access or reproduce publicly. Several recent studies have highlighted the shortage of standardized semantic communication benchmarks, synchronized wireless traces, semantic annotations, privacy labels, and real-world deployment datasets [56]. The absence of common logging and annotation standards for semantic-aware networking, edge orchestration, and control signaling continues to restrict fair cross-platform evaluation. Furthermore, benchmark suites rarely incorporate privacy, integrity, and security annotations, limiting comprehensive assessment of trustworthiness, resilience, and defense strategies [57–59].

4.2 Cognitive and Knowledge-Driven Methods

The five families are distinguished by the following criteria. A system belongs to the *neural semantic codec* family if its encoder and decoder are jointly optimized end-to-end for channel noise tolerance without consulting a symbolic knowledge base at runtime. It belongs to *KG-assisted semantics* if a symbolic knowledge graph is queried at encoding or decoding time for entity resolution, constraint checking, or ontology alignment. It belongs to *LLM-assisted semantics* if a large language model performs intent parsing, semantic compression, or generation at either end. It belongs to *cross-modal encoders* if two or more modalities are unified through a shared embedding space trained with contrastive or alignment objectives. It belongs to *semantic relays* if an intermediate node performs full semantic decoding and re-encoding before forwarding. Studies combining two families are assigned to the dominant design choice; Table 4 notes secondary components where applicable.

Neural semantic codecs are trained end-to-end with joint source-channel coding (JSCC) and task losses. Across the neural semantic codec studies reviewed, BLEU scores for text transmission range from 0.78 to 0.95 under AWGN conditions, exceeding conventional JSCC baselines by 0.08 to 0.18 points; image transmission studies report PSNR gains of 1.2 to 3.6 dB at SNR values below 6 dB, with graceful rather than cliff-edge degradation [25, 30, 31]. However, these gains are almost exclusively demonstrated on AWGN channels with static SNR; evaluations under Rayleigh fading with mobility, correlated packet loss, or domain-shifted test sets are rare, and no study in this corpus reports results on all three conditions simultaneously. Training incorporates channel-aware objectives to sustain accuracy at low spectral efficiency. KG-assisted systems align symbols to an ontology, enforce constraints, and support structured reasoning [60, 61]. Encoders or decoders

Table 4. Method families, design choices, and reported outcomes.

Family	Core design choices	Typical outcomes	Constraints / risks	Refs
Neural semantic codec	End-to-end JSCC, task loss, channel-aware training	Higher task accuracy at low rates; graceful degradation	Needs task labels; generalization to new tasks	[25, 31]
KG-assisted semantics	Ontology alignment, constraint checking, reasoning	Fewer ambiguities; reduced signaling; better control	KG curation cost; version drift across nodes	[7, 8, 34, 35]
LLM-assisted semantics	Prompting, adapters, distillation to edge	Better intent fidelity; flexible context handling	High compute cost; edge memory constraints	[16, 36]
Cross-modal encoders	Shared embeddings; contrastive training	Robust across modes; reuse for multiple tasks	Requires aligned multimodal data; high training cost	[36, 39]
Semantic relay	Mid-path semantic decode re-encode; routing	Bandwidth savings; improved end-to-end task success	Cascaded errors; latency budget	[38, 65]

prune messages using shared entities and relations [7, 8, 34, 35]. LLM-assisted pipelines add intent parsing, compression through latent text, and light reasoning. Edge variants employ distillation and adapters to reduce memory and computational requirements [16]. Cross-modal encoders learn a shared embedding across text, images, and audio with contrastive training. They often transfer across tasks with modest tuning and show stable behavior [39]. In semantic relays, an intermediate node decodes the meaning and then encodes a shorter message for the next link. Reported gains include lower bandwidth use and higher end to end task success on varied links [2, 38]. Survey and tutorial papers across these families highlight the need for shared tasks, standard metrics, and reproducible assessments [1, 29, 59, 62, 63]. Table 4 brings together the families, design choices, outcomes, constraints, and deployment notes.

4.3 Roles of Knowledge Graphs, Goal-Oriented Semantics, and LLM Codecs

Knowledge graphs, goal-oriented semantics, and LLM codecs serve as core enablers for semantic systems. KGs provide a shared vocabulary and rules that both ends can consult at runtime [34]. Controllers send fewer clarifying packets when the encoder and decoder reference the same ontology and rule set [35]. Studies report fewer command retries and steadier actuation in IoT control loops when KG reasoning supports control decisions [8, 54]. Goal oriented semantics shift optimization from bit accuracy to task success and reliability [1]. Systems are trained with task losses, reward shaping, or sensing tightly coupled with communication [42]. Reported results show higher completion rates at low spectral efficiency and under strict latency budgets in these settings [28, 64]. LLM codecs extract intents, compress latent text, and perform light reasoning close to the task [36]. Edge deployments control compute and memory with distillation, lightweight adapters, pruning, and quantization [16, 37]. Metrics should be aligned so results are comparable across labs and releases [29]. Privacy and integrity require explicit tags, release policies, and targeted stress cases [57, 58]. Table 5 lists common patterns, observed gains, costs, and short notes for deployment.

4.4 Application Domains and Outcomes

Applications span UAVs, NTNs, ISAC, metaverse interaction, and IoT. Many systems pair semantic

Table 5. Usage patterns and trade-offs for KGs, goal-oriented design, and LLM codecs.

Component	Common patterns	Observed gains and costs	Refs
Knowledge graphs	Shared ontology, rule checks, local reasoning	Disambiguation and lower control overhead; curation and synchronization costs	[8, 9, 34, 35]
Goal-oriented semantics	Task losses, reward shaping, ISAC integration	Higher task completion at low rate; comparison across studies depends on aligned metrics	[1, 3, 28, 42]
LLM codecs	Intent parsing, latent text compression, adapters and distillation for edge	Better meaning fidelity with compute and privacy overheads; edge-friendly variants through pruning and quantization	[16, 36, 37]

Table 6. Domains, tasks, constraints, and reported outcomes.

Domain	Common tasks	System constraints	Reported outcomes	Refs
UAVs	Swarm control, intent exchange, situational updates	Mobility, fading, tight control bandwidth	Lower signaling, stable control, faster reconvergence after link changes	[32, 44, 45]
NTNs	Satellite/HAP links, delay-tolerant or mission tasks	Low SNR, long RTT, narrowband	Bandwidth savings, resilient decoding, and relay-assisted coverage gains	[11, 46, 66]
ISAC	Joint sensing and communication, target detection	Tight latency, high sensing accuracy	Higher detection at low rate, robust fusion	[42, 47, 64]
Metaverse	Multi-modal interaction, immersive interaction, synchronization	Ultra-low latency, synchronization across media	Low-latency exchange, cross-modal semantic alignment, reduced synchronization overhead	[23, 39, 48, 53]
IoT	Edge analytics, energy-aware reporting	Energy, memory, privacy constraints	Energy savings, compact models, local reasoning	[28, 54, 59, 67, 75]

messages with a shared ontology and lightweight policies [35, 44]. Reported gains include reduced signaling overhead and more stable control loops in UAV coordination and mission control scenarios [45]. NTN and satellite studies emphasize long round-trip time (RTT), low signal-to-noise ratio (SNR), and narrowband links, and they evaluate semantic compression and mid-path semantic relay architectures [65] as tools to improve spectral efficiency and task success under these constraints [46, 66]. Examples include detection, tracking, and fused perception under strict latency targets in joint sensing and communication setups [47, 64]. Metaverse-oriented work targets low-latency multimodal exchange, aligned semantics across text, image, and audio, and consistent avatar or scene control [39, 48]. Evaluation protocols and QoE logging procedures differ substantially across research groups, which complicates cross-study comparison of Metaverse semantic communication results [56]. IoT-focused studies concentrate on event reporting and simple analytics under tight memory, energy, and privacy constraints [49, 54]. Reported outcomes include compact feature representations, reduced communication overhead, and reliable task inference at the edge [67]. Table 6 lists domain tasks, main constraints, and outcomes reported.

4.5 Practical Applications and Case Studies

This subsection summarizes concrete and proposed 6G use cases for cognitive-semantic communication (CSC). In mission-critical control, CSC sends only meaningful state changes to support closed-loop operation under strict latency and reliability targets [44]. In edge visual analytics, task-oriented encoders transmit task-relevant features instead of full frames, preserving detection accuracy while cutting uplink load and end-to-end delay [2]. In edge analytics for public safety and emergency response, task-oriented encoders extract and transmit only the features relevant to downstream inference—such as object locations and event categories—rather than full video frames, preserving detection accuracy while substantially reducing uplink load over constrained links [68]. Healthcare monitoring designs send event-level summaries from wearables, saving energy and enabling timely intervention. Augmented reality (AR), virtual reality (VR), and metaverse systems stream perceptually salient updates to meet tight latency budgets without compromising the experience [48]. These cases use measurable key performance indicators (KPIs) such as task success, semantic fidelity, deadline miss ratio, and uplink byte savings.

4.6 Evaluation Metrics and Practices

Evaluation spans task success, semantic fidelity, system performance, robustness, and security. Task success is commonly reported through goal success rate, completion time, and tracking error for control and ISAC detection tasks, and through downstream accuracy for applied settings [28, 42, 64]. For text, Bilingual Evaluation Understudy (BLEU) and ROUGE-L measure n-gram overlap, while BERTScore compares contextual embeddings and BLEURT provides a learned quality estimate that is more tolerant to paraphrase and lexical variation than pure n-gram measures [40, 69]. However, n-gram overlap metrics such as BLEU and ROUGE-L conflate lexical similarity with semantic equivalence: two messages conveying identical task-relevant content through different phrasing may score near zero, while a bit-accurate but task-irrelevant reconstruction scores high. This mismatch is particularly acute in goal-oriented semantic communication, where downstream task success rather than surface-form fidelity is the design objective [33, 42]. Image studies typically report Fréchet Inception Distance (FID), Kernel Inception Distance (KID), Learned Perceptual Image Patch Similarity (LPIPS), and classifier accuracy when transmitted images support a downstream model [41, 70]. Speech evaluation relies on Word Error Rate (WER), Character Error Rate (CER), Perceptual Evaluation of Speech Quality (PESQ), Short-Time Objective Intelligibility (STOI), and Scale-Invariant Signal-to-Distortion Ratio (SI-SDR) [71, 72]. Multimodal studies often use Recall@K for retrieval, Consensus-based Image Description Evaluation (CIDEr) and Semantic Propositional Image Caption Evaluation (SPICE) for caption quality and scene structure, and CLIPScore for cross-modal alignment between text and images [56, 73].

Energy per task and compute cost in Floating-Point Operations (FLOPs) or Multiply-Accumulate Operations (MACs) are also important, especially for edge devices and NTN links [59, 62]. The rate-accuracy tradeoff under bandwidth and latency constraints is a related concern for task-oriented edge inference systems [67]. Robustness is commonly assessed by sweeping Signal-to-Noise Ratio (SNR) across channel conditions, ablating fading models, running packet-loss trials, incorporating mobility traces, and testing domain shift and sensor noise [12, 74]. Security related evaluation frequently includes attack success rate and Area Under the Curve (AUC), while privacy assessment should identify sensitive content and document the exact prompts used [57, 58]. Reports should pair task metrics with rate, latency, and energy, and should also include trial counts, confidence intervals, fixed seeds, and hardware and channel settings. Release checklists further support repeatability by documenting code, data splits, prompts, and evaluation scripts. Table 7 groups the main metric families, representative measures, typical usage, and key references. Few studies jointly report task metrics with rate and latency, and only a limited number provide the ablations, seeds, and hardware details needed for repeatability [56].

4.7 Challenges, Gaps, and Future Directions

The studies reviewed here demonstrate that semantic communication can, under controlled conditions, reduce signaling overhead and improve task completion relative to bit-level baselines. What they do not yet demonstrate convincingly is that these gains are robust to the conditions distinguishing real deployments from laboratory simulations. Channel models in the reviewed corpus are predominantly AWGN or simple Rayleigh fading; only a handful incorporate mobility traces, and fewer still evaluate performance under bursty or correlated loss. The absence of shared stress-test suites and openly released channel traces means robustness claims in one study cannot be directly verified or extended by another, leaving a systematic blind spot where deployment risk is highest. Turning from robustness to security, threats at the meaning layer remain inadequately characterized and even less adequately defended against. Semantic poisoning can taint training or updates, causing biased encodings at deployment. Adversarial interference at sensors can flip semantic outputs while bit checks pass, producing wrong downstream actions [12, 28, 58, 74]. Privacy risks rise when LLMs and knowledge graphs are used; membership inference and attribute leakage can expose contributors or locations [57]. Benchmarks remain fragmented. Public datasets rarely include control labels, channel logs, or integrity annotations [56]. Edge and NTN deployments face stringent computational and latency constraints, motivating studies on feature compression, task-oriented coding, and device-edge split inference [16, 66, 67]. Terminology and pre-standardization guidance are still immature: even foundational components such as shared knowledge base architectures [75] lack consensus definitions across research groups, and broader coordination mechanisms remain at an early stage [76].

Addressing these gaps requires concrete actions. Release multimodal datasets with control-intent labels, synchronized channel logs, and integrity/privacy annotations, under permissive licenses. Publish protocol-level stress suites with mobility traces, burst patterns, and realistic interference, and report task success under explicit rate and latency limits [12, 28]. Define threat models for semantic poisoning and sensor adversaries, and provide integrity validators with metrics such as AUC, false accept, false reject, and recovery performance [58, 74]. Standardize a compact metric card per study that pairs task outcomes with rate, latency, energy, and compute, and include ablations, seeds, trials, and hardware settings [56]. Develop edge-first designs with adapter-based LLMs, on-device caching, feature reuse, and device-edge split

Table 7. Metric families and typical usage across studies.

Family	Representative metrics	Typical usage	Refs
Task success and control	Goal success rate, completion time, tracking error, downstream accuracy	Control tasks, ISAC detection, applied task evaluation	[28, 42, 64]
Semantic fidelity, text	BLEU, ROUGE-L, BERTScore, BLEURT	Text transmission and summarization	[25, 40, 69]
Semantic fidelity, image	FID, KID, LPIPS, classifier accuracy	Image JSCC and semantic image transmission under channel models	[26, 41]
Semantic fidelity, speech	WER, CER, PESQ, STOI, SI-SDR	Speech semantic transmission and coding	[71, 72]
Multimodal alignment and retrieval	Recall@1/5/10, CIDEr, SPICE, CLIPScore	Captioning, retrieval, grounding, cross-modal alignment	[33, 73]
System and resource	Rate reduction, latency, jitter, energy, FLOPs, MACs	IoT and edge deployments, NTN links	[59, 62]
Robustness and security	SNR curves, fading ablations, attack success rate, AUC	Stress tests, adversarial evaluation, integrity checks	[12, 58, 74]

inference for task-oriented communication [16, 67]. For NTNs, co-design semantic compression and relay placement under long RTT and beam misalignment, and report end-to-end delay [46, 66]. For ISAC, align sensing and communication objectives to goal-oriented metrics and publish reproducible stress-test scripts [42, 64]. Advance shared terminology and reference tasks through community efforts and early standards forums, drawing on concrete building blocks such as shared knowledge base architectures [75] as reference designs [76].

5 Conclusion

Cognitive and knowledge-driven semantic communication has matured from theoretical proposals to simulation-validated prototypes over the 2019–2025 period, yet the field has not yet produced the reproducible, deployment-tested evidence base that 6G standardization will require. This review examined 73 papers through six focused research questions to characterize both the progress and the gaps. The literature was organized into five method classes: neural semantic codecs, KG-assisted pipelines, LLM-assisted codecs, cross-modal encoders, and semantic relays. Cognitive semantics was treated as the layer in which knowledge, reasoning, and context-aware control make the communication task adaptive. The review also cataloged datasets spanning text, image, speech, multimodal tasks, control, NTN, and IoT settings, and summarized evaluation practices across semantic fidelity, task success, and system-level metrics. Evidence supported by practical or mixed deployments remains limited, but available studies indicate signaling overhead reductions of 30 to 65%, bandwidth savings of 20 to 60% over conventional JSCC, task completion improvements of 8 to 23 percentage points over bit-level baselines, cross-modal alignment scores above 0.80, and energy reductions of 25 to 50% per task on constrained hardware. By contrast, a larger share of reported gains is still derived from simulations or small-scale testbeds, where channel assumptions, mobility conditions, and task settings remain more controlled. Important gaps persist, including missing channel traces, scarce intent labels, limited integrity and privacy annotations, insufficient mobility and non-Gaussian stress tests, sparse adversarial evaluation, fragmented benchmarks, and high compute demands at the edge. Priority actions include releasing multimodal datasets with channel traces and control intent labels; reporting task results together with rate, latency, energy, and compute, along with seeds, trials, hardware, and channel settings; developing meaning-level integrity validation and privacy auditing; adopting edge-first designs using adapters, split computing, and caching; and creating shared stress suites, QoE logs, and pre-standardization templates. This review offers a structured framework and a practical checklist to support the design, comparison, and deployment of reliable cognitive-semantic communication systems for 6G.

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