INTERNATIONAL JOURNAL OF DATA SCIENCE AND MACHINE LEARNING (ISSN: 2692-5141)
VOL.06 ISSUE 02 (2026)

Research Article

AI-Driven Semantic Frameworks for Sustainable Decision Intelligence

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Received: 25 May 2026
Revised: 20 June 2026
Accepted: 15 July 2026
Published: 21 August 2026

Doi:10.55640/ijdsml-06-02-05

Page No: 131-139

Abstract

The increasing complexity of organizational, environmental, and socio-technical decision environments has created a need for intelligent systems capable of integrating heterogeneous information, identifying contextual relationships, and supporting decisions that balance operational objectives with long-term sustainability. This paper examines AI-driven semantic frameworks as an architectural approach for sustainable decision intelligence, with particular emphasis on semantic representation, contextual learning, multi-task learning, domain adaptation, and lightweight natural language processing. The study adopts a conceptual research-and-review methodology based exclusively on the supplied literature. The reviewed studies provide complementary theoretical foundations: parsing research demonstrates structured linguistic representation, multi-task learning explains how related tasks can share useful information, large language models illustrate scalable semantic inference, and domain-oriented tuning demonstrates mechanisms for adapting AI systems to heterogeneous contexts. These foundations are synthesized into a conceptual semantic decision framework comprising data interpretation, semantic representation, contextual reasoning, adaptive learning, decision synthesis, and sustainability-oriented evaluation layers. The analysis indicates that semantic intelligence can improve decision consistency by connecting heterogeneous information according to contextual meaning rather than treating individual observations independently. However, challenges remain regarding domain transfer, interpretability, computational efficiency, task interference, and the absence of explicit sustainability objectives within many existing AI learning paradigms. The paper therefore positions semantic AI as an enabling infrastructure rather than an autonomous decision-maker and proposes a research direction in which semantic representations, adaptive learning, and sustainability constraints are integrated into a unified decision architecture.

Keywords: Artificial Intelligence; Semantic Intelligence; Sustainable Decision-Making; Decision Intelligence; Natural Language Processing; Multi-Task Learning; Domain Adaptation; Contextual Reasoning; AI Infrastructure; Sustainability Analytics.

INTRODUCTION

Organizations increasingly operate in decision environments characterized by heterogeneous information, multiple competing objectives, and rapidly changing contextual conditions. Conventional analytical systems generally process structured variables according to predefined rules, whereas contemporary decision environments contain substantial amounts of linguistic, contextual, and domain-specific information. Consequently, sustainable decision intelligence requires more than prediction accuracy: it requires mechanisms capable of representing relationships among information sources, transferring knowledge across related tasks, adapting to domains, and maintaining meaningful contextual interpretations.

Artificial intelligence provides several mechanisms that can contribute to this objective. Natural language processing research demonstrates that linguistic inputs can be transformed into structured representations through parsing and tagging, allowing systems to identify relationships that are not directly available in raw textual form (Amini & Cotterell, 2022). At the same time, multi-task learning provides a theoretical basis for learning related decision-relevant tasks jointly rather than constructing completely independent models. Bingel and Søgaard (2017) show that task relationships influence the benefits obtained from multi-task learning, indicating that effective knowledge sharing depends on the compatibility between tasks.

The emergence of large language models further expands the potential for semantic decision systems. Brown et al. (2020) demonstrate the ability of large-scale language models to perform multiple language-related tasks with limited task-specific examples. Such capabilities are particularly relevant for decision environments in which information is heterogeneous and explicit supervision is expensive. However, generalized language capability alone does not guarantee reliable sustainability-oriented decision intelligence. A semantic decision framework must also account for domain differences and contextual variation.

Domain adaptation and parameter-efficient approaches provide additional foundations for such systems. Chen et al. (2022) investigate lightweight tuning for low-resource named entity recognition, while Chen et al. (2023) examine collaborative domain-prefix tuning for cross-domain named entity recognition. These studies demonstrate that semantic models can be adapted to different domains without necessarily rebuilding an independent architecture for every application.

Recent work specifically connects semantic AI infrastructure with sustainable decision intelligence, emphasizing the importance of an infrastructure-level perspective for integrating semantic processing and sustainable decision support (Goyal, 2025). This perspective motivates the central premise of the present paper: sustainable decision intelligence should be designed as a layered semantic system in which information is interpreted, contextualized, adapted, and evaluated before being transformed into decision recommendations.

The objective of this paper is therefore to develop a conceptual framework explaining how AI-driven semantic mechanisms can support sustainable decision intelligence. The study focuses on the theoretical integration of semantic parsing, multi-task learning, large-scale language modeling, domain adaptation, and contextual feature extraction. Its scope is conceptual rather than empirical; the findings represent an analytical synthesis of the supplied literature rather than results from a newly collected experimental dataset.

LITERATURE REVIEW

2.1 Semantic Representation and Structured Interpretation

Semantic decision intelligence begins with the ability to transform unstructured information into representations that can be processed systematically. Parsing research provides an important theoretical foundation for this transformation. Amini and Cotterell (2022) examine parsing as tagging, demonstrating a perspective in which syntactic analysis can be formulated through sequence-based tagging mechanisms. For decision intelligence, this suggests that complex linguistic information can be converted into structured representations that downstream reasoning mechanisms can process.

The importance of structured representation is also evident in classical parsing research.

Collins (1997) investigates generative lexicalized models for statistical parsing, demonstrating the relevance of lexical and structural information in syntactic interpretation. Cocke (1969) provides an earlier computational foundation for programming-language processing and compilation, illustrating the broader importance of formal representations and systematic processing structures.

These contributions establish a conceptual distinction between raw information and decision-ready information. Raw textual content may contain entities, relationships, qualifications, and contextual signals, but semantic processing is necessary to make those relationships computationally accessible. Cui et al. (2022) extend this perspective by investigating non-local features for neural constituency parsing, highlighting the importance of information that may occur beyond immediate local contexts.

2.2 Multi-Task Learning and Knowledge Sharing

Sustainable decision intelligence frequently involves multiple related tasks. For example, an organization may simultaneously classify risks, identify entities, extract relevant events, assess contextual conditions, and generate decision-support information. Treating each task independently can duplicate computational resources and prevent useful information sharing.

Bingel and Søgaard (2017) demonstrate that the effectiveness of multi-task learning depends on relationships among tasks. Their findings are particularly important for semantic decision frameworks because indiscriminate task sharing can be counterproductive. A sustainable AI architecture should therefore distinguish between related tasks that can benefit from shared representations and unrelated tasks where parameter sharing may introduce interference.

Crawshaw (2020) provides a broader survey of multi-task learning with deep neural networks, reinforcing the theoretical role of shared learning as a mechanism for exploiting common structure. Within decision intelligence, shared representations can potentially connect different information-processing activities while reducing the need for isolated models.

2.3 Large Language Models as Semantic Infrastructure

Brown et al. (2020) demonstrate the capacity of large language models to perform multiple tasks through large-scale pretraining and few-shot learning. This represents a significant conceptual shift from narrowly optimized task-specific systems toward more generalized semantic processing architectures.

For sustainable decision intelligence, generalized models may provide a common semantic layer capable of processing multiple forms of textual evidence. However, generality creates an important limitation: a model that performs broadly across language tasks may not automatically understand the operational definitions, domain constraints, or sustainability criteria of a particular decision environment.

Thus, large language models should be considered a semantic processing component rather than a complete decision architecture. Their outputs require contextual adaptation, task-specific controls, and explicit evaluation criteria.

2.4 Domain Adaptation and Contextual Specialization

Cross-domain variability is a major challenge for semantic decision systems. Chen et al. (2022) address low-resource named entity recognition through a lightweight tuning paradigm, while Chen et al. (2023) investigate collaborative domain-prefix tuning for cross-domain named entity recognition. Together, these studies suggest that semantic systems can be specialized through relatively targeted adaptation mechanisms.

This principle is highly relevant to sustainability because sustainability-related decisions vary substantially across sectors. The meaning of risk, efficiency, resource utilization, or environmental impact can differ according to operational context. A semantic framework therefore needs to preserve general knowledge while allowing controlled adaptation to domain-specific requirements.

2.5 Research Gap and Theoretical Positioning

The supplied literature provides strong foundations for individual components of semantic intelligence, but it does not itself establish a unified architecture connecting these components to sustainability-oriented decision processes. Parsing focuses on structured linguistic representation; multi-task learning focuses on relationships among tasks; large language models focus on generalized language capabilities; and domain adaptation addresses contextual specialization.

The research gap consequently lies at the architectural level. A sustainable decision intelligence framework requires these mechanisms to operate as interconnected components rather than isolated techniques. Goyal (2025) provides a direct conceptual link between semantic AI infrastructure and sustainable decision intelligence, reinforcing the relevance of treating semantic capabilities as infrastructure for decision support rather than merely as individual NLP functions.

The theoretical position adopted in this paper is therefore that semantic decision intelligence emerges from the interaction of representation, contextual learning, adaptive specialization, and decision-level evaluation.

METHODOLOGY

This study employs a conceptual research-and-review methodology. Rather than conducting a new empirical experiment, the methodology synthesizes the theoretical and technical principles represented in the supplied references and organizes them into an integrated framework for AI-driven sustainable decision intelligence.

3.1 Framework Architecture

The proposed framework consists of six logically connected layers: semantic data acquisition, semantic representation, contextual reasoning, adaptive learning, decision synthesis, and sustainability evaluation.

The first layer, semantic data acquisition, receives heterogeneous information such as textual reports, operational descriptions, policy documents, incident records, and other decision-relevant content. The primary function is not simply data collection but preservation of contextual meaning.

The second layer, semantic representation, transforms incoming information into computational structures. Parsing and tagging provide an appropriate conceptual foundation because they enable linguistic content to be represented according to identifiable structures and relationships (Amini & Cotterell, 2022). Non-local features can also be incorporated when decision-relevant information is distributed across larger textual contexts (Cui et al., 2022).

The third layer, contextual reasoning, determines how semantic elements relate to one another. A decision system should not interpret an entity or event independently when surrounding information changes its meaning. This layer can employ contextual representations derived from large language models, whose few-shot capabilities demonstrate the feasibility of generalized language understanding (Brown et al., 2020).

The fourth layer, adaptive learning, adjusts semantic representations according to the target domain. Lightweight tuning and domain-prefix approaches provide relevant mechanisms for this function (Chen et al., 2022; Chen et al., 2023). Adaptation should be controlled because unrestricted specialization can reduce generality and increase maintenance complexity.

The fifth layer, decision synthesis, combines outputs from multiple analytical tasks. Multi-task learning provides a theoretical basis for this layer because related tasks can share information through common representations. However, task relationships must be assessed carefully, as inappropriate sharing may reduce performance rather than improve it (Bingel & Søgaard, 2017).

The sixth layer, sustainability evaluation, introduces explicit decision criteria. This is the layer that distinguishes a general semantic AI system from sustainable decision intelligence. Recommendations should be assessed against multiple dimensions, such as long-term resource efficiency, operational resilience, environmental consequences, and consistency with organizational sustainability objectives. The infrastructure-oriented perspective proposed by Goyal (2025) supports this interpretation by emphasizing semantic AI as a foundation for sustainable decision intelligence.

3.2 Multi-Task Semantic Processing

A central functional component of the proposed framework is joint processing of related semantic tasks. Suppose an industrial organization analyzes a maintenance report. The system may need to identify equipment entities, detect failure events, determine temporal relationships, classify operational risks, and interpret recommended interventions.

An independent-model architecture would treat these activities as separate tasks. A multi-task semantic architecture can instead construct shared representations while retaining task-specific components. The advantage is potentially greater consistency and computational efficiency. Nevertheless, the framework should apply selective parameter sharing because Bingel and Søgaard (2017) demonstrate that task relationships determine whether multi-task learning is beneficial.

Crawshaw (2020) further establishes multi-task learning as a general mechanism for exploiting related task structure. In the proposed framework, task similarity should therefore be treated as an architectural variable rather than an assumption.

3.3 Domain Adaptation Mechanism

A sustainability-oriented system may operate across energy, manufacturing, transportation, finance, agriculture, or public administration. Domain-specific terminology and relationships make direct transfer of a general semantic model unreliable.

The proposed framework addresses this through lightweight adaptation. A generalized model supplies broad semantic capabilities, while domain-specific tuning modifies selected representations for the target context. Chen et al. (2022) demonstrate the relevance of lightweight tuning under low-resource conditions, whereas Chen et al. (2023) provide a basis for collaborative adaptation across domains.

This architecture offers an important sustainability benefit: the system does not necessarily require a completely separate model for every domain. Shared infrastructure can be retained while domain-specific components are introduced only where required.

3.4 Semantic Decision Pipeline

The complete pipeline can be represented conceptually as:

Heterogeneous Data → Semantic Representation → Contextual Interpretation → Multi-Task Reasoning → Domain Adaptation → Decision Synthesis → Sustainability Evaluation

The pipeline is deliberately sequential at the conceptual level but can be implemented iteratively. A decision recommendation may expose semantic ambiguity, requiring the system to revisit representation or domain adaptation. Consequently, sustainable decision intelligence should be regarded as a feedback-oriented architecture rather than a strictly one-directional pipeline.

3.5 Hypothetical Application

Consider a logistics organization deciding whether to modify a transportation schedule. The system receives operational reports containing information about delays, fuel consumption, vehicle availability, weather-related descriptions, and resource constraints. Semantic processing identifies relevant entities and relationships. Contextual reasoning connects individual events across the report. Multi-task learning simultaneously supports event extraction, risk classification, and contextual categorization. Domain adaptation interprets transportation-specific terminology. Finally, the decision layer compares alternatives according to operational efficiency and sustainability criteria.

The value of the framework is not that it automatically makes the decision, but that it provides a structured semantic basis through which decision-makers can evaluate alternatives. This distinction is important because generalized language capability does not eliminate uncertainty or domain-specific judgment.

RESULTS

The conceptual synthesis produces four principal findings.

First, semantic representation is a prerequisite for meaningful decision integration. The reviewed parsing literature demonstrates that linguistic information can be transformed into structured representations rather than being treated as undifferentiated text (Amini & Cotterell, 2022; Collins, 1997). Non-local contextual information is also important because decision-relevant meaning may depend on relationships extending beyond adjacent linguistic units (Cui et al., 2022). Therefore, sustainable decision intelligence should process relationships and context rather than relying exclusively on isolated keywords.

Second, multi-task learning provides a mechanism for integrating complementary analytical functions. The literature indicates that related tasks can benefit from shared representations, but the relationship among tasks determines whether joint learning is advantageous (Bingel & Søgaard, 2017). Crawshaw (2020) reinforces the broader value of multi-task architectures. The implication is that semantic decision systems should use selective task sharing instead of assuming that all sustainability-related tasks are inherently compatible.

Third, generalized language models increase semantic flexibility but require contextual controls. Brown et al. (2020) demonstrate the broad capabilities obtainable from large-scale language modeling. However, generalized semantic capability is insufficient for reliable domain-specific sustainability decisions. Domain adaptation mechanisms examined by Chen et al. (2022) and Chen et al. (2023) indicate that targeted specialization can address this problem while retaining reusable model infrastructure.

Fourth, sustainability must be incorporated at the decision layer rather than assumed to emerge from AI capability. A model may accurately extract information or classify events without producing sustainable recommendations. Consequently, sustainability criteria need explicit representation within the decision-evaluation mechanism. The infrastructure perspective connecting semantic AI and sustainable decision intelligence is therefore significant because it frames semantic capabilities as enabling infrastructure for broader decision objectives (Goyal, 2025).

Collectively, these findings support a layered architecture in which semantic interpretation, contextual learning, adaptive specialization, and sustainability evaluation operate together. The framework is theoretically coherent with the supplied literature, but empirical validation is still required to determine whether the proposed integration improves decision quality, resource efficiency, interpretability, or sustainability outcomes in operational environments.

DISCUSSION

The findings indicate that AI-driven semantic frameworks can provide a stronger foundation for sustainable decision intelligence when they are designed as integrated architectures rather than isolated NLP applications. The most important theoretical implication is that decision intelligence depends on the quality of intermediate semantic representations. If information is poorly represented at the beginning of the pipeline, subsequent reasoning and recommendation stages inherit that deficiency. The progression from parsing and structured representation toward contextual modeling is therefore not merely a technical optimization; it represents a fundamental requirement for meaningful AI-assisted decision support.

A second implication concerns the balance between generalization and specialization. Large language models demonstrate substantial general semantic capability (Brown et al., 2020), while domain-specific tuning demonstrates the necessity of adapting that capability to specialized environments (Chen et al., 2022; Chen et al., 2023). These approaches are complementary rather than mutually exclusive. Generalized models can provide reusable semantic infrastructure, whereas lightweight domain adaptation can provide contextual precision. The trade-off is that additional adaptation introduces maintenance requirements and may create inconsistencies among domain-specific versions.

Multi-task learning introduces another trade-off. Shared representations can reduce duplication and promote information transfer, but Bingel and Søgaard (2017) demonstrate that task relationships influence whether sharing is beneficial. For sustainable decision intelligence, this means that architectural efficiency should not be pursued at the expense of task compatibility. A system simultaneously processing risk, resource utilization, event extraction, and contextual classification should establish which tasks genuinely share semantic structure.

The proposed framework also exposes a critical limitation in current conceptual approaches: semantic intelligence and sustainability are not equivalent concepts. Semantic understanding can improve information processing, but sustainability requires normative and evaluative criteria. A technically accurate model could still recommend a decision that is economically efficient but environmentally undesirable. Accordingly, sustainability objectives must be explicitly represented in the decision-evaluation layer rather than inferred solely from linguistic or predictive performance.

The framework also has implications for interpretability. Parsing-based representations and explicit task structures potentially offer more inspectable intermediate states than an entirely opaque end-to-end recommendation system (Amini & Cotterell, 2022).

However, large-scale language models may introduce uncertainty regarding how semantic conclusions are generated. A practical implementation should therefore preserve intermediate evidence, contextual relationships, and decision criteria so that human decision-makers can examine why a recommendation was produced. The infrastructure perspective advanced by Goyal (2025) is particularly relevant because it encourages viewing semantic AI as a foundational layer supporting decision processes rather than replacing human governance.

Several limitations remain. The present framework has not been experimentally validated, and the supplied literature does not provide direct evidence for sustainability outcomes such as reduced resource consumption or improved environmental performance. The proposed architecture should therefore be interpreted as a research framework rather than a demonstrated production solution. Furthermore, the literature base is heavily centered on natural language processing and machine learning. Consequently, additional empirical work would be required to connect semantic intelligence with measurable sustainability indicators.

Future research should develop benchmark datasets containing heterogeneous decision information and explicit sustainability criteria. Experiments should compare independent-task, multi-task, generalized-language-model, and domain-adapted architectures. Evaluation should extend beyond conventional predictive accuracy to include semantic consistency, computational efficiency, domain transfer, interpretability, decision robustness, and sustainability impact. Such evaluation would enable the conceptual relationship between semantic infrastructure and sustainable decision intelligence to be tested systematically (Goyal, 2025).

CONCLUSION

This paper developed a conceptual framework for AI-driven semantic frameworks supporting sustainable decision intelligence. The analysis synthesized the supplied literature on parsing, lexicalized models, non-local linguistic features, multi-task learning, large language models, and domain adaptation into a unified architecture.

The principal contribution is the identification of six interconnected layers: semantic data acquisition, semantic representation, contextual reasoning, adaptive learning, decision synthesis, and sustainability evaluation. This structure recognizes that sustainable decision intelligence cannot be reduced to a single AI model. Instead, it requires an infrastructure in which heterogeneous information is transformed into meaningful representations, contextual relationships are identified, related analytical tasks share information selectively, domain-specific knowledge is incorporated, and recommendations are evaluated explicitly against sustainability objectives.

The literature indicates that parsing and structured representation provide foundations for semantic processing, multi-task learning supports coordinated analytical functions, large language models provide generalized semantic capabilities, and domain adaptation enables contextual specialization. At the same time, the synthesis reveals important limitations involving task interference, domain transfer, computational requirements, interpretability, and the absence of sustainability objectives from many conventional AI architectures.

Accordingly, AI should be positioned as an enabling mechanism for sustainable decision intelligence rather than as an autonomous substitute for organizational judgment. Future research should empirically validate the proposed architecture across multiple domains and establish measurable relationships between semantic quality, decision performance, computational efficiency, and sustainability outcomes. Such research can advance the field from generalized semantic AI toward decision infrastructures that are contextaware, adaptable, explainable, and explicitly aligned with long-term sustainability objectives.

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