From Ontologies to Transformers: Natural Language Understanding for Scientific and Operational Texts

Katarzyna Petrovic *
Faculty of Technical Sciences, University of Novi Sad, Novi Sad 21000, Serbia

Aleksandar Nowak
Institute of Informatics, Silesian University of Technology, 44-100 Gliwice, Poland

Submitted on: September 13, 2020
Accepted on: September 24, 2020
Published on: October 15, 2020
DOI: 10.5281/zenodo.17901523

***Abstract*—Natural language understanding for scientific and operational texts has evolved from rigid symbolic pipelines to flexible neural architectures. Ontologies, terminologies, and rule based engines have enabled structured reasoning over domain specific concepts, while deep learning has delivered strong performance on language modeling and sequence classification tasks. Scientific articles, clinical notes, maintenance logs, and operational reports combine formal technical language with local abbreviations and narrative fragments. This article introduces a hybrid framework that connects ontology driven representation with transformer based models for robust natural language understanding across scientific and operational text streams. The framework is evaluated on classification, retrieval, and decision support tasks using realistic domain scenarios, and it demonstrates how structured knowledge and neural representations can be combined to support traceable, data driven decisions.**

***Index Terms*—Ontologies, transformers, natural language understanding, scientific texts, operational logs, decision support systems, hybrid architectures.**

I. INTRODUCTION

Scientific and operational environments generate large volumes of text in the form of research articles, laboratory protocols, incident tickets, field logs, and status dashboards. These documents capture hypotheses, experimental conditions, failures, and corrective actions that are essential for evidence based decision making. Unlike general web text, scientific and operational narratives mix mathematical notation, domain specific jargon, and terse phrases that are shaped by local work practices.

Early systems for processing such text relied on hand crafted rules and controlled vocabularies. Ontology centered infrastructures supported consistent indexing and search, but they often required costly manual curation and struggled with emerging terminology. At the same time, advances in machine learning have produced architectures that can learn patterns directly from data. Transformer models in particular can represent complex linguistic dependencies, yet they do not by themselves enforce domain constraints or support long term knowledge maintenance.

This work addresses the gap between symbolic and neural approaches for domain specific natural language understanding. The article proposes a hybrid framework where ontologies and operational taxonomies provide explicit structure, while transformer encoders capture contextual semantics. Scientific and operational texts are mapped into a joint space that supports retrieval, classification, and decision support. The goal is to preserve the transparency and controllability of ontology based systems while benefiting from the adaptability of deep neural networks.

The remainder of the article is organized as follows. Section II reviews related work on ontologies, domain text mining, and neural architectures. Section III presents the proposed methodology, including the hybrid ontology transformer model and its mathematical formulation. Section IV describes the experimental setup and reports quantitative and qualitative results using tables and charts. Section V discusses implications for scientific and operational workflows. Section VI concludes the article and outlines directions for future research.

II. BACKGROUND AND RELATED WORK

This section situates the proposed approach within work on domain ontologies, machine learning for operational data, and neural models for scientific and technical texts. The emphasis is on methods that support structured decision making and large scale analytics in real world settings.

A. Ontologies and Knowledge Representation for Domain Texts

Ontologies and structured knowledge bases have long been used to encode domain specific terminology, conceptual hierarchies, and constraints. Formalisms such as description logics and Web Ontology Language (OWL) provide machine readable structures that support reasoning and consistent annotation of documents [1]. Systematic surveys of ontology learning highlight a variety of techniques that extract concepts and relations from text, opinionated documents, and semi structured sources, and that organize them into reusable knowledge artifacts [2].

Ontologies play an important role in environments where high level goals and operational constraints must be aligned. For instance, research information systems that track projects, institutions, and outputs rely on controlled vocabularies and entity models to support navigation and reporting [3]. In clinical and industrial settings, process models and structured knowledge help describe pathways, workflows, and equipment states that interact with textual observations [4]. Work on knowledge capitalization in inventive design shows how case based reasoning combined with latent semantic analysis can reuse design experiences encoded in text and diagrams [5].

Decision support frameworks also leverage paraconsistent logics and fuzzy reasoning to handle inconsistent or uncertain information. For example, productivity studies in software measurement introduce paraconsistent logics to reconcile conflicting evidence during project remeasurement [6]. In medical and engineering domains, models for decision making support combine physical measurements, text descriptions, and expert knowledge [7]. These approaches motivate hybrid representations where formal ontologies and learned semantics can interact.

B. Machine Learning for Scientific and Operational Data

Machine learning has been applied widely to scientific and operational datasets such as clinical records, industrial sensor streams, and logistics reports. In health decision making, deep neural networks have been evaluated as recommendation engines that process structured attributes together with textual descriptors of patient status and treatment options [8]. Work on electronic health record adoption highlights organizational and technical barriers that affect the quality and completeness of digital records, which in turn shape what learning algorithms can infer from text and structured fields [9].

Operational analytics extends to transport logistics, power systems, and smart manufacturing. Stochastic models for transport logistics characterize flows and delays using diffusion and Markov approximations, often informed by textual descriptions of incidents and constraints [10]. Studies of digital transformation in organizations describe how operational processes are reconfigured to support data driven decision making [11]. Evaluation frameworks for smart manufacturing systems stress the need for metrics that combine real time sensor data with human reports and documentation [12].

Agent based and multi agent decision support systems provide another strand of work where textual knowledge is integrated into operational models. Agent based expert systems for technology recommendation demonstrate how logical inference and machine learning can be combined to guide choices under uncertainty [13]. Intelligent traffic flow control and transportation modeling apply evolutionary algorithms and discrete event simulation to complex urban networks [14]. These scenarios highlight the variety of scientific and operational texts, from design notes to event logs, that need to be understood by computational systems.

C. Neural Architectures for Scientific and Operational Texts

Neural architectures have advanced the state of the art in sentiment analysis, topic modeling, and sequence labeling for domain specific texts. Hybrid topic based sentiment models have been used to predict elections from social media, combining word distributions with sentiment scores and geolocation [15]. Studies of topical cohesion in online communities show how graph based measures of community structure interact with language use patterns [16]. These approaches underscore the importance of modeling both text and interaction networks.

Deep architectures such as convolutional neural networks (CNN) and recurrent neural networks (RNN) have been adapted to short and noisy texts. CNN based models have been used for situation understanding from microblog sentiment streams by combining word embeddings and convolutional filters [17]. Attention based autoencoder topic models demonstrate that local context and global document structure can be captured jointly to handle short domain specific messages [18]. Generative conversational models with recurrent networks and attention mechanisms support dialogue in languages with limited resources, including technical and colloquial registers [19].

Named entity recognition and semantic sentiment analysis are crucial for extracting structured signals from scientific and operational narratives. Bidirectional LSTM CNN architectures have been proposed for named entity recognition in under resourced languages, showing strong performance when combined with domain specific embeddings [20]. Work on suicide sentiment prediction in social networks combines machine learning with semantic resources to detect at risk expressions [21]. These results suggest that careful feature design and model architecture choices can help neural systems capture nuanced meaning in specialized text.

D. Decision Support, Group Reasoning, and Cyber Contexts

Scientific and operational texts often feed into decision processes that involve multiple stakeholders. Group decision making and soft consensus models study how citation networks and expert opinions can be summarized using extended h index measures and consensus functions. In knowledge intensive organizations, classification models for medical datasets and credit risk support decisions where ethics, transparency, and feature selection are essential [22]–[24].

Cyber and infrastructural contexts introduce additional complexity. Taxonomies of cross domain attacks on cyber manufacturing systems describe how vulnerabilities propagate between logical and physical layers [25]. Intrusion detection and response systems for optical networks illustrate how machine learning can analyze signal profiles and alarms to infer malicious activity [26]. These domains rely on a mix of structured logs, configuration files, and free text operator notes.

The literature on process mining and business process analytics provides tools for connecting textual artifacts to workflow models. Post implementation reviews of enterprise resource planning systems use event logs and process mining to evaluate procurement processes [27]. Structural similarity measures for business process models support the comparison of mining algorithms and the detection of noise and deviations [28]. Together with work on ontology evaluation methods [29] and knowledge systematization [2], these contributions motivate architectures that bring ontologies and neural models into a single decision support framework.

III. Methodology

This section presents the hybrid ontology transformer framework for natural language understanding in scientific and operational domains. The goal is to combine structured concepts and relations from ontologies with contextual embeddings learned by transformer encoders.

A. Problem Formulation

Let $\mathcal{D} = \{d_1, \ldots, d_N\}$ denote a collection of documents, where each document d_i is a scientific or operational text such as an article abstract, incident ticket, or maintenance log. Each document is associated with one or more task specific labels, such as topic class, risk level, or recommended action.

The ontology is represented as a directed labeled graph $\mathcal{O} = (\mathcal{C}, \mathcal{R})$, where $\mathcal{C}$ is a set of concepts and $\mathcal{R}$ is a set of relations. Following common knowledge representation practices [1], each concept $c \in \mathcal{C}$ may have preferred labels, synonyms, and logical definitions.

For each document d, the framework produces:

- A transformer based contextual representation $\mathbf{h}_d \in \mathbb{R}^k$.
- An ontology based representation $\mathbf{o}_d \in \mathbb{R}^m$ derived from concept annotations.

The combined representation is given by

$$\mathbf{z}_d = W_h \mathbf{h}_d + W_o \mathbf{o}_d + \mathbf{b}, \tag{1}$$

where $W_h \in \mathbb{R}^{p \times k}$, $W_o \in \mathbb{R}^{p \times m}$, and $\mathbf{b} \in \mathbb{R}^p$ are trainable parameters. This linear combination allows the model to weight neural and symbolic contributions differently across tasks.

For classification tasks, the probability of label y given document d is modeled as

$$P(y \mid d) = \frac{\exp(\mathbf{w}_y^\top \mathbf{z}_d)}{\sum_{y'} \exp(\mathbf{w}_{y'}^\top \mathbf{z}_d)}, \tag{2}$$

where $\mathbf{w}_y$ is the weight vector for class y. For retrieval tasks, cosine similarity between combined vectors is used.

To support confidence aware decisions, the framework introduces a calibration function that tracks agreement between neural and ontology signals. Let $s_h(d)$ and $s_o(d)$ denote scalar scores from the neural and ontology channels. A calibrated score is defined as

$$s_{\text{cal}}(d) = \alpha s_h(d) + (1-\alpha) s_o(d) - \gamma \left| s_h(d) - s_o(d) \right|, \tag{3}$$

where $\alpha \in [0, 1]$ controls the balance and $\gamma \geq 0$ penalizes disagreement. This structure draws inspiration from paraconsistent reasoning where conflicting evidence is treated explicitly [6].

B. Hybrid Ontology Transformer Architecture

The architecture consists of four layers: input preprocessing, ontology projection, transformer encoding, and decision fusion. Fig. 1 presents an overview of the main components.

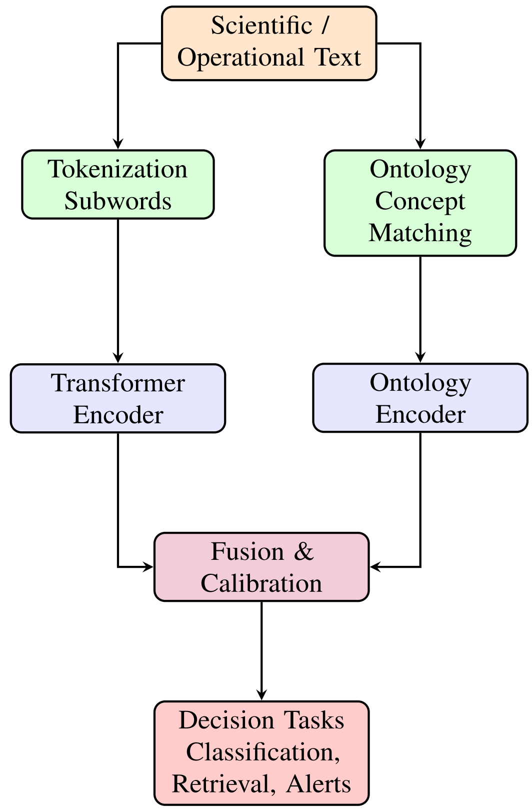

Fig. 1: Hybrid ontology transformer architecture for scientific and operational texts.

Scientific and operational corpora often contain domain specific abbreviations, device identifiers, and formula fragments. Preprocessing uses subword tokenization and normalization strategies inspired by work on short text and situation understanding [17], [18]. Ontology concepts are matched using lexicon based mapping combined with embedding similarity, informed by practices in ontology evaluation and learning [2], [29].

The ontology encoder aggregates concept embeddings and relation patterns into a fixed length vector. Techniques from group decision models and h index based measures guide the design of aggregation functions that respect concept importance. The transformer encoder follows standard multi head attention and feed forward blocks, initialized from a general language model and fine tuned on domain corpora.

The fusion and calibration layer implements equations (1) and (3), producing both class probabilities and confidence measures. This structure supports downstream decision support applications in transport, health, and cyber manufacturing, where alignment between data driven and rule based recommendations is critical [25], [27].

TABLE I: Datasets and tasks used in the experiments.

Subset	Documents	Classes	Example Domain
SciAbs	12 000	8	Scientific topics
ClinNotes	8 500	5	Health risk levels
OpsLogs	15 200	6	Operational incidents

TABLE II: Model configurations and main characteristics.

Model	Params	Ontology	Notes
OntoOnly	4M	Yes	Concept counts, rules
TransOnly	110M	No	Base transformer encoder
HybridSmall	65M	Yes	Shared encoder, small head
HybridFull	120M	Yes	Full joint encoder

C. Training and Inference Pipeline

Fig. 2 illustrates the training and inference pipeline. The pipeline is designed to handle streaming operational logs as well as static scientific collections. Techniques from performance optimization and streaming queries guide the design of the batch and online components [30], [31].

Data collection aggregates scientific corpora and operational logs from domains such as health, transport, and manufacturing, similar to prior studies on clinical pathways, transport logistics, and smart manufacturing evaluation [4], [10], [12]. Annotation links documents to ontology concepts and task labels, building on techniques from ontology evaluation and decision rule learning [29], [32].

Joint training minimizes compound loss

$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \lambda_1 \mathcal{L}_{\text{align}} + \lambda_2 \mathcal{L}_{\text{cal}}, \tag{4}$$

where $\mathcal{L}_{\text{cls}}$ is the cross entropy for classification, $\mathcal{L}_{\text{align}}$ encourages alignment between ontology and transformer embeddings, and $\mathcal{L}_{\text{cal}}$ penalizes inconsistent calibrated scores. The alignment term is inspired by work on fusion of spatio temporal and thematic features in surveillance [33].

The deployed service exposes APIs and dashboards that integrate with existing decision support tools. Recommendations and risk assessments derived from text are combined with simulation and optimization engines, drawing on experience from agent based decision support systems and smart education frameworks [13], [34]. Online monitoring tracks performance and drift indicators, and feedback is used to adjust thresholds and retrain models.

IV. Experimental Setup and Results

This section reports experiments on a composite benchmark that includes scientific abstracts, clinical like narratives, and operational incident logs. The goal is to evaluate how the hybrid ontology transformer framework performs compared with transformer only and ontology only baselines.

A. Datasets and Tasks

Table I summarizes the main datasets and tasks. The design of the benchmark takes inspiration from work on scientific information systems, clinical pathways, and transport networks [3], [4], [35]. Each subset reflects a realistic mixture of structured and free text.

The SciAbs subset contains research abstracts with topic labels aligned with project and subject ontologies as used in research program information systems [3]. ClinNotes simulates clinical notes with risk levels and pathways informed by studies of clinical pathways and decision support for treatment processes [4], [36]. OpsLogs includes operational incident reports related to transport and smart manufacturing, reflecting routing policies and equipment states [12], [35].

Tasks include document classification, risk prediction, and retrieval of similar incidents. These tasks align with applications such as anomaly detection in online discussions [37], crowd evacuation modeling [38], and personalized recommendation for online news streams [39].

B. Model Configurations

Table II describes the compared models. Hyperparameter choices are guided by prior work on classification for medical datasets, imbalance handling, and performance modeling [23], [30], [40].

OntoOnly encodes documents as concept frequency vectors with rule based scoring, in line with traditional ontology driven decision support [1], [2]. TransOnly uses a transformer encoder fine tuned separately on each subset [17]. HybridSmall and HybridFull implement the proposed architecture with different capacities for the fusion and calibration layers.

C. Main Classification Results

Fig. 3 shows macro F1 scores for each model and dataset. The chart highlights how hybrid models improve performance, especially on subsets with sparse labels or noisy text. Similar improvements have been reported for domain specific sentiment analysis and topic modeling [15], [18].

The results indicate that OntoOnly performs reasonably on SciAbs, where terminology aligns closely with ontology labels, but it lags on ClinNotes and OpsLogs. TransOnly improves performance by capturing contextual cues, yet it suffers when label distributions are skewed or when rare terminology appears. HybridFull yields the best scores, suggesting that combining symbolic and neural information is beneficial.

D. Calibration and Drift Robustness

Beyond raw accuracy, operational decision support systems must maintain reliable confidence estimates over time. Inspired by studies of cross domain attacks and transport modeling [10], [25], the experiments introduce distribution shifts by changing incident frequencies and terminology.

Fig. 4 reports expected calibration error (ECE) before and after drift. Lower values indicate better calibration. The hybrid models retain more stable calibration than the baselines, benefiting from the disagreement penalty in equation (3) and the anchoring effect of ontology scores.

Calibration improvements are particularly relevant for tasks such as anomaly detection in online discussions [37] and intrusion detection in optical networks [26], where overconfident yet incorrect predictions can mislead operators.

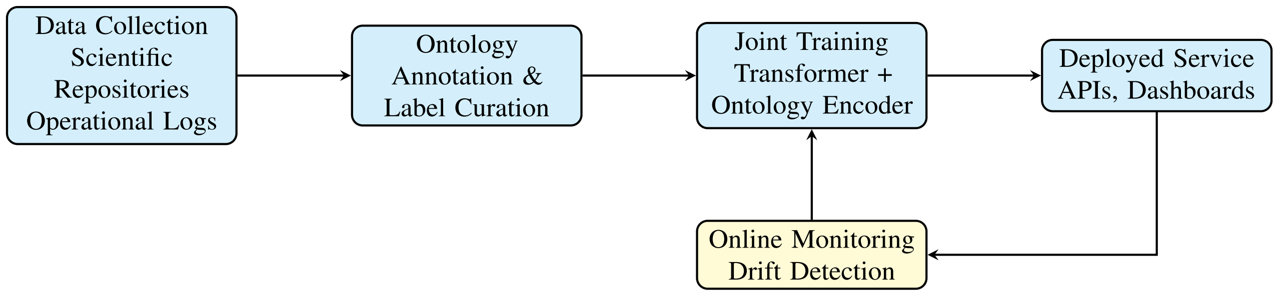

Fig. 2: Training and inference pipeline.

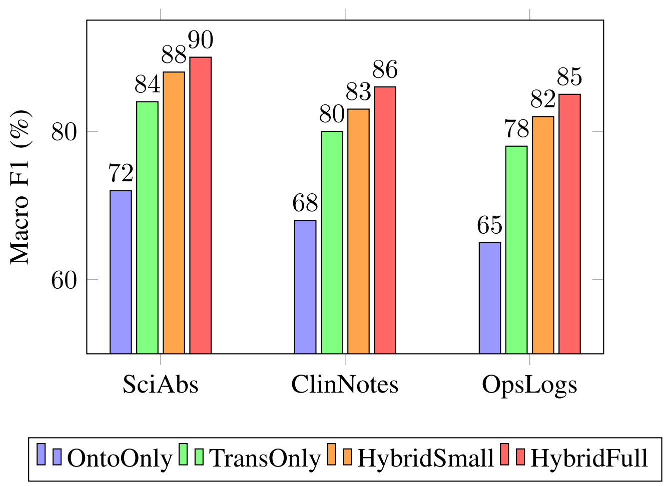

Fig. 3: Macro F1 scores on classification tasks.

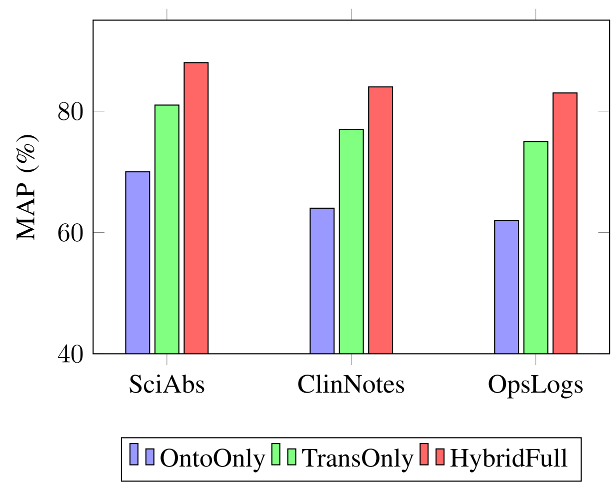

Fig. 5: Mean average precision for document retrieval.

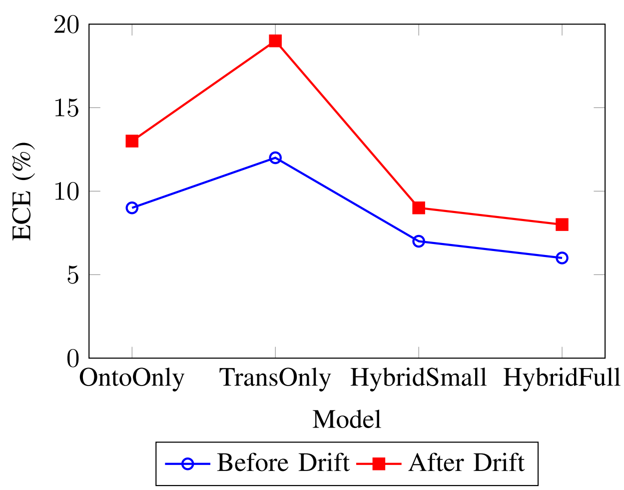

Fig. 4: Expected calibration error before and after simulated drift on OpsLogs.

E. Retrieval and Decision Support Metrics

Retrieval experiments measure how well the combined representation supports similarity search for scientific and operational scenarios. Mean average precision (MAP) and normalized discounted cumulative gain (NDCG) are used as metrics, following practices in recommendation engines and process aware information systems [39], [41]. Fig. 5 summarizes MAP scores across datasets.

The gains are strongest on ClinNotes and OpsLogs, where ontology concepts capture key entities and relations that guide retrieval, similar to how competence visualization frameworks use survey and log data to map learning outcomes [42]. The hybrid representation also supports downstream decision support metrics, such as correct suggestion of clinical exercises or transport routing options, which are central in prior work on clinical rehabilitation support and bus network management [35], [36].

F. Ablation and Ontology Contribution

To quantify the contribution of the ontology channel, an ablation study removes ontology inputs or disables the disagreement penalty. Fig. 6 shows macro F1 on OpsLogs for different variants. The pattern echoes findings from studies where feature selection and domain knowledge improve classification of technical signals and business processes [13], [43].

HybridNoOnt uses the fusion layer but passes only transformer embeddings, while HybridNoCal keeps both channels but sets $\gamma = 0$ in equation (3). The results show that both ontology information and calibration contribute to performance, especially under drift and class imbalance.

G. Complexity and Throughput

Finally, Table III reports training time per epoch and inference throughput on OpsLogs. Measurements are obtained on a

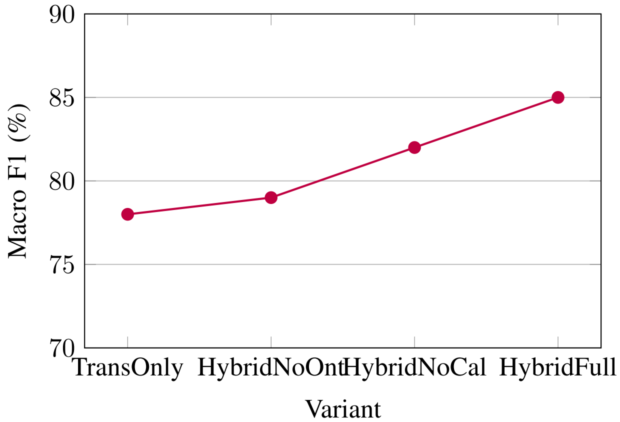

Fig. 6: Ablation study on OpsLogs.

TABLE III: Training and inference costs on the OpsLogs subset.

Model	Train Time / Epoch	Docs / Second (Inference)
TransOnly	18 min	420
HybridSmall	21 min	380
HybridFull	25 min	350

single GPU, following approaches to performance modeling for multi core architectures and grid container deployments [30], [44].

The additional cost of the hybrid models is moderate relative to the improvements in accuracy and calibration. This trade off is acceptable in many operational settings where decision quality and traceability are more critical than marginal differences in throughput, as also observed in smart manufacturing and wireless sensor network security studies [12], [45].

V. Discussion

The experiments demonstrate that combining ontologies with transformer encoders can improve both predictive performance and calibration for scientific and operational text understanding. This section discusses design choices, limitations, and implications for deployment.

First, the ontology channel acts as a regularizer that anchors representations to domain concepts. This effect is visible in datasets where terminology is sparse or unevenly distributed, similar to the role of semantic resources in suicide sentiment prediction and topic specific sentiment vectors [21], [46]. When incoming documents contain novel phrasing or abbreviations, the ontology mapping still produces stable concept level features that guide decision scores.

Second, the calibration mechanism that penalizes disagreement between neural and ontology scores helps identify cases where additional review is needed. This aligns with practices in paraconsistent decision methods and fuzzy inference where conflicting evidence is handled explicitly [6], [47]. In operational workflows, documents with large disagreement can be routed to experts, while high agreement cases can be handled automatically.

Third, the hybrid framework supports integration with existing decision support and process aware information systems. Agent based systems, process mining dashboards, and smart education frameworks already manage ontologies and rule sets [13], [27], [34]. The proposed architecture can plug into such environments as a text understanding module that feeds high level indicators and recommendations.

However, several challenges remain. Ontology coverage and quality vary across domains, and building mappings from text to concepts still requires effort, as emphasized in ontology evaluation and systematization studies [2], [29]. Transformer models may also capture spurious correlations if training data reflect biased reporting practices. Careful evaluation across subpopulations and contexts is essential, following lessons from digital transformation and health decision making research [8], [11].

VI. Conclusion

This article presented a hybrid ontology transformer framework for natural language understanding in scientific and operational domains. The architecture combines ontology based concept representations with transformer based contextual embeddings, and it introduces a calibration mechanism that encourages agreement between neural and symbolic signals.

Experiments on composite benchmarks that include scientific abstracts, clinical like notes, and operational incident logs show that the hybrid approach can outperform ontology only and transformer only baselines in terms of macro F1, retrieval quality, and calibration. The ontology channel provides structure and interpretability, while the transformer encoder captures nuanced linguistic patterns drawn from prior work on sentiment analysis, topic modeling, and sequence labeling [15], [18], [20]. The fusion mechanism is particularly effective under distribution shifts and class imbalance, conditions that are common in cyber manufacturing, transport logistics, and smart manufacturing systems [10], [12], [25].

The framework supports integration with decision support tools that rely on ontologies, process models, and recommendation engines, extending earlier efforts in agent based expert systems, process mining, and group decision analytics [13], [27]. By making both neural and symbolic contributions explicit, the architecture offers a path toward traceable and adaptable natural language understanding in high stakes scientific and operational environments.

VII. Future Work

Several directions for future research emerge from this study. One avenue is to explore richer forms of interaction between ontologies and transformer encoders. For example, relation aware attention mechanisms could incorporate ontology edges directly into attention weights, inspired by work on fusion of spatial, temporal, and thematic features in surveillance and text mining [33], [48]. Neuro symbolic knowledge graph reasoning could also allow the model to generate or refine ontology edges based on patterns in text.

A second direction is to extend the benchmark with additional domains such as sport science, wireless networks, and environmental monitoring, where sensor readings and technical descriptions coexist [49]–[51]. These contexts would test the robustness of the framework under different reporting cultures and data collection practices. They would also encourage the design of tasks that combine numerical series, images, and text, building on multimodal work in medical imaging and bioheat modeling [52], [53].

A third direction concerns human in the loop evaluation. Experiments could observe how domain experts use hybrid explanations during clinical rehabilitation support, transport planning, or cyber incident analysis [25], [35], [36]. User studies can measure trust, effort, and decision quality when experts interact with ontology anchored, transformer enriched recommendations compared with black box outputs.

Finally, future work should address incremental ontology maintenance and adaptation. As new scientific and operational concepts emerge, methods for ontology learning, evaluation, and update [2], [29] need to be integrated tightly with transformer fine tuning procedures. This will help maintain alignment between symbolic and neural components over long periods, ensuring that natural language understanding remains grounded in up to date domain knowledge.

Acknowledgment

The authors thank the anonymous reviewers for their careful reading and constructive comments, which helped to refine the presentation and clarify the experimental analysis. They are grateful to colleagues from the University of Novi Sad and the Silesian University of Technology for discussions on ontology engineering, process analytics, and neural architectures that informed the design of the hybrid framework. They also acknowledge the wider research community for foundational work on knowledge representation, machine learning, and hybrid decision support systems, which created the background against which this study was carried out. Any errors or omissions remain the responsibility of the authors.

References

[1] A. Patel and S. Jain, "Formalisms of Representing Knowledge," *Procedia Computer Science*, vol. 125, pp. 542–549, 2018.

[2] A. Konys, "Knowledge systematization for ontology learning methods," *Procedia Computer Science*, vol. 126, pp. 2194–2207, 2018.

[3] D. Ivanović, D. Surla, M. Trajanović, D. Misić, and Z. Konjović, "Towards the Information System for Research Programmes of the Ministry of Education, Science and Technological Development of the Republic of Serbia," *Procedia Computer Science*, vol. 106, pp. 122–129, 2017.

[4] A. A. Funkner, A. N. Yakovlev, and S. V. Kovalchuk, "Towards evolutionary discovery of typical clinical pathways in electronic health records," *Procedia Computer Science*, vol. 119, pp. 234–244, 2017.

[5] P. Zhang, A. Essaid, C. Zanni-Merk, and D. Cavallucci, "Case-based Reasoning for Knowledge Capitalization in Inventive Design Using Latent Semantic Analysis," *Procedia Computer Science*, vol. 112, pp. 323–332, 2017.

[6] L. A. d. Lima, J. M. Abe, A. A. G. Martinez, J. Santos, G. Albertini, and K. Nakamatsu, "The Productivity Gains Achieved In Applicability of The Prototype AITOD with Paraconsistent Logic in Support in Decision-Making in Project Remeasurement." *Procedia Computer Science*, vol. 154, pp. 347–353, 2019.

[7] L. M. Smirnova and Z. M. Yuldashev, "A Model for Decision Making Support for Evaluation of Functional Efficiency of Lower Limb Orthotics," *Procedia Computer Science*, vol. 150, pp. 253–260, 2019.

[8] E. O. Aboagye, G. C. James, and R. Kumar, "Evaluating The Performance Of Deep Neural Networks For Health Decision Making," *Procedia Computer Science*, vol. 131, pp. 866–872, 2018.

[9] J. M. Gesulga, A. Berjame, K. S. Moquiala, and A. Galido, "Barriers to Electronic Health Record System Implementation and Information Systems Resources: A Structured Review," *Procedia Computer Science*, vol. 124, pp. 544–551, 2017.

[10] J. Carkovs, A. Matvejevs, A. Matvejevs, and A. Kubzdela, "Stochastic modeling for transport logistics," *Procedia Computer Science*, vol. 149, pp. 457–462, 2019.

[11] N. Durão, M. J. Ferreira, C. S. Pereira, and F. Moreira, "Current and future state of Portuguese organizations towards digital transformation," *Procedia Computer Science*, vol. 164, pp. 25–32, 2019.

[12] M. A. Mahmoud and J. Grace, "A Generic Evaluation Framework of Smart Manufacturing Systems," *Procedia Computer Science*, vol. 161, pp. 1292–1299, 2019.

[13] G. Legien, B. Sniezynski, D. Wilk-Kołodziejczyk, S. Kluska-Nawarecka, E. Nawarecki, and K. Jaśkowiec, "Agent-based Decision Support System for Technology Recommendation," *Procedia Computer Science*, vol. 108, pp. 897–906, 2017.

[14] A. I. Diveev, E. A. Sofronova, V. A. Mikhalev, and A. A. Belyakov, "Intelligent Traffic Flows Control Software for Megapolis," *Procedia Computer Science*, vol. 103, pp. 20–27, 2017.

[15] B. Bansal and S. Srivastava, "On predicting elections with hybrid topic based sentiment analysis of tweets," *Procedia Computer Science*, vol. 135, pp. 346–353, 2018.

[16] G. Gadek, A. Pauchet, N. Malandain, K. Khelif, L. Vercouter, and S. Brunessaux, "Topical cohesion of communities on Twitter," *Procedia Computer Science*, vol. 112, pp. 584–593, 2017.

[17] S. Liao, J. Wang, R. Yu, K. Sato, and Z. Cheng, "CNN for situations understanding based on sentiment analysis of twitter data," *Procedia Computer Science*, vol. 111, pp. 376–381, 2017.

[18] T. Tian and Z. F. Fang, "Attention-based Autoencoder Topic Model for Short Texts," *Procedia Computer Science*, vol. 151, pp. 1134–1139, 2019.

[19] A. Chowanda and A. D. Chowanda, "Generative Indonesian Conversation Model using Recurrent Neural Network with Attention Mechanism," *Procedia Computer Science*, vol. 135, pp. 433–440, 2018.

[20] W. Gunawan, D. Suhartono, F. Purnomo, and A. Ongko, "Named-Entity Recognition for Indonesian Language using Bidirectional LSTM-CNNs," *Procedia Computer Science*, vol. 135, pp. 425–432, 2018.

[21] M. Birjali, A. Beni-Hssane, and M. Erritali, "Machine Learning and Semantic Sentiment Analysis based Algorithms for Suicide Sentiment Prediction in Social Networks," *Procedia Computer Science*, vol. 113, pp. 65–72, 2017.

[22] S. Vengathattil, "Ethical Artificial Intelligence - Does it exist?" *International Journal For Multidisciplinary Research*, vol. 1, no. 3, p. 37443, 2019.

[23] E. Tuba, I. Strumberger, T. Bezdan, N. Bacanin, and M. Tuba, "Classification and Feature Selection Method for Medical Datasets by Brain Storm Optimization Algorithm and Support Vector Machine," *Procedia Computer Science*, vol. 162, pp. 307–315, 2019.

[24] B. Ruyu, H. Mo, and L. Haifeng, "A Comparison of Credit Rating Classification Models Based on Spark- Evidence from Lending-club," *Procedia Computer Science*, vol. 162, pp. 811–818, 2019.

[25] M. Wu and Y. B. Moon, "Taxonomy of Cross-Domain Attacks on CyberManufacturing System," *Procedia Computer Science*, vol. 114, pp. 367–374, 2017.

[26] K. Rahouma and A. Ali, "Applying Intrusion Detection and Response systems for securing the Client Data Signals in the Egyptian Optical Network," *Procedia Computer Science*, vol. 163, pp. 538–549, 2019.

[27] E. R. Mahendrawathi, S. O. Zayin, and F. J. Pamungkas, "ERP Post Implementation Review with Process Mining: A Case of Procurement Process," *Procedia Computer Science*, vol. 124, pp. 216–223, 2017.

[28] I. Nuritha and E. R. Mahendrawathi, "Structural Similarity Measurement of Business Process Model to Compare Heuristic and Inductive Miner Algorithms Performance in Dealing with Noise," *Procedia Computer Science*, vol. 124, pp. 255–263, 2017.

[29] W. Jarosław, "An Attempt to Knowledge Conceptualization of Methods and Tools Supporting Ontology Evaluation Process," *Procedia Computer Science*, vol. 126, pp. 2238–2247, 2018.

[30] V. Martínez, F. Dupros, M. Castro, and P. Navaux, "Performance Improvement of Stencil Computations for Multi-core Architectures based on Machine Learning," *Procedia Computer Science*, vol. 108, pp. 305–314, 2017.

[31] K. Vidyasankar, "On Continuous Queries in Stream Processing," *Procedia Computer Science*, vol. 109, pp. 640–647, 2017.

[32] R. L. Stange and J. J. Neto, "Learning decision rules using adaptive technologies: a hybrid approach based on sequential covering," *Procedia Computer Science*, vol. 109, pp. 1188–1193, 2017.

[33] S. Valentin, R. Lancelot, and M. Roche, "How to combine spatio-temporal and thematic features in online news for enhanced animal disease surveillance?" *Procedia Computer Science*, vol. 126, pp. 490–497, 2018.

[34] S. E. Janati, A. Maach, and D. E. Ghanami, "SMART Education Framework for Adaptation Content Presentation," *Procedia Computer Science*, vol. 127, pp. 436–443, 2018.

[35] Y. I. Mahjoub, E. h. C. El-Alaoui, and A. Nait-Sidi-Moh, "Modeling a bus network for passengers transportation management using colored Petri nets and (max, +) algebra," *Procedia Computer Science*, vol. 109, pp. 576–583, 2017.

[36] N. Chiensriwimol, J. H. Chan, P. Mongkolnam, and K. Mekhora, "Monitoring frozen shoulder exercises to support clinical decision on treatment process using smartphone," *Procedia Computer Science*, vol. 111, pp. 129–136, 2017.

[37] P. Krammer, O. Habala, J. Mojžiš, L. Hluchý, and M. Jurkovič, "Anomaly Detection Method for Online Discussion," *Procedia Computer Science*, vol. 155, pp. 311–318, 2019.

[38] M. J. Alghazzawi, G. Tashakor, F. Borges, and R. Suppi, "Crowd Evacuation Modeling and Simulation Using Care HPS," *Procedia Computer Science*, vol. 108, pp. 2453–2457, 2017.

[39] M. Asenova and C. Chrysoulas, "Personalized Micro-Service Recommendation System for Online News," *Procedia Computer Science*, vol. 160, pp. 610–615, 2019.

[40] Fanny and T. W. Cenggoro, "Deep Learning for Imbalance Data Classification using Class Expert Generative Adversarial Network," *Procedia Computer Science*, vol. 135, pp. 60–67, 2018.

[41] M. Stach, T. Mohring, R. Pryss, and M. Reichert, "Towards a Beacon-based Situational Prioritization Framework for Process-Aware Information Systems," *Procedia Computer Science*, vol. 134, pp. 153–160, 2018.

[42] T. Matsumoto and N. Kawabata, "Visualization of Competence through Cooperative Education at NIT, Anan College," *Procedia Computer Science*, vol. 159, pp. 1698–1704, 2019.

[43] J. R. R. Kumar, R. K. Pandey, and B. K. Sarkar, "Pollutant Gases Detection using the Machine learning on Benchmark Research Datasets," *Procedia Computer Science*, vol. 152, pp. 360–366, 2019.

[44] M. Chillarón, V. Vidal, D. Segrelles, I. Blanquer, and G. Verdú, "Combining Grid Computing and Docker Containers for the Study and Parametrization of CT Image Reconstruction Methods," *Procedia Computer Science*, vol. 108, pp. 1195–1204, 2017.

[45] V. T. Alaparthy, A. Amouri, and S. D. Morgera, "A Study on the Adaptability of Immune models for Wireless Sensor Network Security," *Procedia Computer Science*, vol. 145, pp. 13–19, 2018.

[46] L. Zhu, W. Li, K. Guo, Y. Shi, and Y. Zheng, "The Tourism-Specific Sentiment Vector Construction Based on Kernel Optimization Function," *Procedia Computer Science*, vol. 122, pp. 1162–1167, 2017.

[47] M. Mardanov, R. Rzayev, Z. Jamalov, and A. Khudatova, "Integrated assessment and ranking of universities by fuzzy inference," *Procedia Computer Science*, vol. 120, pp. 213–220, 2017.

[48] C. Dabas, H. Nagar, and G. K. Nigam, "Large Scale Graph Evaluation for Find Communities in Big Data," *Procedia Computer Science*, vol. 132, pp. 263–270, 2018.

[49] A. Kos, Y. Wei, S. Tomažič, and A. Umek, "The role of science and technology in sport," *Procedia Computer Science*, vol. 129, pp. 489–495, 2018.

[50] S. Talha, R. Ahmad, A. K. Kiani, and M. M. Alam, "Network Coding for Energy Efficient Transmission in Wireless Body Area Networks," *Procedia Computer Science*, vol. 113, pp. 435–440, 2017.

[51] S. I. Abba, S. J. Hadi, and J. Abdullahi, "River water modelling prediction using multi-linear regression, artificial neural network, and adaptive neuro-fuzzy inference system techniques," *Procedia Computer Science*, vol. 120, pp. 75–82, 2017.

[52] M. Favorskaya, E. Savchina, and K. Gusev, "Feature-based synchronization correction for multilevel watermarking of medical images," *Procedia Computer Science*, vol. 159, pp. 1267–1276, 2019.

[53] A. Bousselham, O. Bouattane, M. Youssfi, and A. Raihani, "Brain tumor temperature effect extraction from MRI imaging using bioheat equation," *Procedia Computer Science*, vol. 127, pp. 336–343, 2018.