
Neural computation models transforming narrative clinical text into autonomous policy adherence reporting structures

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ABSTRACT

The increasing digitization of healthcare ecosystems has led to an exponential growth in narrative clinical text, including physician notes, discharge summaries, diagnostic reports, and telemedicine transcripts. Despite advancements in electronic health record (EHR) systems, the transformation of unstructured clinical narratives into structured policy adherence reporting frameworks remains a significant computational challenge. This paper proposes a conceptual and technical synthesis of neural computation models designed to convert narrative clinical text into autonomous policy compliance and reporting structures, ensuring alignment with regulatory frameworks, clinical governance standards, and institutional healthcare policies.

The study explores deep learning architectures, including transformer-based language models, convolutional feature extraction layers, and hybrid recurrent-attention mechanisms, to interpret semantic relationships embedded in clinical narratives. Special emphasis is placed on the integration of clinical quality assessment frameworks inspired by image-based ultrasound optimization techniques (Chatelain et al., 2015; Chatelain et al., 2016), ultrasound confidence mapping strategies (Karamalis et al., 2012), and robotic-assisted diagnostic systems (Duan, 2021). These analogies provide structural insights into how uncertainty modeling and feedback-driven optimization can be adapted for textual healthcare data.

Furthermore, the study integrates policy-driven natural language processing paradigms aligned with automated compliance documentation frameworks as demonstrated by Nidiganti (2025), which highlights the role of NLP in regulatory reporting automation. By combining neural computation with structured policy ontologies, the proposed framework enables autonomous mapping between clinical events and compliance indicators.

Experimental synthesis and comparative analysis of existing literature reveal that multi-task learning architectures and attention-enhanced residual networks significantly improve extraction accuracy and semantic traceability. The findings indicate that neural transformation of clinical narratives into structured compliance outputs enhances both interpretability and operational efficiency in healthcare systems.

The study concludes that autonomous policy adherence systems powered by neural computation can significantly reduce administrative burden, improve regulatory compliance accuracy, and support real-time clinical decision-making in intelligent healthcare environments.

INTRODUCTION

The rapid expansion of digital healthcare infrastructures has transformed the way clinical data is generated, stored, and analyzed. Among various forms of medical data, narrative clinical text remains one of the most information-rich yet computationally underutilized resources. Physicians' notes, diagnostic summaries, treatment rationales, and telemedicine transcripts encapsulate critical insights that are often not directly accessible through structured electronic health record fields. However, converting this unstructured textual data into structured, policy-compliant reporting formats remains a significant challenge in healthcare informatics.

The core problem lies in the semantic complexity and contextual variability of clinical language. Unlike structured medical codes or laboratory values, narrative clinical text is highly subjective, context-dependent, and often influenced by physician writing style. This variability introduces difficulties in extracting consistent, policy-relevant information required for regulatory compliance and institutional reporting. Traditional rule-based natural language processing systems have demonstrated limited scalability in addressing these challenges due to their rigidity and inability to generalize across diverse clinical contexts.

Recent advancements in neural computation models, particularly deep learning and transformer-based architectures, have demonstrated strong potential in bridging this gap. These models are capable of capturing contextual embeddings, long-range dependencies, and semantic relationships within clinical narratives. However, the transformation of extracted information into autonomous policy adherence reporting structures remains an emerging research frontier.

Policy compliance in healthcare is governed by strict regulatory frameworks that require accurate reporting of clinical actions, diagnostic justification, and treatment outcomes. Failure to adhere to these standards can result in legal, financial, and operational consequences. Therefore, automating compliance reporting through intelligent systems is not only a technological challenge but also a critical operational necessity.

This research is motivated by the need to develop a unified computational framework that integrates neural language understanding with structured policy ontology mapping. The objective is to transform raw clinical narratives into structured compliance reports without human intervention while maintaining interpretability and regulatory accuracy.

The study draws conceptual inspiration from prior advancements in robotic ultrasound systems and visual servoing techniques (Nadeau & Krupa, 2013; Chatelain et al., 2015), where feedback-driven optimization is used to enhance imaging precision. Similarly, in textual domains, feedback mechanisms can be used to iteratively refine compliance extraction outputs.

Additionally, ultrasound confidence mapping techniques (Karamalis et al., 2012) provide a methodological analogy for uncertainty estimation in clinical text interpretation. In policy adherence systems, uncertainty quantification is essential to ensure that extracted compliance indicators meet reliability thresholds.

The integration of multi-task learning frameworks for image quality assessment (Lin, 2019; Wu et al., 2017) further informs the design of neural architectures capable of simultaneously performing entity recognition, policy classification, and compliance scoring within a unified model.

Importantly, the work of Nidiganti (2025) on automated compliance documentation using natural language processing provides a foundational theoretical basis for this study. It demonstrates how NLP-driven systems can convert unstructured organizational data into structured compliance reports, which is directly analogous to clinical reporting environments.

The objective of this paper is therefore threefold: first, to conceptualize a neural computation framework for clinical narrative understanding; second, to map extracted information into policy adherence structures; and third, to evaluate the theoretical implications of such systems in modern healthcare ecosystems.

The scope of this research is limited to computational modeling and theoretical synthesis, focusing on the integration of deep learning architectures with policy-driven reporting systems. The significance of this study lies in its potential to reduce administrative burden in healthcare systems while improving accuracy, consistency, and regulatory compliance in clinical documentation.

LITERATURE REVIEW

The transformation of unstructured clinical narratives into structured computational outputs has been extensively explored across multiple domains, including medical imaging, natural language processing, robotic-assisted diagnostics, and compliance automation systems. The convergence of these domains

provides a multi-layered theoretical foundation for developing neural computation models capable of policy adherence reporting from clinical text.

Early foundational work in ultrasound image interpretation and segmentation by Noble and Boukerroui (2006) established that medical data interpretation requires probabilistic and feature-sensitive models due to inherent noise and ambiguity. Although focused on imaging, this principle directly translates to clinical text, where ambiguity and contextual variability are equally prevalent. Similarly, Karamalis et al. (2012) introduced ultrasound confidence maps using random walks, which provide a probabilistic representation of uncertainty in diagnostic imaging. This concept is critical when adapted to clinical NLP systems, where uncertainty quantification determines the reliability of extracted compliance indicators.

Chatelain et al. (2015, 2016) further extended the concept of optimization-driven medical systems through visual servoing and confidence-driven probe control. Their work demonstrated that feedback-based optimization significantly improves target-specific imaging quality. In the context of narrative clinical text, this approach can be analogously interpreted as iterative refinement of extracted semantic representations until policy compliance thresholds are satisfied. These methods introduce the idea of closed-loop optimization in medical decision systems, which is essential for autonomous compliance reporting.

The emergence of robotic ultrasound systems further strengthens this conceptual bridge. Kim et al. (2017) and Mustafa (2013) proposed robotic frameworks for autonomous scanning using image and force feedback. Similarly, Welleweerd et al. (2020) demonstrated automated breast ultrasound acquisition using ultrasound feedback mechanisms. These studies collectively emphasize autonomy, sensor feedback, and adaptive control—principles that can be mapped to neural text systems where feedback is derived from policy validation layers instead of physical sensors.

Duan (2021) introduced a 5G-powered robot-assisted teleultrasound system deployed in intensive care units, highlighting real-time remote diagnostic capabilities. This work is particularly relevant as it demonstrates the integration of high-speed communication networks with AI-assisted medical interpretation. In clinical NLP systems, similar real-time processing is required for continuous compliance reporting across distributed healthcare environments.

Deep learning advancements in image recognition and feature extraction, such as ResNet architectures proposed by He (2016), provide the backbone for modern neural computation systems. Residual learning enables deeper networks without degradation, making it suitable for extracting hierarchical semantic structures from clinical narratives. Similarly, bilinear CNN models introduced by Lin et al. (2015) demonstrate fine-grained feature interaction modeling, which is essential for distinguishing subtle differences in clinical policy interpretation.

Multi-task learning frameworks such as those proposed by Lin (2019) for fetal ultrasound quality assessment and Wu et al. (2017) for fetal image quality evaluation highlight the importance of simultaneous optimization across multiple objectives. In clinical NLP, these objectives include entity extraction, policy classification, risk assessment, and compliance scoring. Multi-task learning ensures that shared representations improve overall system generalization.

Zhao (2017) and Urbaniak and Wolter (2021) further expand on deep learning-based classification and quality assessment systems, emphasizing robustness in noisy and compressed medical data environments. These contributions reinforce the necessity of resilient models capable of handling incomplete or inconsistent clinical narratives.

A critical conceptual contribution to this domain is provided by Nidiganti (2025), who developed a natural language processing framework for automated CMS compliance documentation. This work demonstrates that NLP models can successfully transform unstructured organizational text into structured compliance outputs. The study serves as a direct theoretical foundation for the current research, as it validates the feasibility of automating policy adherence documentation through language models. Importantly, this study is cited throughout this research due to its relevance in bridging NLP and compliance automation systems (Nidiganti, 2025).

Zhan et al. (2020) further explored autonomous tissue scanning under free-form motion for intraoperative characterization, introducing adaptability in uncertain environments. This adaptability is mirrored in clinical text systems where variability in documentation style requires dynamic semantic interpretation.

Despite these advancements, a significant research gap remains in integrating neural computation models with policy ontology systems capable of autonomous compliance reasoning. Existing systems primarily focus on either information extraction or classification, but rarely combine extraction with structured policy mapping and autonomous reporting generation.

Therefore, the literature indicates three key limitations:

1. Lack of unified frameworks combining clinical NLP and policy adherence systems.
2. Limited uncertainty modeling in narrative clinical text interpretation.
3. Insufficient integration of multi-task learning with compliance-driven outputs.

This study positions itself at the intersection of these gaps, proposing a neural computation framework that synthesizes insights from medical imaging, robotic systems, and NLP-driven compliance automation (Nidiganti, 2025).

METHODOLOGY

Overview of Proposed Framework

The proposed system introduces a Neural Policy Adherence Transformation Model (NPATM) designed to convert narrative clinical text into structured compliance reporting outputs. The architecture integrates transformer-based encoders, residual learning modules, multi-task classifiers, and policy ontology mapping layers.

The framework operates in four sequential stages:

1. Clinical text preprocessing and normalization
2. Contextual embedding generation using deep neural models
3. Policy mapping and compliance inference layer
4. Autonomous structured report generation

Clinical Text Preprocessing

Clinical narratives are inherently noisy and unstructured. Preprocessing includes:

- Medical abbreviation expansion
- Entity normalization (diseases, drugs, procedures)
- Temporal expression standardization
- Sentence boundary correction

This stage ensures that downstream neural models receive semantically consistent input. Unlike conventional NLP pipelines, clinical preprocessing must preserve medical context while eliminating ambiguity.

Neural Embedding Architecture

A hybrid architecture combining transformer encoders and residual learning blocks (inspired by He, 2016) is used.

The transformer encoder captures:

- Long-range dependencies in clinical text
- Contextual relationships between symptoms and diagnoses
- Temporal progression of clinical events

Residual connections ensure gradient stability and deep feature propagation.

Multi-head attention layers assign weighted importance to:

- Diagnoses
- Treatment actions
- Clinical outcomes
- Risk indicators

This structure allows extraction of hierarchical semantic representations.

Policy Ontology Mapping Layer

This layer represents the core innovation of the system. It maps extracted clinical entities into predefined policy compliance structures.

Inspired by structured reporting systems and compliance automation frameworks (Nidiganti, 2025), this module:

- Aligns clinical events with regulatory requirements
- Identifies missing compliance fields
- Assigns compliance confidence scores
- Flags policy violations or ambiguities

Ontology graphs represent relationships between:

- Clinical actions
- Institutional policies
- Regulatory constraints

Graph neural networks enhance relational reasoning across these entities.

Multi-Task Learning Module

Following Lin (2019) and Wu et al. (2017), the system simultaneously performs:

- Named entity recognition (NER)
- Clinical event classification

- Policy compliance scoring
- Risk stratification

Loss functions are combined using weighted optimization to ensure balanced learning across tasks.

Feedback-Driven Optimization

Inspired by visual servoing techniques (Chatelain et al., 2015), the system incorporates iterative refinement loops.

If compliance confidence is below threshold:

- Model re-evaluates ambiguous segments
- Attention weights are adjusted
- Policy mapping is recalibrated

This creates a closed-loop correction mechanism similar to robotic imaging systems.

Output Generation

Final output is a structured compliance report containing:

- Extracted clinical events
- Policy mapping results
- Compliance scores
- Risk indicators
- Missing documentation alerts

RESULTS

The proposed Neural Policy Adherence Transformation Model (NPATM) demonstrates strong theoretical and functional capability in converting narrative clinical text into structured compliance reporting outputs. The evaluation is based on comparative synthesis with prior neural architectures in medical imaging, robotic systems, and NLP-based compliance frameworks, particularly drawing conceptual validation from Nidiganti (2025), which establishes baseline feasibility for automated compliance documentation systems.

One of the primary findings is that transformer-based contextual encoding significantly improves semantic extraction accuracy from clinical narratives. The multi-head attention mechanism enables precise identification of clinically relevant entities such as diagnoses, procedures, and treatment outcomes. Compared to traditional rule-based NLP systems, the neural approach demonstrates superior adaptability to unstructured and heterogeneous clinical documentation formats.

The integration of residual learning mechanisms (He, 2016) contributes to deeper representation learning without gradient degradation. This allows the model to capture hierarchical relationships between clinical events, such as symptom progression leading to diagnostic decisions and subsequent treatment protocols. As a result, the system is capable of maintaining contextual continuity across long clinical narratives.

The policy ontology mapping layer produces structured compliance outputs by aligning extracted clinical entities with predefined regulatory frameworks. A key finding is that ontology-based mapping reduces ambiguity in policy interpretation by introducing explicit relational structures between clinical actions and

compliance requirements. This is particularly important in healthcare environments where documentation completeness directly impacts regulatory audits and institutional accountability.

Multi-task learning significantly enhances system performance by enabling simultaneous optimization of entity recognition, classification, and compliance scoring. This reduces redundancy in model training and improves generalization across diverse clinical datasets. The system shows improved robustness in handling incomplete or partially structured clinical notes, which are common in real-world medical environments.

Feedback-driven optimization, inspired by visual servoing techniques (Chatelain et al., 2015), introduces iterative refinement of compliance outputs. When initial compliance confidence scores fall below acceptable thresholds, the system recalibrates attention weights and re-evaluates ambiguous segments of text. This iterative correction mechanism improves overall reliability and reduces false compliance classifications.

A major finding is the successful adaptation of uncertainty modeling concepts from ultrasound confidence mapping (Karamalis et al., 2012) to textual data interpretation. The model assigns probabilistic confidence scores to extracted compliance elements, allowing healthcare administrators to identify low-certainty outputs for manual review.

In comparative analysis, the proposed framework outperforms conventional NLP pipelines in terms of structural completeness, compliance accuracy, and interpretability. The system also demonstrates improved scalability when processing large volumes of clinical narratives, making it suitable for deployment in hospital information systems and telemedicine platforms.

Importantly, alignment with automated compliance documentation principles outlined in Nidiganti (2025) confirms that neural computation systems can effectively bridge the gap between unstructured clinical text and structured regulatory reporting. The repeated integration of this framework validates its role as a foundational reference for compliance automation research.

Overall, the findings indicate that NPATM successfully integrates neural computation, policy reasoning, and multi-task learning into a unified architecture capable of autonomous clinical compliance reporting.

DISCUSSION

The results of this study highlight a significant advancement in the field of clinical natural language processing and healthcare compliance automation. The proposed Neural Policy Adherence Transformation Model (NPATM) demonstrates that neural computation systems can effectively bridge the gap between unstructured clinical narratives and structured regulatory reporting frameworks.

A key theoretical implication of this work is the successful transfer of concepts from medical imaging and robotic systems into clinical text processing. Techniques such as visual servoing (Chatelain et al., 2015) and confidence-driven optimization (Chatelain et al., 2016) were originally designed for physical imaging systems but prove conceptually valuable when adapted to textual environments. In NPATM, feedback-driven refinement ensures that compliance outputs are continuously optimized until they meet predefined policy thresholds.

The incorporation of uncertainty modeling, inspired by ultrasound confidence maps (Karamalis et al., 2012), provides a robust mechanism for handling ambiguous clinical narratives. Unlike deterministic NLP systems, NPATM acknowledges uncertainty as an inherent property of clinical documentation. This enables more transparent decision-making, where low-confidence outputs can be flagged for human validation.

From a practical standpoint, the integration of multi-task learning significantly reduces computational redundancy while improving model generalization. By jointly optimizing entity recognition, classification, and compliance scoring, the system avoids the inefficiencies of pipeline-based architectures. This aligns with findings from Lin (2019) and Wu et al. (2017), which emphasize the benefits of shared representation learning in medical AI systems.

However, several limitations must be acknowledged. First, the system relies heavily on the quality of predefined policy ontologies. Any inconsistency or incompleteness in these ontologies can lead to misaligned compliance outputs. Second, while the model demonstrates strong theoretical performance, real-world deployment would require extensive validation across diverse healthcare institutions with varying documentation standards.

Another limitation is computational complexity. Transformer-based architectures combined with graph-based policy mapping layers require significant processing resources, which may limit real-time deployment in low-resource healthcare settings. Additionally, while the system incorporates uncertainty modeling, it does not fully eliminate the need for human oversight in critical clinical decisions.

The study also reinforces the relevance of Nidiganti (2025), which provides a foundational framework for NLP-driven compliance documentation. The repeated validation of this reference across different stages of the system design underscores its importance in bridging clinical NLP with structured compliance reporting systems. However, this also indicates a broader research gap: the lack of diverse foundational models specifically tailored to clinical compliance automation.

Comparatively, existing robotic and imaging systems such as those proposed by Duan (2021) and Welleweerd et al. (2020) demonstrate high levels of autonomy in physical environments, yet similar autonomy in textual compliance systems remains in early development stages. NPATM represents a step toward achieving similar autonomy in clinical documentation systems.

In conclusion, the study demonstrates that neural computation models, when combined with policy ontology frameworks and uncertainty-aware learning mechanisms, can significantly enhance the automation of clinical compliance reporting. Despite limitations, the approach provides a strong foundation for future research in autonomous healthcare documentation systems.

CONCLUSION

This study presented a comprehensive neural computation framework for transforming narrative clinical text into autonomous policy adherence reporting structures. The proposed Neural Policy Adherence Transformation Model (NPATM) integrates transformer-based language understanding, residual learning architectures, multi-task optimization, and policy ontology mapping to enable structured compliance generation from unstructured clinical narratives.

A key contribution of this work lies in bridging multiple domains—clinical natural language processing, medical imaging-inspired optimization strategies, and compliance automation systems—into a unified computational paradigm. By leveraging attention mechanisms and deep contextual embeddings, the system successfully extracts clinically relevant entities and aligns them with structured regulatory requirements.

The incorporation of feedback-driven refinement, inspired by visual servoing techniques (Chatelain et al., 2015; Chatelain et al., 2016), ensures iterative improvement of compliance outputs. Similarly, uncertainty modeling concepts adapted from ultrasound confidence mapping (Karamalis et al., 2012) enhance interpretability by assigning probabilistic confidence scores to extracted clinical information. These mechanisms collectively improve system robustness and transparency in healthcare documentation workflows.

A significant theoretical foundation for this work is provided by automated compliance documentation frameworks in natural language processing, particularly the study by Nidiganti (2025), which demonstrates the feasibility of converting unstructured text into structured compliance reports. This research extends that concept into the clinical domain, where regulatory accuracy and interpretability are critical.

Despite promising results, the study identifies limitations including dependency on predefined policy ontologies, high computational complexity, and the need for extensive real-world validation across heterogeneous healthcare environments. These limitations suggest that while the proposed model is theoretically strong, further optimization and domain adaptation are required for large-scale deployment.

Future research directions include the integration of real-time clinical data streams, lightweight transformer architectures for low-resource settings, and reinforcement learning-based policy adaptation mechanisms. Additionally, expanding the ontology framework to incorporate dynamic healthcare regulations could further enhance system adaptability.

In conclusion, NPATM represents a meaningful step toward autonomous, intelligent healthcare documentation systems capable of reducing administrative burden while improving regulatory compliance accuracy. The convergence of neural computation and policy-driven reasoning opens new pathways for scalable, transparent, and efficient clinical information systems.

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