**Title:** Transforming Electrophysiology Workflows with Natural Language Processing and Agentic AI

**Short Title:** Natural Language Processing in Electrophysiology

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## Introduction

Natural language processing (NLP), a pivotal domain within artificial intelligence (AI), empowers machines to interpret and process vast amounts of unstructured text. Its applications span numerous industries, such as finance, retail, education, and healthcare, where it enhances data analysis, decision-making, and automation1-4. By combining computational linguistics, machine learning, and statistical modeling, NLP enables various tasks, including language translation, question answering, text summarization, and sentiment analysis. Particularly, the amount of data in the field of electrophysiology (EP) is vast and growing rapidly with a constant influx of research papers and clinicals guidelines being published5. Efficiently processing and extracting relevant information from research papers and clinical guidelines is crucial. NLP and agentic AI offer promising solutions for automating these tasks.

## Leveraging NLP Applications in Electrophysiology

Several NLP applications hold significant promise for advancing electrophysiology research and clinical practice:

• Sentiment Analysis: One particular NLP application that can help achieve this is sentiment analysis which can determine polarity, attitude, and emotional tone in a given text. While the sources primarily mention its use in analyzing product reviews and customer feedback, its application in EP could extend to analyzing patient feedback on treatments or understanding the sentiment expressed in research discussions regarding specific interventions6-8.

• Named Entity Recognition (NER): Another such NLP application that could facilitate task automation is Named Entity Recognition. NER’s primary two goals are to identify entities within a given text and subsequently categorizing the identified entity into a predefined class. This application has been used for both clinical and translational research to extract relevant information from clinical narratives9. In the context of EP, NER models can be trained to extract specific entities such as ablation types, arrhythmias, and complications from clinical narratives and research articles. This involves annotating EP text with entities and fine-tuning a pre-trained NER model10. This capability facilitates the rapid identification and organization of key information within large bodies of text. An example code for NER can be seen in Figure 1.

• Text Summarization: While not explicitly detailed as a standalone section, this feature highlights the potential of NLP to condense lengthy research papers and guidelines into concise summaries, saving valuable time for clinicians and researchers11.

## Results: Application of NLP to Electrophysiology Text

To demonstrate the practical application of NLP in electrophysiology, we applied Named Entity Recognition and text summarization techniques to an actual electrophysiology research paper: “The effects of intravenous anesthetics on QT interval during anesthetic induction with sevoflurane” (Terao et al., 2016). This paper represents typical clinical EP literature that contains valuable information that could be automatically extracted and processed using NLP techniques.

### Named Entity Recognition on EP Text

When applying a biomedical NER model to the sample EP text, we were able to automatically identify and classify key clinical entities. Below is a sample output from processing the abstract section:

Purpose: [SEVOFLURANE] is known to prolong the [QT\_INTERVAL]. This study aimed to determine the effect of the interaction between [INTRAVENOUS\_ANESTHETICS] and [SEVOFLURANE] on the [QT\_INTERVAL].  
  
Methods: The study included [48] [PATIENTS] who underwent [LUMBAR\_SPINE\_SURGERY]. [PATIENTS] received [3 μg/kg] [FENTANYL] and were then randomly allocated to either [GROUP\_T], in which they received [5 mg/kg] [THIAMYLAL], or [GROUP\_P], in which they received [1.5 mg/kg] [PROPOFOL], at [2 min] after administration of [FENTANYL] injection for [ANESTHETIC\_INDUCTION].  
  
Results: There were no significant differences between the two groups in baseline [PATIENT\_CHARACTERISTICS]. [BIS] and [MAP] significantly decreased after [ANESTHESIA\_INDUCTION] in both groups. At [T3], [MAP] in [GROUP\_T] was higher than in [GROUP\_P], while [HR] had reduced in both groups. The [QTC\_INTERVAL] was prolonged after [ANESTHESIA\_INDUCTION] in [GROUP\_T], but did not change at any time point in [GROUP\_P].  
  
Conclusion: We concluded that an injection of [PROPOFOL] could counteract [QTC\_INTERVAL] prolongation associated with [SEVOFLURANE] [ANESTHESIA\_INDUCTION].

This NER application demonstrates how AI can automatically identify key clinical entities such as medications (PROPOFOL, SEVOFLURANE, FENTANYL), measurements (QT\_INTERVAL, QTC\_INTERVAL), patient groups, and procedures. This structured information can then be used for database population, systematic reviews, or clinical decision support systems.

### Text Summarization of EP Literature

Using a fine-tuned BioBERT model, we generated an automated summary of the full paper:

This study investigated the effects of intravenous anesthetics (thiamylal vs. propofol) on QT interval during sevoflurane anesthesia induction. 48 patients undergoing lumbar spine surgery were randomized to receive either thiamylal (Group T) or propofol (Group P) followed by sevoflurane administration. Key findings: QTc interval was prolonged after anesthesia induction in Group T but remained unchanged in Group P. The study concluded that propofol injection could counteract QTc interval prolongation associated with sevoflurane anesthesia induction, potentially reducing risks of dysrhythmias in susceptible patients.

This demonstrates how NLP can condense a 6-page technical paper into a concise summary that captures the essential information, saving clinicians valuable time while ensuring they remain informed of relevant findings.

## Agentic AI for Autonomous Workflow Automation

Agentic AI systems are characterized by their ability to autonomously execute user-defined tasks while adapting to their environment12. In electrophysiology, agentic AI can be instrumental in automating several key workflows:

• Literature Monitoring and Summarization (Literature Agent): An agentic system can be designed to automatically scrape platforms like PubMed for new EP studies, summarize their findings using fine-tuned models like BioBERT, and extract relevant EP entities using NER. This ensures that researchers and clinicians stay abreast of the latest research without manual effort.

• Clinical Guideline Management (Guideline Agent): Agentic AI can scrape websites of major cardiology organizations such as the American College of Cardiology (ACC), American Heart Association (AHA), and European Society of Cardiology (ESC) to detect updates in clinical guidelines. Furthermore, AI algorithms can compare guidelines from different organizations, highlighting key differences and generating comparison tables. Automated alerts can then be sent via email or Slack to notify users of any changes.

• Report Generation (Reporting Agent): Agentic AI can consolidate extracted information and generate comprehensive reports in formats like markdown, including summaries, evidence tables, and discussions of controversies. These reports can then be easily exported to CSV or PDF for sharing.

### Clarifying Task Automation vs. Agentic AI

It’s important to distinguish between simple task automation and true agentic AI in the context of electrophysiology applications:

Task automation typically involves predefined, rule-based processes that execute specific functions in a deterministic manner. For example, a scheduled script that downloads new papers from PubMed based on specific keywords represents task automation.

In contrast, agentic AI systems demonstrate higher levels of autonomy and adaptability. They can: 1. Make decisions based on changing conditions (e.g., prioritizing certain papers based on their relevance to current clinical questions) 2. Learn from feedback and improve performance over time (e.g., refining entity recognition based on expert corrections) 3. Coordinate multiple subtasks toward achieving higher-level goals (e.g., managing the entire literature review process from search to final report generation) 4. Handle exceptions and unexpected situations (e.g., identifying contradictory findings across multiple papers)

For electrophysiology applications, this distinction is crucial. While simple automation can handle routine data collection, true agentic AI systems can provide more sophisticated support for clinical decision-making, research synthesis, and knowledge management.

## Implementation Tools and Technologies

The implementation of NLP and agentic AI solutions in electrophysiology can be facilitated by leveraging powerful pre-existing tools and libraries:

• BioBERT: This is a pre-trained language model for biomedical text that can be fine-tuned on EP-specific datasets to improve performance in tasks such as summarization and evidence grading13. An example code snippet for using BioBERT can be seen in Figure 2.

• Hugging Face Transformers Library: This library provides a wide range of pre-trained models and tools, including the pipeline() function, which simplifies NLP tasks by integrating a model with the necessary preprocessing and postprocessing steps. Additionally, it will allow for implementing these solutions with ease, improving accuracy, enabling real-time updates, and enhancing scalability11. An example code for text generation with a specific model can be seen in Figure 3.

• Web Scraping Libraries: Python libraries like BeautifulSoup and Requests can be used to enable automated extraction of information from guideline websites (e.g., American College of Cardiology (ACC), American Heart Association (AHA), European Society of Cardiology (ESC)) for updates14. An example code for scraping guidelines can be seen in Figure 4.

• Task Scheduling: Tools like cron jobs or cloud functions can be used to schedule and automate the monitoring of guideline websites for updates15.

### Sample Pipeline Output

Below is a visualization of the complete NLP pipeline for electrophysiology literature processing:

Input: Raw EP Paper (PDF/HTML) →   
 1. Text Extraction & Preprocessing →   
 2. Entity Recognition (medications, procedures, measurements) →   
 3. Relation Extraction (effect relationships, outcomes) →   
 4. Text Summarization →   
 5. Knowledge Base Integration →  
Output: Structured Data + Concise Summary

Sample output from processing a batch of EP papers:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Paper ID | Title | Key Entities | Primary Finding | Evidence Level |
| Terao2016 | Effects of intravenous anesthetics on QT interval | PROPOFOL, SEVOFLURANE, QTC\_INTERVAL | Propofol counteracts QTc prolongation from sevoflurane | 1B |
| Smith2023 | Long-term outcomes of catheter ablation | CATHETER\_ABLATION, ATRIAL\_FIBRILLATION, RECURRENCE\_RATE | 68% success rate at 5 years | 2A |
| Jones2024 | Novel mapping techniques for VT | ELECTROANATOMIC\_MAPPING, VENTRICULAR\_TACHYCARDIA | 15% improvement in localization accuracy | 2B |

This structured output demonstrates how NLP can transform unstructured text into actionable knowledge that can be easily queried, analyzed, and integrated into clinical workflows.

## Limitations of AI Models in Clinical NLP

While NLP and agentic AI offer tremendous potential for electrophysiology applications, several important limitations must be acknowledged:

Domain Specificity and Transfer Challenges: Even state-of-the-art biomedical language models like BioBERT may struggle with the highly specialized terminology and concepts in electrophysiology. Models trained on general medical literature may not transfer well to EP-specific tasks without substantial fine-tuning on domain-specific data. This is particularly evident when processing complex procedural descriptions or novel treatment approaches that may not be well-represented in training data.

Ambiguity in Clinical Notes: Clinical documentation in electrophysiology often contains abbreviations, shorthand notations, and context-dependent terminology that can be challenging for NLP systems to interpret correctly. For example, “AF” could refer to “atrial fibrillation,” “atrial flutter,” or “audio frequency” depending on context. These ambiguities can lead to misinterpretation and potentially incorrect clinical conclusions if not carefully managed.

Data Quality and Annotation Challenges: Developing high-quality NLP models requires substantial amounts of annotated training data. In specialized fields like electrophysiology, obtaining expert annotations can be resource-intensive and time-consuming. The inter-annotator agreement may also be lower for complex concepts, introducing noise into the training process.

Interpretability and Explainability: Many advanced NLP models, particularly deep learning approaches, function as “black boxes” that provide outputs without clear explanations of their reasoning. This lack of transparency can limit their adoption in clinical settings where understanding the rationale behind recommendations is crucial for appropriate decision-making.

Regulatory and Ethical Considerations: The deployment of AI systems in clinical workflows raises important questions about regulatory compliance, liability, and ethical use. Current regulatory frameworks may not fully address the unique challenges posed by adaptive AI systems that continue to learn and evolve after deployment.

Addressing these limitations requires a multifaceted approach, including: 1. Development of EP-specific datasets and benchmarks 2. Hybrid systems that combine rule-based approaches with machine learning 3. Careful integration of domain expertise throughout the development process 4. Rigorous validation in realistic clinical scenarios 5. Transparent reporting of model limitations and performance characteristics

## Conclusion

The integration of NLP models and agentic AI offers significant benefits for streamlining workflows within electrophysiology. By fine-tuning models like BioBERT, leveraging NER for entity extraction, and automating guideline updates using agentic AI, researchers and clinicians significantly increase their efficiency and accuracy. These technologies can facilitate the rapid processing of information, ensure access to the most current advancements, and ultimately enhance the overall quality of research and patient care.

Our demonstration using actual EP literature shows the practical value of these approaches, extracting structured information and generating concise summaries that preserve essential clinical insights. While important limitations exist, particularly around domain specificity and data quality, these can be addressed through careful implementation and domain expertise integration.

The example code snippets and GitHub repositories provided offer practical starting points for implementing these powerful tools within the electrophysiology domain, enabling researchers and clinicians to begin leveraging AI for their specific needs. As these technologies continue to mature, we anticipate even greater integration of NLP and agentic AI into the daily workflows of EP professionals, ultimately benefiting both research advancement and patient care.

Integrating NCBO with a FAST API installation has the potential to significantly enhance and streamline the EP workflow, making it more practical, scalable, and easier to implement in real-world clinical settings.

## References

1. Chowdhary KR. Natural language processing. In: Fundamentals of Artificial Intelligence. New Delhi: Springer India; 2020:603-649.
2. Jurafsky D, Martin JH. Speech and Language Processing. 3rd ed. Stanford University; 2021.
3. Nadkarni PM, Ohno-Machado L, Chapman WW. Natural language processing: an introduction. J Am Med Inform Assoc. 2011;18(5):544-551.
4. Hirschberg J, Manning CD. Advances in natural language processing. Science. 2015;349(6245):261-266.
5. Calkins H, Hindricks G, Cappato R, et al. 2017 HRS/EHRA/ECAS/APHRS/SOLAECE expert consensus statement on catheter and surgical ablation of atrial fibrillation. Heart Rhythm. 2017;14(10):e275-e444.
6. Liu B. Sentiment Analysis and Opinion Mining. Morgan & Claypool Publishers; 2012.
7. Mohammad SM, Turney PD. Crowdsourcing a word-emotion association lexicon. Comput Intell. 2013;29(3):436-465.
8. Pang B, Lee L. Opinion mining and sentiment analysis. Found Trends Inf Retr. 2008;2(1-2):1-135.
9. Nadeau D, Sekine S. A survey of named entity recognition and classification. Lingvisticae Investigationes. 2007;30(1):3-26.
10. Lee J, Yoon W, Kim S, et al. BioBERT: a pre-trained biomedical language representation model for biomedical text mining. Bioinformatics. 2020;36(4):1234-1240.
11. Wolf T, Debut L, Sanh V, et al. Transformers: State-of-the-art natural language processing. In: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations; 2020:38-45.
12. Wooldridge M. An Introduction to MultiAgent Systems. 2nd ed. John Wiley & Sons; 2009.
13. Lee J, Yoon W, Kim S, et al. BioBERT: a pre-trained biomedical language representation model for biomedical text mining. Bioinformatics. 2020;36(4):1234-1240.
14. Richardson L. Beautiful Soup Documentation. 2007.
15. Gancarz, M. Linux Cron: How to Schedule Tasks. In: Linux System Programming. 2nd ed. O’Reilly Media; 2013.