**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. However, even with the extensive functionality of any given tool to process large amounts of linguistic data, many NLP models need to be specialized further in order to provide more catered results to the user. 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. This article explains a developing model that aims to effectively extract important details from complex bodies of text. A visualization of the overall workflow model is shown in Figure 1.

**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 categorize 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 2.

*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.

**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. It is important to clarify that the agentic AI systems described in this paper are not intended to operate with full autonomy or clinical authority. Rather, they perform workflow-specific automation tasks (e.g., summarization, extraction, notification) that support human users. This distinction between assistive automation and agentic autonomy is critical. While the term “agentic AI” implies adaptive execution of predefined tasks, it does not suggest independent clinical decision-making without oversight. Future development should continue to prioritize safety, human oversight, and explainability to ensure ethical integration into clinical practice. 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. An example code snippet utilizing BioBERT can be found in Figure 3.

*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.

**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:

**Module Imports, Configuration, and Logging**

Model configuration begins with initialization sequences. These include importing relevant modules to execute downstream functions. The functions *os, fitz,* and *transformers* modules assist in accessing environment variables for ease of file handling, extract text from a file, and utilize the Hugging Face Transformer 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.

Additionally, we configurate the model to access the file directly. A specific summary model is chosen from the Hugging Face library so that different models can be tested easily. All other variables denoted in the Configuration, Logging, and Utilities section are there to help with obtaining full functionality of modules defined earlier and error handling for developers. Refer to Figure 4 below for initialization code.

*Utilities*

Four functions are defined to provide the core functionality of the model. The *extract\_pdf\_text* file is crucial for interpreting the complex text in electrophysiology papers and is often used in high-volume literature reviews. The *summarize\_text* function utilizes the Hugging Face tool to generate concise summaries for each section of a large amount of text – a useful tool in reducing clinician time reading full-length documents. The *get\_ner\_pipeline* function is an helper function that helps the *extract\_ner* function execute properly. The NER functions are utilizing the BioBERT model for biomedical text that can be used to fine tune understanding electrophysiology-specific datasets to improve summarization and evidence grading 13. Refer to Figure 5 for Utilities code.

To call all functions, the Main Workflow section incorporates each call to output both summaries and extracted entities to the console. Refer to Figure 6 for Main Workflow code.

* **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 updates13. An example code for scraping guidelines can be seen in Figure 7.
* **Task Scheduling:** Tools like cron jobs or cloud functions can be used to schedule and automate the monitoring of guideline websites for updates14.

**Conclusion**

The integration of NLP models and agentic AI offer 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. Example code snippets for utilizing BioBERT, NER, web scraping for guidelines, guideline comparison, and an EP literature agent are referenced in Figures 8-10, providing practical starting points for implementing these powerful tools within the electrophysiology domain.

While NLP and agentic AI systems offer significant promise, their implementation in clinical workflows must acknowledge certain limitations. Large language models (LLMs) are prone to generating hallucinations—confident but incorrect outputs—particularly in the presence of noisy, ambiguous, or domain-shifted input common in clinical narratives15,16. Clinical text often contains abbreviations, shorthand, and inconsistent terminology that can impair the performance of models trained on general corpora16. Furthermore, the variability in electronic health record (EHR) documentation and the lack of standardization across institutions can reduce model generalizability.

To mitigate these issues, strategies such as domain-specific fine-tuning (e.g., using BioBERT), hybrid human-in-the-loop systems, and post-processing rule sets can enhance accuracy and reliability. Reinforcement learning from human feedback (RLHF) and adversarial validation can also help reduce hallucination risk16. While agentic AI systems can automate many repetitive tasks, they must remain subordinate to clinical judgment and function as assistive tools rather than autonomous agents in critical decision-making contexts.

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