Review of Contemporary Philosophy
ISSN: 1841-5261, e-ISSN: 2471-089X
Vol 22 (1), 2023
Pp 3593 - 3599

Leveraging Natural Language Processing for Enhanced Research and Clinical Management of Thyroid Disorders through Mining Electronic Health Records: Review

[1]-Shama Rshaid Bin Zwayed,[2]-Rowaf Zghir A Alrowaili,[3]- Mohammed Abdullah Ail Al Nosyan,[4]-Ali Mohammed Kleibi,[5] -Dalia Nawash Alanzi,[6]-Nawal Ibrahim Yaqub Qadah,[7]-Hanan Abraham Al Gezani,[8]- Albandary Awadh Almutairi,[9]_Majed Mislat Eid Albaqami,[10]-Zahra Ahmed Bosilly,[11]-Mofarhe Yahya Mashike,[12]-Ghaliah Musallam Alhawiti

1. Ksa, Ministry Of Health, The First Health Cluster In Riyadh
2. Ksa, Ministry Of Health, Turaif General Hospital.
3. Ksa, Ministry Of Health, National Guard Health Affairs
4. Ksa, Ministry Of Health, Jazan Health Cluster
5. Ksa, Ministry Of Health, Maternity And Children's Hospital In Tabuk
6. Ksa, Ministry Of Health, Sabya General Hospital
7. Ksa, Ministry Of Health, Bish General Hospital
8. Ksa, Ministry Of Health, Riyadh Specialized Dental Center
9. Ksa, Ministry Of Health, King Salman Hospital
10. Ksa, Ministry Of Health, Ahad Al-Masrah General Hospital
11. Ksa, Ministry Of Health, Bish General Hospital
12. Ksa, Ministry Of Health, Maternity And Children's Hospital In Tabuk

Abstract

Background: Natural Language Processing (NLP) has emerged as a vital tool in the healthcare sector, particularly for mining Electronic Health Records (EHRs) to enhance research and patient care. Despite the wealth of unstructured data in EHRs, extracting useful information for clinical decision-making remains challenging. This review focuses on the applications of NLP in understanding and managing thyroid disorders, which are prevalent yet often under-researched.

Methods: A systematic review was conducted, sourcing publications from 2012 to 2023 across databases such as MEDLINE, EMBASE, and Scopus. The search strategy, developed by an experienced librarian, targeted studies utilizing NLP to analyze EHR data related to thyroid disorders, including nodules and cancer.

Results: The review highlighted various NLP algorithms designed to classify thyroid nodules and predict cancer outcomes with impressive accuracy rates ranging from 77% to 100%. Notable studies demonstrated the ability of NLP to extract key data from radiology and pathology reports, improving the understanding of patient quality of life and treatment responses. Despite these advancements, the integration of NLP applications into clinical practice remains limited, with only one study employing a prospective design.

Conclusion: NLP holds significant promise for transforming the management of thyroid disorders by facilitating the extraction and analysis of unstructured data from EHRs. However, challenges such as variability in methodologies, data representation, and the need for extensive validation hinder widespread adoption. Future research should focus on optimizing NLP techniques and addressing these barriers to enhance clinical utility.

Keywords: Natural Language Processing, Electronic Health Records, Thyroid Disorders, Machine Learning, Clinical Decision-Making

Received: 13 october 2023 **Revised:** 27 November 2023 **Accepted:** 11 December 2023

1. Introduction

Artificial intelligence (AI) aspires to replicate human-like intelligence in entities (e.g., machines) that can process information and execute actions similar to human behavior. Furthermore, machine learning is a swiftly advancing domain within computer science that endeavors to train machines with data sets to undertake laborious tasks that usually necessitate human cognitive capabilities [1,2]. The capacity to address tangible challenges across multiple sectors, including healthcare, has prompted heightened investigation into its applications. By incorporating diverse AI modalities into physicians' decision-making processes, this technology could advance the medical field by augmenting diagnostic test accuracy, optimizing provider workflows, facilitating improved disease and therapeutic monitoring, and ultimately yielding superior patient outcomes [3].

Natural language processing (NLP) constitutes the convergence of linguistics and artificial intelligence, facilitating the analysis of text and speech to attain human-like comprehension of language. Despite its extensive history exceeding 50 years, the increasing relevance in medicine has generated considerable interest in these technologies, particularly by surmounting prior limitations through advancements in machine and deep learning [4,5]. In healthcare, NLP models have predominantly been employed to identify and extract information from unstructured data within electronic health records (EHRs). The adoption of EHRs has resulted in a dramatic increase in the volume of healthcare data over the last two decades. Approximately 20% of Electronic Health Record (EHR) data is projected to be formatted as diagnostic or billing codes, along with basic clinical variables such as vital signs or laboratory findings [6].

Conversely, the majority of data in Electronic Health Records (EHRs) is unstructured, presented as free text, such as clinical notes or diagnostic reports, rendering their utilization in research laborious and complex [7]. To mitigate this issue, Natural Language Processing (NLP) techniques have been developed to effectively extract and standardize varied medical data from textual sources, including elements such as medical history, physical examinations, laboratory results, diagnostic reports, and treatment documentation. For instance, in radiology, NLP has been employed to identify specific features of interest within imaging reports. Likewise, in oncology, it has been utilized to extract and categorize information from pathology reports, thereby facilitating the staging and prediction of outcomes for different cancer types [8,9].

Thyroid diseases are frequent in the general population. Recent studies have evidenced the efficacy of diverse NLP systems in extracting pertinent information from EHRs in thyroidology. These NLP-driven methodologies have exhibited potential in augmenting and validating diagnostic and prognostic instruments for various thyroid pathologies, including functional thyroid disorders, thyroid nodules, and thyroid cancer [20,21]. Notwithstanding these encouraging advancements, the current literature is deficient in a thorough overview. This review might be essential for physicians, researchers, and other stakeholders seeking to comprehend the use of NLP in enhancing the treatment of patients with thyroid disorders. This research aimed to address this gap by thoroughly examining the uses of natural language processing in thyroid-related disorders. We sought to encapsulate the existing issues and provide insights into future prospects in this emerging subject.

2. Methods

A thorough search was performed across several scientific databases for publications published from 2012 to 2023. The databases used were MEDLINE, EMBASE, Cochrane Central Register of Controlled Trials, Cochrane Database of Systematic Reviews, and Scopus. An experienced librarian (L.P.) devised and executed the search strategy for references using NLP in patients with thyroid disorders.

3. Applications of Natural Language Processing in Thyroid Nodules

Numerous NLP algorithms were created and trained on extensive datasets to categorize nodules as benign or malignant based on documented radiologic features (accuracy, 86%-88%; sensitivity, 84%-92%; and

positive predictive value, 94%). Additionally, other NLP models focused on extracting detailed radiology characteristics from ultrasound reports (accuracy, 77%-98%; sensitivity, 85%-98%; and positive predictive value, 74%-98%) [22,23].

Incidental thyroid abnormalities often occur in nonthyroid-related imaging, resulting in heightened identification of nodules and a possible diagnosis of thyroid cancer. Drake et al. used a natural language processing method to assess the incidence of incidental observations across several imaging modalities [24-29]. Canton et al. [15] created a very precise model for identifying thyroid lesions in imaging investigations often used in trauma evaluations within emergency department contexts (sensitivity, 90%; specificity, 95.3%).

The Thyroid Imaging, Reporting, and Data System (TI-RADS) is often used to standardize reporting methods for thyroid nodule attributes [30]. Chen et al. [19] created a model to address the essential deficiencies of TI-RADS. Furthermore, Short et al. [31] developed a natural language processing pipeline designed to identify radiologic reports that meet the requirements for follow-up evaluations. Their model demonstrated notable accuracy (96.5%), sensitivity (92.1%), and specificity (96%). Additionally, Santos et al. [30] created a methodology intended to amalgamate TI-RADS findings with patient demographic data and concomitant conditions. This model achieved prospective validation (accuracy, 0.89; F1 score, 0.99) and was tested at an external facility (accuracy, 0.85; F1 score, 0.94). Additionally, Zhang et al [32-34] developed a multistep model that integrates data from thyroid images, pathology reports, and radiology reports, attaining an accuracy rate of 83%.

4. Applications of Natural Language Processing in Thyroid Cancer

Lian et al [24] developed an NLP pipeline to measure and categorize health-related quality of life based on narrative interviews with patients who underwent surgical treatment (area under the curve, 0.76; accuracy, 70.09; SN, 70.02%; and PPV, 70.20%).25 In addition, Yoo et al [12] developed an NLP algorithm to determine thyroid cancer diagnosis and stage based on retrospective information from medical records, specifically using surgical pathology and whole-body scan reports (SN, 100%; PPV, 100%). Another application successfully extracted information from internet papers and genomic databases to discover genes associated with nonmedullary thyroid cancer, which accounts for 95%-97% of all thyroid malignancies [35]. Zhou et al. [36] used a natural language processing system to extract genes associated with nonmedullary thyroid carcinoma from web resources.

5. Applications of NLP in Functional and Autoimmune Disorders

Grani et al. [22] used a natural language processing pipeline to gather data from text conversations in an online open medical forum to examine patient experiences with hypothyroidism and their worries about treatment. Park and Hong [27] sought to elucidate patients' viewpoints on thyroid hormone replacement therapy using online health forums (WebMD) and assess its influence on treatment satisfaction. In a separate study, Zheng et al. [35] developed an NLP-based tool that extracts clinical characteristics of hypothyroid patients from EHRs, utilizing phenotypes gathered from various medical resources, achieving an accuracy rate exceeding 97%. Additionally, Luft et al. [25] employed NLP to extract clinical features from EHRs of pediatric patients with mood and anxiety disorders, correlating these features with abnormal thyroid-stimulating hormone levels.

The digitalization of health care seeks to enhance patient care, optimize health care processes, and transform clinical and health care delivery research [37-40]. Natural Language Processing (NLP) can extract extensive narrative data and convert it into computable elements for subsequent analyses, a task that was formerly constrained by labor-intensive and time-consuming manual extraction by human annotators. As in all sectors of health care, the potential applications and advantages of NLP in thyroid diseases are substantial. We observed a rising quantity of NLP-focused thyroid papers, particularly in the last three years, with over fifty percent of the included articles published during this period. This seems to be the first systematic review of NLP applications within the realm of thyroidology [41-44]. Our comprehensive analysis revealed that, while still constrained, NLP is now used to investigate thyroid illnesses, namely

thyroid nodules and thyroid cancer, which constituted 54% and 29% of the papers in our review, respectively.

Research has utilized natural language processing to extract features of thyroid nodules from radiology reports by employing advanced deep learning models. Moreover, while certain models concentrated on fundamental tasks, such as identifying the presence of thyroid incidentalomas in computed tomography, magnetic resonance imaging, or ultrasound reports, others demonstrated the capability to ascertain whether the reported incidentaloma warranted further ultrasound evaluation and monitored the completion of such assessments. In comparison to traditional manual extraction of unstructured data, these models effectively leveraged extensive datasets, thereby facilitating observational research, enhancing quality improvement initiatives, standardizing unstructured documentation, and developing real-time predictive tools for clinical practice. NLP models successfully constructed extensive data sets by extracting features from various unstructured text sources, such as diagnostic and pathology reports and clinician documentation. Additionally, certain models standardized unstructured data from multiple institutions to create multicenter data sets.

While the majority of models used EHR data, other important data sources have also been investigated. Zheng et al. [35] used phenotypes derived using NLP from several web sites. Others employed NLP tools to streamline abstract screening for systematic literature reviews concerning genetic associations in thyroid cancer, as well as to automate the analysis and integration of findings from previously published studies. These initiatives enabled researchers to utilize data more efficiently and comprehensively from the rapidly expanding corpus of literature and genetic repositories. Moreover, Park and Hong used natural language processing on social media postings to discern concerns pertaining to thyroid hormone replacement from patient medication evaluations. This tool can offer a comprehensive understanding of the patient experience, encompassing their emotional and social reactions to their condition and treatments, which may not be adequately documented in clinical records. This facilitates the identification of themes for discussion during shared decision-making sessions and delineates factors to be considered in future treatment or quality-of-life research.

Despite the encouraging outcomes of NLP, none of the applications examined in this study are now accessible for use in clinical practice. Among the 24 studies identified, only one employed a prospective design, and two validated their NLP models in an external healthcare setting. The integration of these NLP interventions into standard research or clinical practice faces numerous challenges that require meticulous consideration and collaborative efforts to overcome. Specifically in the thyroid field, we hypothesize that the uptake of NLP methods is associated with the complexity of the thyroid-related domains, variations in language expression and reporting styles, completeness and accuracy of clinical documentation (ie, data on patient-specific concerns, complaints, or severity of symptoms depends on the accuracy of providers' documentation), semantic (ie, misspellings, abbreviations, acronyms, or synonyms), and context (ie, it is challenging to create algorithms that can appropriately extract chronologic descriptions or simultaneous references in situations like a thyroid ultrasound report that includes several nodules), which can affect the NLP outcome, decrease the performance of the algorithm when applied to different institutions, and limit the portability and scalability of the interventions [7,21,34,43]. In addition, data sources need to be representative of the population to avoid the incorporation of inequities and social bias into the models [44]. Finally, using NLP methods requires high optimization for the local environment and extensive domain knowledge, which can be expensive, and stakeholders' lack of financial resources or prioritization could halt their implementation. Consequently, efficacy and cost-effectiveness studies are essential to validate the intervention's usefulness and promote its adoption.

This research highlights a significant variation in NLP methodologies within the field of thyroidology. Deep learning has been the predominant technique in natural language processing, with several research use pretrained big language models, followed by rule-based methodologies. It is important to note that several research did not provide detailed details about the NLP approaches used.

In considering the future of NLP in thyroid nodule and cancer care, it is clear that improving reporting systems and integrating models, especially via big language models, would greatly enhance the importance of NLP. This integration signifies a transition towards more advanced, efficient, and adaptable uses of NLP in the treatment of thyroid nodules and cancer.

We recognize many limitations that must be taken into account while assessing our findings. The variability in methodology, outcomes, and performance criteria across the included research rendered it impractical to uniformly summarize individual study findings and to do a meta-analysis. Furthermore, we must acknowledge the possibility of publication bias, which may result in an overrepresentation of positive outcomes. Nonetheless, despite these constraints, it is essential to emphasize the merits of our systematic study. Our results provide a thorough and strong definition of the current state of NLP in thyroidology, presenting significant implications for doctors, researchers, and other stakeholders involved in this area of inquiry.

6. Conclusion

The use of NLP in thyroidology has increasing interest and has the potential to enhance research and patient treatment, while alleviating the strain on healthcare system stakeholders. It is important to note that the areas of focus in thyroidology and the used NLP approaches are fairly limited. Thus, significant opportunities remain for additional investigation into the unexplored potential of NLP applications in many thyroid disorders that have not previously been examined.

References

1. Sarker IH. AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart sys- tems. SN Comput Sci. 2022;3(2):158.
2. Silva GFS, Fagundes TP, Teixeira BC, Chiavegatto Filho ADP. Machine learning for hypertension prediction: a systematic re- view. Curr Hypertens Rep. 2022;24(11):523-533.
3. Kaul V, Enslin S, Gross SA. History of artificial intelligence in medicine. Gastrointest Endosc. 2020;92(4):807-812.
4. Toro-Tobon D, Loor-Torres R, Duran M, et al. Artificial intelligence in thyroidology: a narrative review of the current applications, associated challenges, and future directions. Thyroid. 2023;33(8):903-917.
5. Nadkarni PM, Ohno-Machado L, Chapman WW. Natural lan- guage processing: an introduction. J Am Med Inform Assoc. 2011; 18(5):544-551.
6. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. Nat Med. 2019;25(1):24-29.
7. Hossain E, Rana R, Higgins N, et al. Natural language processing in electronic health records in relation to healthcare decision- making: a systematic review. Comput Biol Med. 2023;155: 106649.
8. HIT Consultant. Why unstructured data holds the key to intel- ligent healthcare systems. https://hitconsultant.net/2015/03/31/ tapping-unstructured-data-healthcares-biggest-hurdle-realized/.
9. Demner-Fushman D, Chapman WW, McDonald CJ. What can natural language processing do for clinical decision support? J Biomed Inform. 2009;42(5):760-772.
10. Mithun S, Jha AK, Sherkhane UB, et al. Clinical concept-based radiology reports classification pipeline for lung carcinoma. J Digit Imaging. 2023;36(3):812-826.
11. Yim WW, Yetisgen M, Harris WP, Kwan SW. Natural language processing in oncology: a review. JAMA Oncol. 2016;2(6):797- 804.
12. Yoo S, Yoon E, Boo D, et al. Transforming thyroid cancer diag- nosis and staging information from unstructured reports to the observational medical outcome partnership common data model. Appl Clin Inform. 2022;13(3):521-531.
13. Idarraga AJ, Luong G, Hsiao V, Schneider DF. False negative rates in benign thyroid nodule diagnosis: machine learning for detecting malignancy. J Surg Res. 2021;268:562-569.
14. Greenhalgh T, Robert G, Macfarlane F, Bate P, Kyriakidou O, Peacock R. Storylines of research in diffusion of innovation: a meta-narrative approach to systematic review. Soc Sci Med. 2005;61(2):417-430.

15. Canton SP, Dadashzadeh E, Yip L, Forsythe R, Handzel R. Automatic detection of thyroid and adrenal incidentals using radiology reports and deep learning. J Surg Res. 2021;266: 192-200.
16. Chen D, Shi C, Wang M, Pan Q. Thyroid nodule classification using hierarchical recurrent neural network with multiple ultra- sound reports. In: Neural Information Processing; 24th Interna- tional Conference, ICONIP 2017, Guangzhou, China, November 14-18, 2017, Proceedings, Part V 24. Springer; 2017:765-773.
17. Chen D, Zhang J, Li W. Thyroid nodule classification using two levels attention-based bi-directional LSTM with ultrasound reports. In: 2018 9th International Conference on Information Technology in Medicine and Education (ITME). IEEE; 2018.
18. Chen KJ, Dedhia PH, Imbus JR, Schneider DF. Thyroid ultra- sound reports: will the thyroid imaging, reporting, and data sys- tem improve natural language processing capture of critical thyroid nodule features? J Surg Res. 2020;256:557-563.
19. Chen P, Feng C, Huang L, Chen H, Feng Y, Chang S. Exploring the research landscape of the past, present, and future of thy- roid nodules. Front Med (Lausanne). 2022;9:831346.
20. Dedhia PH, Chen K, Song Y, et al. Ambiguous and incomplete: natural language processing reveals problematic reporting styles in thyroid ultrasound reports. Methods Inf Med. 2022;61(1-2): 11-18.
21. Drake T, Gravely A, Westanmo A, Billington C. Prevalence of thyroid incidentalomas from 1995 to 2016: a single-center, retrospective cohort study. J Endocr Soc. 2020;4(1):bvz027.
22. Grani G, Lenzi A, Velardi P. Supporting personalized health care with social media analytics: an application to hypothyroidism. ACM Trans Comput Healthcare. 2022;3(1):1-28.
23. Kongburan W, Padungweang P, Krathu W, Chan JH. Semi-auto- matic construction of thyroid cancer intervention corpus from biomedical abstracts. In: 2016 Eighth International Conference on Advanced Computational Intelligence (ICACI). IEEE; 2016:150-157.
24. Lian R, Hsiao V, Hwang J, et al. Predicting health-related quality of life change using natural language processing in thyroid can- cer. Intell Based Med. 2023;7:100097.
25. Luft MJ, Aldrich SL, Poweleit E, et al. Thyroid function screening in children and adolescents with mood and anxiety disorders. J Clin Psychiatry. 2019;80(5):18m12626.
26. Miao S, Jing M, Sheng R, et al. The analysis of differential diag- nosis of benign and malignant thyroid nodules based on ultra- sound reports. Gland Surg. 2020;9(3):653-660.
27. Park SH, Hong SH. Identification of primary medication concerns regarding thyroid hormone replacement therapy from online patient medication reviews: text mining of social network data. J Med Internet Res. 2018;20(10):e11085.
28. Park J, You SC, Jeong E, et al. A framework (SOCRATex) for hierarchical annotation of unstructured electronic health re- cords and integration into a standardized medical database: development and usability study. JMIR Med Inform. 2021;9(3): e23983.
29. Pathak A, Yu Z, Paredes D, et al. Extracting thyroid nodules char- acteristics from ultrasound reports using transformer-based natural language processing methods. AMIA Annu Symp Proc. 2023: 1193-1200.
30. Santos T, Kallas ON, Newsome J, Rubin D, Gichoya JW, Banerjee I. A fusion NLP model for the inference of standardized thyroid nodule malignancy scores from radiology report text. AMIA Annu Symp Proc.; 2021;2021:1079-1088.
31. Short RG, Dondlinger S, Wildman-Tobriner B. Management of incidental thyroid nodules on chest CT: using natural language processing to assess white paper adherence and track patient outcomes. Acad Radiol. 2022;29(3):e18-e24.
32. Zhang Z, Yao L, Wang W, Jiang B, Xia F, Li X. A bibliometric analysis of 34,692 publications on thyroid cancer by machine learning: how much has been done in the past three decades? Front Oncol. 2021;11:673733.
33. Zhang Q, Zhang S, Li J, et al. Improved diagnosis of thyroid can- cer aided with deep learning applied to sonographic text re- ports: a retrospective, multi-cohort, diagnostic study. Cancer Biol Med. 2021;19(5):733-741.

34. Zhang J, Mazurowski MA, Allen BC, Wildman-Tobriner B. Multi- step Automated Data Labelling Procedure (MADLaP) for thy- roid nodules on ultrasound: an artificial intelligence approach for automating image annotation. Artif Intell Med. 2023;141: 102553.
35. Zheng NS, Feng Q, Kerchberger VE, et al. PheMap: a multi- resource knowledge base for high-throughput phenotyping within electronic health records. J Am Med Inform Assoc. 2020; 27(11):1675-1687.
36. Zhou J, Singh P, Yin K, et al. Non-medullary thyroid cancer sus- ceptibility genes: evidence and disease spectrum. Ann Surg Oncol. 2021;28(11):6590-6600.
37. Zuo M, Zhao H, Huang M, Chen D. Knowledge-Powered Thy- roid Nodule Classification with Thyroid Ultrasound Reports. In: 2021 IEEE International Conference on Dependable, Autonomic and Secure Computing, International Conference on Pervasive Intel- ligence and Computing, International Conference on Cloud and Big Data Computing, International Conference on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech). IEEE; 2021:597-604.
38. Tessler FN, Middleton WD, Grant EG, et al. ACR thyroid im- aging, reporting and data system (TI-RADS): white paper of the ACR TI-RADS committee. J Am Coll Radiol. 2017;14(5):587- 595.
39. Horvath E, Majlis S, Rossi R, et al. An ultrasonogram reporting system for thyroid nodules stratifying cancer risk for clinical management. J Clin Endocrinol Metab. 2009;94(5):1748-1751.
40. Sharma A, Harrington RA, McClellan MB, et al. Using digital health technology to better generate evidence and deliver evidence-based care. J Am Coll Cardiol. 2018;71(23):2680- 2690.
41. Kim E, Rubinstein SM, Nead KT, Wojcieszynski AP, Gabriel PE, Warner JL. The evolving use of electronic health records (EHR) for research. Semin Radiat Oncol. 2019;29(4):354-361.
42. Yang LWY, Ng WY, Foo LL, et al. Deep learning-based natural language processing in ophthalmology: applications, challenges and future directions. Curr Opin Ophthalmol. 2021;32(5):397- 405.
43. Newman-Griffis DR, Hurwitz MB, McKernan GP, Houtrow AJ, Dicianno BE. A roadmap to reduce information inequities in disability with digital health and natural language processing. PLoS Digit Health. 2022;1(11):e0000135.
44. Newman-Griffis DR, Desmet B, Zirikly A, Tamang S, Chang CH. Artificial intelligence for human function and disability. Frontiers in Digital Health. 2023;5:1282287.

استخدام معالجة اللغة الطبيعية لتحسين البحث والإدارة السريرية لاضطرابات الغدة الدرقية من خلال تحليل السجلات الصحية الإلكترونية: مراجعة

الملخص

الخلفية :ظهرت معالجة اللغة الطبيعية (NLP) كأداة أساسية في قطاع الرعاية الصحية، خاصة في تحليل السجلات الصحية الإلكترونية (EHRs) لتعزيز البحث ورعاية المرضى. على الرغم من الكم الهائل من البيانات غير المهيكلة في السجلات الصحية الإلكترونية، لا يزال استخراج المعلومات المفيدة لاتخاذ القرارات السريرية يمثل تحديًا. تركز هذه المراجعة على تطبيقات NLP في فهم وإدارة اضطرابات الغدة الدرقية، وهي اضطرابات شائعة ولكنها غالبًا ما تكون غير مدروسة بشكل كافٍ.

الطرق :تم إجراء مراجعة منهجية، حيث تم جمع المنشورات من عام 2012 إلى 2023 باستخدام قواعد بيانات مثل MEDLINE و EMBASE و .Scopusاستهدفت استراتيجية البحث، التي تم تطويرها بواسطة أمين مكتبة متخصص، الدراسات التي استخدمت NLP لتحليل بيانات السجلات الصحية الإلكترونية المتعلقة باضطرابات الغدة الدرقية، بما في ذلك العقيدات وسرطان الغدة الدرقية.

النتائج :سلطت المراجعة الضوء على خوارزميات NLP المختلفة التي تم تصميمها لتصنيف عقيدات الغدة الدرقية والتنبؤ بنتائج السرطان بدقة مذهلة تراوحت بين 77% و100%. أظهرت الدراسات البارزة قدرة NLP على استخراج البيانات الرئيسية من تقارير الأشعة والتقارير المرضية، مما أدى إلى تحسين فهم جودة حياة المرضى واستجابتهم للعلاجات. على الرغم من هذه التقدمات، لا يزال دمج تطبيقات NLP في الممارسات السريرية محدودًا، حيث أن دراسة واحدة فقط استخدمت تصميمًا مستقبليًا.

الاستنتاج :تتمتع معالجة اللغة الطبيعية بوعود كبيرة في تحسين إدارة اضطرابات الغدة الدرقية من خلال تسهيل استخراج وتحليل البيانات غير المهيكلة من السجلات الصحية الإلكترونية. ومع ذلك، فإن التحديات مثل التباين في المنهجيات، وتمثيل البيانات، والحاجة إلى التحقق الشامل، تعيق التبني الواسع. يجب أن تركز الأبحاث المستقبلية على تحسين تقنيات NLP ومعالجة هذه العوائق لتعزيز فائدتها السريرية.

الكلمات المفتاحية :معالجة اللغة الطبيعية، السجلات الصحية الإلكترونية، اضطرابات الغدة الدرقية، التعلم الآلي، اتخاذ القرار السريري.