The Language Processing Technologies to Reduce Nurse Charting Burden: A Scoping Review. (Global Vers.)

Chu-Yin Weng

Abstract
Healthcare systems worldwide face significant challenges due to dwindling nursing workforces and high rates of nurse burnout, exacerbated by extensive and demanding documentation processes. This review investigates the potential of a comprehensive suite of artificial intelligence technologies—including speech-to-text (STT) for transcription, large language models (LLMs) for automated document generation, and image analysis for lab results interpretation—to revolutionize nursing documentation globally. By automating and enhancing the accuracy and efficiency of clinical documentation, these technologies aim to reduce the administrative burden on nurses, thereby increasing job satisfaction and making the nursing profession more appealing. The paper discusses the integration, benefits, and multifaceted challenges of these technologies, such as the need for extensive training, integration complexities, and maintaining data security. Conclusively, while AI technologies offer significant promise for transforming nursing documentation, their successful implementation necessitates careful navigation of technological capabilities and practical constraints to truly benefit global healthcare systems.

Introduction
Global healthcare systems face a growing challenge due to a decline in the nursing workforce. This decline is exacerbated by demanding workloads and extensive working hours, leading to high burnout rates and diminished appeal of the profession. This high incidence of burnout not only diminishes the appeal of the nursing profession but also threatens the overall quality of patient care and healthcare system efficiency. Optimizing indirect nursing tasks, particularly clinical documentation, offers a promising solution. Improved documentation efficiency can enhance patient care quality, make nursing more attractive, and increase nurse job satisfaction. While accurate, concise, and clear medical records are essential for patient care continuity, communication among healthcare providers, and legal defensibility, the current time-consuming manual data entry process significantly contributes to nurse burnout. This review explores STT technologies specifically engineered to address these challenges by enhancing documentation efficiency and reducing nurse burnout.

Efficient clinical documentation is vital for patient care continuity, communication among healthcare providers, and legal defensibility. However, the traditional manual data entry process is time-consuming and significantly contributes to nurse burnout. To address this, our review investigates the integration of speech-to-text (STT) technologies as a potential solution to alleviate the documentation burden. These technologies, which convert spoken language into written text, could free up nurses for more direct patient care, thereby enhancing job satisfaction and making nursing a more attractive profession.

This review focuses explicitly on the effectiveness of artificial intelligence technologies in promoting documentation efficiency and consequently reducing nurse burnout within the Taiwanese context. By comprehensively examining the existing research, we aim to gain valuable insights into how STT can address this pressing issue and contribute to a more sustainable and fulfilling nursing environment.

Nurse Burnout

Alarmingly high rates of nurses experience burnout, with a staggering 68.6% of nurses who resigned from their positions cited burnout as the primary cause. Burnout, characterized by occupational exhaustion, disconnection, and a sense of personal unfulfillment, is a pervasive problem in nursing. There are many required duties in the nursing profession. These tasks can be divided into three groups: direct, indirect, and related nursing. Direct nursing involves providing hands-on care directly to patients. This includes managing admissions and discharges, monitoring vital signs, administering medications, offering patient education, and performing various therapeutic and nursing procedures. Indirect nursing includes administrative tasks that do not require direct face-to-face interaction with patients or their families but are still related to patient care, such as verifying medical orders, nursing records, tracking test results, making rounds, and handling medical orders. Related nursing pertains to tasks related to patient rights or nursing, namely activities that maintain the operation of the nursing unit but are not related to direct patient care, such as handovers, staffing, coordination, on-the-job education, and meetings. Research indicates that despite direct patient care being a core responsibility of nurses, over half their time is dedicated to indirect care activities. Notably, a significant portion of this indirect care involves creating and maintaining comprehensive patient documentation. Therefore, tackling the documentation process within indirect nursing can effectively decrease nurse burnout. Nurses are responsible for maintaining various detailed medical records, including admission notes, progress notes, operative notes, patient summaries, handover notes, and discharge summaries. These notes detail a patient's medical history, physical exam findings, diagnoses, treatment plans, progress over time, surgical procedures, hospital stay, and post-discharge care recommendations. These documents require strict adherence to protocols and meticulous writing, often within complex electronic health record (EHR) systems.

Accurate and comprehensive patient documentation is a cornerstone of quality healthcare delivery. It is a detailed record of a patient's medical history, treatment plan, and progress. This information is crucial for ensuring continuity of care across different providers, facilitating informed clinical decision-making, and monitoring treatment efficiency. Moreover, documentation plays a vital role in patient safety by minimizing the risk of errors and ensuring clear communication among healthcare professionals. This documentation process significantly contributes to nurse burnout. Spending significant time documenting data can reduce time spent on direct patient care and other essential duties, leading to feeling overwhelmed and overworked. Additionally, the repetitive nature of these tasks, especially with complex EHR systems, can be frustrating and time-consuming. Inefficient documentation processes, such as outdated systems or poorly designed workflows, further exacerbate these challenges, increasing stress and burnout. Furthermore, nurses may sometimes perceive documentation as irrelevant to patient care, creating a sense of disconnect and frustration with the process. Although accurate, concise, and clear medical records are crucial for ensuring continuity of care, communication between healthcare providers, and legal defensibility, the current approach often requires writing notes in one go without the ability to edit or rewrite sections. While essential for maintaining accurate records, this meticulous approach adds to the overall documentation burden. Thus, we aim to streamline this documentation process to alleviate nurse burnout.

Technology Background

The past five years have witnessed an exponential surge in artificial intelligence (AI) development. Machine Learning (ML) serves as the powerful engine driving this progress. ML is a subfield of AI that ingests and analyzes vast amounts of data, enabling computers to autonomously improve at specific tasks without explicit programming.

Natural Language Processing (NLP), another subfield of AI, combines the power of computational linguistics with machine learning algorithms and deep learning. Computational linguistics is a data science-driven approach to analyzing language and speech. NLP encompasses tasks like sentiment analysis, where a computer can discern the emotional undercurrent of a piece of text. Large Language Models (LLMs) represent a specialized type of NLP system. Trained on massive text datasets, LLMs can generate human-quality text, translate languages, create creative content, and answer questions informally. LLMs have demonstrated remarkable abilities in understanding context, generating coherent responses, and performing tasks that require a deep understanding of language.

In the context of documentation, NLP and LLMs can significantly enhance the efficiency and accuracy of generating and managing written content. In healthcare, the application of these models for documentation involves challenges such as integrating them with existing Electronic Health Record (EHR) systems and ensuring they can handle the unique aspects of medical jargon and patient confidentiality. Detailed insights into the integration process and the specific technical requirements can help address these challenges effectively. NLP techniques can automatically extract relevant information from unstructured text, summarize documents, and ensure consistency in terminology and style. LLMs can assist in drafting documents by generating initial drafts based on given inputs, suggesting improvements, and even translating documentation into multiple languages to cater to diverse user bases. These capabilities can streamline the documentation process through reducing the manual effort required and improving the overall quality of the documents produced.

Automatic Speech Recognition (ASR) tackles the challenge of converting spoken language into text. These technologies work to create intelligent systems that facilitate natural and intuitive human-computer interaction. Typical approaches to ASR take three steps. First, pre-processing cleans the input audio and primes the recording for processing by removing noise and silence and performing channel equalization. Next, feature extraction identifies speech characteristics and features from the processed audio. These features typically fall into linguistic and acoustic categories. Linguistic features represent spoken words' information, usually including specific words, their grammatical alterations, or higher semantic and pragmatic markers. Acoustic features are primarily extracted using the models of the human auditory system. Prosodic features encompass aspects like length, tone, accent, and intonation. Spectral features relate to frequency content, while temporal features address changes in the speech signal over time (speech rate, rhythm, formant changes). These features are then fed into a machine learning or deep learning model that determines which sequences of words are most likely to be spoken.

Recent advancements in speech technology explore training systems directly from raw speech data. This approach, called end-to-end learning, relies on powerful convolutional neural networks (CNNs) and is often combined with Revolutional Neural Networks (RNNs). Initially developed for image recognition, CNNs have been adapted for natural language processing (NLP) tasks. They excel at capturing local patterns within structured inputs, which in NLP translates to identifying local features in sentences, such as n-grams, regardless of their position. On the other hand, RNNs are better suited to handling sequential data. They process information word-by-word, capturing context and dependencies between words, which is crucial for understanding the overall meaning of a sentence. This collaborative approach between CNNs and RNNs leads to a more comprehensive language understanding.

This end-to-end approach has multiple advantages over the traditional three-step process, such as reducing the complexity of the speech processing pipeline by eliminating the need for separate steps for feature extraction, feature selection, and model training. This streamlined process can lead to more efficient system development and maintenance. Additionally, CNNs can automatically learn relevant features from the raw data, potentially discovering more informative and task-specific features than those manually engineered. End-to-end learning also minimizes human intervention, allowing the model to learn unbiased, data-driven representations.

Researchers have recently been combining the power of large language models (LLMs) with ASR technologies to improve speech-to-text accuracy through generative error correction. Normally, ASR technologies produce the N-best hypothesis for the inputted audio, then choose the option with the best chance of being correct. With the invention of multimodal LLMs, which take several inputs, ML rescoring has been able to rerank the original N-best hypotheses and yield more accurate results. This convergence of advancements has created crucial human-computer interaction enablers, such as text-to-speech and speech-to-text technologies.

Aside from language processing technologies, image analysis is also crucial in the medical field. Image recognition and analysis have become indispensable in medical imaging, where the accurate interpretation of visual data can significantly impact patient outcomes. Initially developed for image recognition tasks, convolutional Neural Networks (CNNs) have been at the forefront of advancements in this domain. CNNs are particularly well-suited for image analysis because of their ability to detect and learn hierarchical features from raw pixel data automatically. In medical imaging, CNNs are applied to various tasks, such as identifying abnormalities in X-rays, CT scans, MRIs, and other imaging modalities. The layers of a CNN progressively extract higher-level features from the input images, starting from simple edges and textures to more complex shapes and patterns. This hierarchical feature extraction is crucial for detecting subtle anomalies indicating diseases.

For example, in radiology, CNNs can assist in detecting tumors, fractures, and other pathologies with high accuracy. These models are trained on large datasets of medical images annotated by experts, enabling them to learn the visual characteristics associated with different conditions. The ability of CNNs to learn from vast amounts of data allows them to achieve performance comparable to, and sometimes exceeding, that of human experts.

Building upon the foundation of these technologies and AI, we have infinite possibilities for enhancing nursing documentation. By utilizing these available technologies in different combinations, we can cover all aspects and tasks in nursing that require documentation. Thus, we will significantly reduce the time nurses spend on documentation, eliminating repetitive typing and prompting for specific details. This allows nurses to focus more on patient care rather than administrative tasks.

Implementation of the Nursing Avatar

Introducing a nursing avatar in healthcare presents a transformative opportunity to streamline the documentation processes associated with various stages of patient care. The nursing avatar is designed to provide hands-free, eyes-free, and keyboard-free services. It assists with generating essential medical documents by interacting directly with patients and healthcare professionals and interfacing with Electronic Health Records (EHR). This section details the design and implementation of this technology, focusing on the interaction between patients/nurses and the nursing avatar for each documentation process.

Interaction Details for Each Documentation Process

Admission Note

Interaction:

Upon a patient's arrival at a hospital, the nursing avatar acts as the first point of contact. The avatar initiates the admission process by conversing with the patient to gather necessary information such as medical history, current symptoms, and previous treatments.

Process:

- Greeting and Introduction: The avatar greets the patient, introduces itself, and explains the purpose of the interaction.
- Data Collection: The avatar asks questions to collect basic information, including the patient's personal details, medical history, and current health concerns. The patient responds verbally, and the ASR converts these responses into text.
- Information Sorting: The collected information is processed using NLP to categorize it into predefined fields within the EHR.
- Summary Generation: Using LLMs, the avatar generates a comprehensive text summary of the patient's initial condition and needs, which is then saved in the EHR.

Progress Report

Interaction:

The progress report feature captures updates on a patient's condition provided by nurses during their shifts. Nurses can interact with the avatar through voice commands to update the patient's status, vital signs, and any changes in treatment.

Process:

- Shift Start: At the beginning of a shift, the nurse can activate the avatar using a voice command. The avatar prompts the nurse to provide updates on the patient's condition.
- Data Entry: The nurse verbally describes the patient's condition, including any changes in vital signs, mood, or response to treatment. The ASR system converts this speech into text.
- Real-Time Integration: The avatar integrates these updates with existing treatment plans from doctors, ensuring all patient care information is current and accurately recorded.
- Medication Suggestions: The avatar can suggest medication options based on the patient's diagnosis using machine learning algorithms, assisting the nurse in decision-making.

Operation Note

Interaction:

For documenting surgical procedures, the nursing avatar extracts information from the EHR and assists in transcribing the details of the operation in real time. Surgeons and nurses can interact with the avatar through voice commands during and after the procedure.
Process:
Pre-Operation: The avatar retrieves relevant information about the scheduled surgery from the EHR and prepares a preliminary report.
During operations, surgeons and nurses use voice commands to update the avatar on the progress of the operation. The avatar records these details in real-time.
Post-Operation: After the surgery, the avatar asks for specific details about the operation, such as any complications, tissues removed, and post-operative instructions. This information is transcribed and summarized using LLMs.
Summary Generation: The avatar generates a comprehensive summary of the surgical procedure and updates the EHR.

Resuscitation Record
Interaction:
In critical care scenarios, the avatar assists in documenting resuscitation efforts. Nurses and doctors interact with the avatar using voice commands to ensure rapid and accurate record-keeping during emergencies.
Process:
- Emergency Activation: In the event of a cardiopulmonary arrest, the nurse or doctor activates the avatar using a specific voice command.
- Data Collection: The avatar collects data on vital signs and the resuscitation process from medical devices and the EHR.
- Real-Time Updates: During resuscitation, the avatar prompts the medical team for specific details, such as administered medications and the timing of interventions. This information is recorded in real-time.
- Record Completion: After the resuscitation, the avatar compiles all the collected data into a detailed resuscitation record.

Patient Summary
Interaction:
The patient summary concisely overviews a patient's hospital stay, including diagnoses, treatments, and outcomes. Nurses can interact with the avatar to review and update the summary.
Process:
- Weekly Updates: The avatar automatically generates a patient summary from the EHR records, encompassing diagnoses, treatments, medications, and noted problems.
- Review and Edit: Nurses can review the generated summary and provide additional details or corrections through voice commands.
- Finalization: The avatar finalizes the summary, ensuring it includes all necessary information for continuity of care.

Handoff Record
Interaction:

During shift changes, the nursing avatar documents the transfer of care between nurses. Nurses interact with the avatar to ensure a seamless transition and comprehensive patient care.
Process:

- Shift End: The outgoing nurse activates the avatar and begins the handoff process by summarizing the patient's condition and any significant events during the shift.
- Data Capture: The avatar records the conversation between the outgoing and incoming nurses, capturing essential information such as patient identification, current condition, medications, and treatments.
- Information Extraction: Using NLP, the avatar extracts and organizes the information into a detailed handoff report.
- Report Generation: The avatar generates a comprehensive handoff record, ensuring continuity of care through detailed and accessible shift reports.

Discharge Record
Interaction:
After a patient's hospital stay, the avatar generates a discharge record. Healthcare professionals interact with the avatar to ensure the record is complete and accurate.
Process:

- Preparation: The avatar retrieves comprehensive details from the EHR, including diagnoses, treatments administered, and follow-up care instructions.
- Review: Healthcare professionals review the generated discharge record and provide any additional details or corrections through voice commands.
- Finalization: The avatar finalizes the discharge record, providing a clear and complete account of the patient's hospital journey and subsequent care guidelines.

Additionally, while current nurse predictions for various statistics, such as fall risk, are already accurate, these tasks remain cumbersome and time-consuming. To alleviate this burden, the nursing avatar will incorporate artificial intelligence through processes such as transfer learning to fine-tune general-purpose models to identify specific risks that patients may face. With the development of advanced machine learning platforms like QOCA Hospital, the trend prediction of various patient risks has become more streamlined and accurate. These platforms leverage large datasets and sophisticated algorithms to analyze patient data, predict potential risks, and provide actionable insights. By integrating these predictive models into the nursing avatar system, we can enhance the accuracy and efficiency of risk assessments, allowing nurses to focus more on direct patient care and less on administrative tasks.

The nursing avatar leverages cutting-edge AI technologies to revolutionize nursing documentation. Automating and streamlining the documentation process significantly reduces nurse burnout and enhances patient care. This implementation serves as a blueprint for developing similar systems, providing a detailed account of the technology stack, design components, and development process and the specific interactions that facilitate efficient and effective documentation. This digital transformation of patient documentation supports healthcare professionals and improves the overall patient experience by ensuring precise and timely communication of medical information. Practitioners and nurses will become more efficient in transcriptions, increase productivity in healthcare systems, and reduce the time doctors need to spend with each patient by using readily available information. Voice-based assistants can maintain patients' EHRs and provide relevant information when needed, saving time, increasing efficiency, and allowing nurses to make more detailed notes with relevant details.

Features	Current Supporting Technology	Gaps in Technological Advancements	Areas of Improvement
Transcription	ASR systems such as Google Speech-to-Text, IBM Watson	Accuracy in noisy environments, lack of training in medical jargon, limited language support	• Fine-tune models with datasets containing background noise. • Implement noise-canceling microphones. • Train models with medical terminology using medical textbooks. • Include training data with different languages and dialects spoken in Taiwan.
Summarization/ Document generation	Large Language Models (LLMs) like GPT-4 for text generation	Contextual understanding, ensuring accuracy and relevance of generated text	• Improve context awareness with CNNs. • Train models on previously used medical documents written by current nurses.
Lab Result Analysis	Basic data analysis tools, EHR-integrated lab result reporting systems	Advanced predictive analytics, lack of diverse and representative datasets for training	• Develop advanced machine learning models for predictive analysis. • Gather and use diverse datasets for training. • Enhance real-time anomaly detection capabilities.
Care Plan Generation	Large Language Models (LLMs) like GPT-4 for text generation	Personalization based on patient history, dynamic updating based on real-time data, and lack of knowledge in care plan generation	• Fine tune general purpose LLMs through transfer learning with related textbooks and example care plans • Implement machine learning models using various patient data and their care plans.
Risk Analysis	Risk assessment tools using machine learning on patient data (e.g., risk calculators, predictive models)	Real-time risk prediction, incorporating unstructured data	• Develop models for real-time risk prediction, including analysis of unstructured data (e.g., clinician notes, patient feedback). • Utilize NLP to interpret and analyze unstructured data for risk assessment.

Figure 1. Current Supporting Technology, Gaps in Technological Advancements, and Areas of Improvement for Nursing Avatar Features

Literature Review

This review was conducted in compliance with the 2020 PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. We systematically searched PubMed, ScienceDirect, and Google Scholar to retrieve articles published from 2014 to 2024. The search queries included keywords such as "clinical documentation," “nursing,” “healthcare,” "speech recognition," "artificial intelligence," "machine learning," and "speech technology." We then filtered for free full-text articles, yielding an initial result of 39,373 articles. Inclusion in the review required that the articles were written in English and included essential metadata (authors, title, publication year) and an abstract. After applying these filters, we identified 54 studies from 30 journals. We selected only articles related to the feasibility of applying artificial technologies for documentation in a healthcare environment.

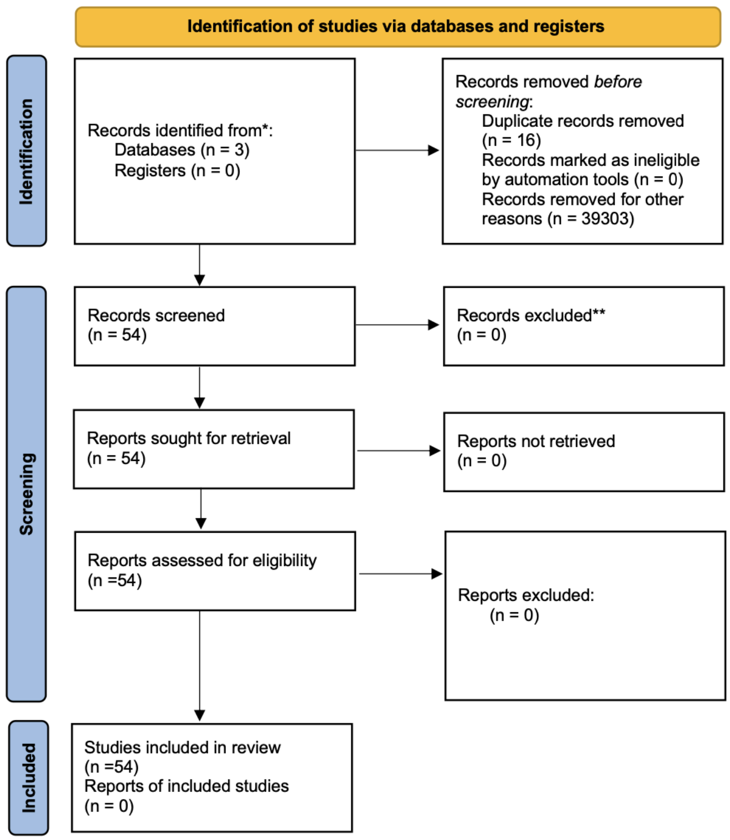

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 flow diagram.

Discussion

This review examined 54 studies investigating the use of automatic speech recognition (ASR), large language models, and image analysis technology in healthcare, spanning various countries and specialties. These studies unanimously support the ongoing development of technologies that facilitate this application. While the majority believe that it already has the capabilities to be beneficial, some raise concerns about its accuracy. Since no studies have been conducted on the implications of this technology on burden, we benchmark through efficiency, measured by the time spent on documentation.

The review identified several potential benefits associated with using Automatic Speech Recognition (ASR) in healthcare documentation. The findings suggest that ASR can significantly reduce the time nurses spend on documentation, thereby freeing up valuable time for other crucial patient care activities, resulting in improved care. Another significant benefit of ASR is its potential to reduce errors and the chance of missing information. Several studies reported a decrease in documentation errors associated with using ASR. This improvement can be attributed to the elimination of manual data entry errors and the potential for real-time dictation and correction. Additionally, the transcription service ensures that all spoken information is documented. Furthermore, studies indicate that ASR can alleviate the documentation burden on nurses. By automating the documentation process, ASR allows nurses to focus on direct patient care and interaction.

The review further elaborates on integrating automated documentation and image analysis technologies in streamlining healthcare documentation processes. Automated documentation systems, which use advanced algorithms to transcribe and organize spoken information into structured medical records, drastically reduce the time nurses spend manually entering data. This shift minimizes human errors and significantly decreases the overall documentation time.

Additionally, image analysis technologies transform how medical images are processed and interpreted in healthcare settings. These technologies utilize artificial intelligence (AI) to automatically analyze medical images such as X-rays, MRIs, and CT scans. By providing rapid, accurate interpretations, image analysis tools can flag critical findings and suggest annotations, which help in creating comprehensive and precise medical records faster. Integrating these technologies reduces the burden of mechanical documentation for nurses, allowing them to focus more on patient assessment, care planning, and direct interaction, which are essential for holistic patient care.

The combined use of automated documentation and image analysis enhances the efficiency of medical documentation and supports nurses in providing timely and focused care. By reducing the time required for administrative tasks, these technologies contribute to a more dynamic and responsive healthcare environment, ultimately leading to improved patient care and reduced nurse burnout.

However, challenges remain. Some studies highlighted concerns regarding the potential for clinically significant errors with ASR technology. It is crucial to ensure that ASR systems achieve a high level of accuracy in capturing medical information to avoid compromising patient care. Another point of consideration is the potential workflow shift associated with ASR implementation. Studies raised concerns about transitioning from writing to reviewing documents for nurses. Careful planning and training are necessary to ensure a smooth transition and maximize the benefits of this technology.

Limitations

While promising, the integration of speech-to-text (STT) technologies into nursing documentation faces several significant limitations that can be broadly categorized into implementation and technological challenges.

Training nurses to use STT technology effectively during the integration phase requires considerable time and energy, which could initially exacerbate burnout rather than alleviate it. Nurses must become proficient with the new system, and this learning curve can add to their already substantial workload. Furthermore, the privacy and security of recorded and digitized data are crucial concerns. Ensuring that sensitive patient information is protected throughout the data lifecycle requires robust encryption protocols and security measures, which can be complex and resource-intensive.

One of the primary technological limitations is the lack of large, comprehensive datasets required for training speech recognition technologies specific to the various Taiwanese languages and dialects. Taiwan's linguistic diversity includes multiple languages and dialects, and without extensive data representing this diversity, STT systems may struggle with accurate recognition and transcription. Additionally, the clinical environment where this technology is intended to be used is often noisy, further complicating the accuracy of STT systems. Background noise can significantly degrade the performance of speech recognition models, making it challenging to obtain clear and accurate transcriptions. Moreover, STT models require continuous training to maintain and improve their performance. This ongoing need for model refinement can be resource-intensive, necessitating constant updates and training to adapt to new language patterns, medical terminology, and evolving user needs.

Despite the potential benefits, the studies reviewed also highlight several methodological limitations that may affect the generalizability of the findings. Many studies suffer from weak methodologies, such as small participant pools that do not accurately represent the broader nursing population and short study periods that fail to reveal the long-term effects of STT on burnout and workflow integration. Research conducted in single hospitals or clinics may not account for variations across different healthcare settings, limiting the applicability of the results.

The current research also identifies significant knowledge gaps that future studies must address. It is essential to explore the impact of specific STT features, such as voice commands and correction tools, on documentation efficiency and user experience. Longer studies are necessary to investigate the long-term impact of STT on nurse burnout, workflow, and any unforeseen consequences. Identifying optimal implementation strategies for STT in various healthcare settings will be crucial for successful integration.

Several potential barriers exist for STT implementation in Taiwanese clinical settings. The costs of acquiring, installing, and maintaining STT systems must be weighed against potential benefits. Integrating these systems with existing electronic health record (EHR) systems is crucial, and nurses may require training and support to adapt to STT technology. Addressing potential user resistance or concerns about accuracy is vital, as are robust data security measures to ensure patient confidentiality.

Beyond these implementation barriers, technical challenges specific to Taiwan's healthcare context must be addressed. Training accurate speech recognition models requires large datasets of Taiwanese Mandarin, including medical terminology and regional variations. Technical concerns also include the potential vulnerability of STT systems to adversarial attacks, where intentional manipulation of audio input can lead to errors. Maintaining high accuracy in noisy environments like hospital wards is essential, necessitating advancements in noise cancellation and speech enhancement techniques. Additionally, ethical considerations must be explored, ensuring that nurses and patients are informed about STT use and their right to opt out of voice-based documentation.

The integration of large language models (LLMs) also presents unique challenges. LLMs often reflect biases in their training data, which can result in inaccuracies, especially in linguistically diverse regions like Taiwan. Furthermore, the adaptability of LLMs to specialized medical jargon is limited by the availability of comprehensive and up-to-date training data. An over-reliance on these technologies could lead to a degradation of manual documentation skills among nurses, potentially affecting the quality of patient records. Ethical considerations also arise, particularly concerning the consent of patients and healthcare providers regarding using their data for training such models. Continual learning and model updating pose additional logistical and financial burdens, while the models' performance in stressful or emergency conditions remains a concern. By addressing these limitations, knowledge gaps, and technical challenges, artificial intelligence technologies can become valuable tools for reducing nurse burnout and improving documentation efficiency in Taiwan's healthcare system.

Conclusion

This review highlights the significant potential of speech-to-text (STT) technologies to transform nursing documentation in Taiwan. By automating the documentation process, STT can reduce the administrative burden on nurses, addressing one of the primary factors contributing to nurse burnout. The ability to accurately and efficiently convert spoken language into written text can free up valuable time for direct patient care, enhancing the quality of healthcare delivery.

The integration of Natural Language Processing (NLP) and Large Language Models (LLMs) into these systems can further improve the efficiency and accuracy of documentation. These technologies can assist in drafting documents, summarizing unstructured text, and ensuring consistency in medical records, thus reducing the manual effort required from nurses. Moreover, advancements in Automatic Speech Recognition (ASR) and image recognition technologies, such as Convolutional Neural Networks (CNNs), offer additional opportunities to enhance nursing documentation. These technologies can assist in various tasks, from transcribing patient interactions to analyzing medical images, thereby supporting comprehensive and accurate patient records.

However, several challenges remain. The need for extensive training and integration, concerns about data privacy and security, and the limitations of current technological capabilities, such as handling background noise and the need for continuous training, must be addressed. Additionally, ensuring the accuracy of STT systems in capturing medical information is crucial to avoid compromising patient care. In conclusion, while the implementation of STT technologies in nursing documentation holds great promise, careful consideration of these limitations and challenges is essential. By addressing these issues, the healthcare system can leverage these advanced technologies to reduce nurse burnout, improve job satisfaction, and ultimately enhance patient care in Taiwan.

Works Cited

Ahlgrim, Christoph, et al. "Introduction of Digital Speech Recognition in a Specialised Outpatient Department: A Case Study." *BMC Medical Informatics and Decision Making*, vol. 16, no. 1, 18 Oct. 2016. *PubMed*, https://doi.org/10.1186/s12911-016-0374-4. Accessed 28 June 2024.

Ajami, Sima. "Use of Speech-to-text Technology for Documentation by Healthcare Providers." *The National Medical Journal of India*, 29 June 2016, pp. 148-52. *PubMed*, pubmed.ncbi.nlm.nih.gov/27808064/. Accessed 27 June 2024.

Baker, Kelley M., et al. "Understanding Nursing Workflow for Inpatient Education Delivery: Time and Motion Study." *JMIR Nursing*, vol. 2, no. 1, 1 Nov. 2019, p. e15658. *PubMed*, https://doi.org/10.2196/15658. Accessed 28 June 2024.

Balch, Jeremy A., et al. "Machine Learning–Enabled Clinical Information Systems Using Fast Healthcare Interoperability Resources Data Standards: Scoping Review." *JMIR Medical Informatics*, vol. 11, 24 Aug. 2023, p. e48297. *PubMed*, https://doi.org/10.2196/48297. Accessed 27 June 2024.

Balloch, Jasmine, et al. "Use of an Ambient Artificial Intelligence Tool to Improve Quality of Clinical Documentation." *Future Healthcare Journal*, June 2024, p. 100157. *ScienceDirect*, https://doi.org/10.1016/j.fhj.2024.100157. Accessed 27 June 2024.

Banner, Laura, and Christine M. Olney. "Automated Clinical Documentation." *CIN: Computers, Informatics, Nursing*, vol. 27, no. 2, Mar. 2009, pp. 75-81. *Computers Informatics Nursing*, https://doi.org/10.1097/ncn.0b013e318197287d. Accessed 1 July 2024.

Basak, Sneha, et al. "Challenges and Limitations in Speech Recognition Technology: A Critical Review of Speech Signal Processing Algorithms, Tools and Systems." *Computer Modeling in Engineering & Sciences*, vol. 135, no. 2, 2023, pp. 1053-89. *ResearchGate*, https://doi.org/10.32604/cmes.2022.021755. Accessed 28 June 2024.

Bin Sawad, Abdullah, et al. "A Systematic Review on Healthcare Artificial Intelligent Conversational Agents for Chronic Conditions." *Sensors*, vol. 22, no. 7, 29 Mar. 2022, p. 2625. *PubMed*, https://doi.org/10.3390/s22072625. Accessed 28 June 2024.

Blackley, Suzanne V., et al. "Speech Recognition for Clinical Documentation from 1990 to 2018: A Systematic Review." *Journal of the American Medical Informatics Association*, vol. 26, no. 4, 11 Feb. 2019, pp. 324-38. *PubMed*, https://doi.org/10.1093/jamia/ocy179. Accessed 27 June 2024.

---. "Physician Use of Speech Recognition versus Typing in Clinical Documentation: A Controlled Observational Study." *International Journal of Medical Informatics*, vol. 141, Sept. 2020, p. 104178. *ScienceDirect*, https://doi.org/10.1016/j.ijmedinf.2020.104178. Accessed 27 June 2024.

Bongurala, Archana Reddy, et al. "Transforming Health Care with Artificial Intelligence: Redefining Medical Documentation." *Mayo Clinic Proceedings: Digital Health*, vol. 2, no. 3, Sept. 2024, pp. 342-47. *ScienceDirect*, https://doi.org/10.1016/j.mcpdig.2024.05.006. Accessed 27 June 2024.

Brian, Tran D., and Mangu Ramya. "Automatic Speech Recognition Performance for Digital Scribes: a Performance Comparison between General-purpose and Specialized Models Tuned for Patient-clinician Conversations." *AMIA Annu Symp Proc.*, 29 Apr. 2023, pp. 1072-80. *PubMed*, pubmed.ncbi.nlm.nih.gov/37128439/. Accessed 27 June 2024.

Coiera, Enrico, et al. "The Digital Scribe." *Npj Digital Medicine*, vol. 1, no. 1, 16 Oct. 2018. *PubMed*, https://doi.org/10.1038/s41746-018-0066-9. Accessed 27 June 2024.

Coiera, Enrico, and Sidong Liu. "Evidence Synthesis, Digital Scribes, and Translational Challenges for Artificial Intelligence in Healthcare." *Cell Reports Medicine*, vol. 3, no. 12, Dec. 2022, p. 100860. *PubMed*, https://doi.org/10.1016/j.xcrm.2022.100860. Accessed 27 June 2024.

Combi, Carlo, and Giuseppe Pozzi. "Clinical Information Systems and Artificial Intelligence: Recent Research Trends." *Yearbook of Medical Informatics*, vol. 28, no. 01, Aug. 2019, pp. 083-094. *PubMed*, https://doi.org/10.1055/s-0039-1677915. Accessed 27 June 2024.

Davenport, Thomas, and Ravi Kalakota. "The Potential for Artificial Intelligence in Healthcare." *Future Healthcare Journal*, vol. 6, no. 2, June 2019, pp. 94-98. *PubMed*, https://doi.org/10.7861/futurehosp.6-2-94. Accessed 27 June 2024.

Decker, Hannah, et al. "Large Language Model−Based Chatbot vs Surgeon-Generated Informed Consent Documentation for Common Procedures." *JAMA Network Open*, vol. 6, no. 10, 9 Oct. 2023, p. e2336997. *PubMed*, https://doi.org/10.1001/jamanetworkopen.2023.36997. Accessed 27 June 2024.

Deepa, P., and Rashmita Khilar. "Speech Technology in Healthcare." *Measurement: Sensors*, vol. 24, Dec. 2022, p. 100565. *ScienceDirect*, https://doi.org/10.1016/j.measen.2022.100565. Accessed 27 June 2024.

Derman, Yaron D., et al. "Speech Recognition Software and Electronic Psychiatric Progress Notes: Physicians' Ratings and Preferences." *BMC Medical Informatics and Decision Making*, vol. 10, no. 1, 25 Aug. 2010. *PubMed*, https://doi.org/10.1186/1472-6947-10-44. Accessed 27 June 2024.

De Toledo, Thiago Ferreira, et al. "Web System Prototype Based on Speech Recognition to Construct Medical Reports in Brazilian Portuguese." *International Journal of Medical Informatics*, vol. 121, Jan. 2019, pp. 39-52. *ScienceDirect*, https://doi.org/10.1016/j.ijmedinf.2018.10.010. Accessed 27 June 2024.

Dinari, Fatemeh, et al. "Benefits, Barriers, and Facilitators of Using Speech Recognition Technology in Nursing Documentation and Reporting: A Cross‐sectional Study." *Health Science Reports*, vol. 6, no. 6, June 2023. *PubMed*, https://doi.org/10.1002/hsr2.1330. Accessed 27 June 2024.

Drăgoi, Andrei-Lucian, and Roxana-Maria Nemeș. "The 'Electronic Pediatrician (EPed®)' – a Clinically Tested Prototype Software for Computer-assisted Pathophysiologic Diagnosis and Treatment of Ill Children." *International Journal of Medical Informatics*, vol. 178, Oct. 2023, p. 105169. *ScienceDirect*, https://doi.org/10.1016/j.ijmedinf.2023.105169. Accessed 27 June 2024.

Ghatnekar, Shilpa, et al. "Digital Scribe Utility and Barriers to Implementation in Clinical Practice: A Scoping Review." *Health and Technology*, vol. 11, no. 4, 2 June 2021, pp. 803-09. *PubMed*, https://doi.org/10.1007/s12553-021-00568-0. Accessed 27 June 2024.

Goss, Foster R., et al. "A Clinician Survey of Using Speech Recognition for Clinical Documentation in the Electronic Health Record." *International Journal of Medical Informatics*, vol. 130, Oct. 2019, p. 103938. *ScienceDirect*, https://doi.org/10.1016/j.ijmedinf.2019.07.017. Accessed 27 June 2024.

Hamilton, Alisa J., et al. "Machine Learning and Artificial Intelligence: Applications in Healthcare Epidemiology." *Antimicrobial Stewardship & Healthcare Epidemiology*, vol. 1, no. 1, 2021. *PubMed*, https://doi.org/10.1017/ash.2021.192. Accessed 27 June 2024.

Hobensack, Mollie, et al. "Machine Learning Applied to Electronic Health Record Data in Home Healthcare: A Scoping Review." *International Journal of Medical Informatics*, vol. 170, Feb. 2023, p. 104978. *Pubmed*, https://doi.org/10.1016/j.ijmedinf.2022.104978. Accessed 27 June 2024.

Hodgson, Tobias, and Enrico Coiera. "Risks and Benefits of Speech Recognition for Clinical Documentation: A Systematic Review." *Journal of the American Medical Informatics Association*, vol. 23, no. e1, 17 Nov. 2015, pp. e169-e179. *PubMed*, https://doi.org/10.1093/jamia/ocv152. Accessed 27 June 2024.

Hodgson, Tobias, et al. "Efficiency and Safety of Speech Recognition for Documentation in the Electronic Health Record." *Journal of the American Medical Informatics Association*, vol. 24, no. 6, 27 July 2017, pp. 1127-33. *PubMed*, https://doi.org/10.1093/jamia/ocx073. Accessed 27 June 2024.

---. "Evaluating the Usability of Speech Recognition to Create Clinical Documentation Using a Commercial Electronic Health Record." *International Journal of Medical Informatics*, vol. 113, May 2018, pp. 38-42. *ScienceDirect*, https://doi.org/10.1016/j.ijmedinf.2018.02.011. Accessed 27 June 2024.

Hou, Shih-Yen, et al. "Code-Switching Automatic Speech Recognition for Nursing Record Documentation: System Development and Evaluation." *JMIR Nursing*, vol. 5, no. 1, 7 Dec. 2022, p. e37562, https://doi.org/10.2196/37562. Accessed 27 June 2024.

Hu, Yuchen, et al. "Listen Again and Choose the Right Answer: A New Paradigm for Automatic Speech Recognition with Large Language Models." *arXiv*, https://doi.org/10.48550/ARXIV.2405.10025. Accessed 28 June 2024.

Hudelson, Carly, et al. "Selection and Implementation of Virtual Scribe Solutions to Reduce Documentation Burden: A Mixed Methods Pilot." *AMIA Joint Summits on Translational Science Proceedings*, 31 May 2024, pp. 230-38. *PubMed*, pubmed.ncbi.nlm.nih.gov/38827085/. Accessed 28 June 2024.

IBM. "What Is NLP (Natural Language Processing)?" *IBM*, www.ibm.com/topics/natural-language-processing#:~:text=Natural%20language%20processing%20(NLP)%20is,and%20communicate%20with%20human%20language. Accessed 17 June 2024.

---. "What Is Speech Recognition?" *IBM*, www.ibm.com/topics/speech-recognition#:~:text=While%20speech%20recognition%20is%20commonly,identify%20an%20individual%20user's%20voice. Accessed 17 June 2024.

Jelassi, Mariem, et al. "Revolutionizing Radiological Analysis: The Future of French Language Automatic Speech Recognition in Healthcare." *Diagnostics*, vol. 14, no. 9, 25 Apr. 2024, p. 895. *PubMed*, https://doi.org/10.3390/diagnostics14090895. Accessed 27 June 2024.

Kelly, Lesly A., et al. "A Nurse Leader's Guide to Reducing Burnout:." *Nurse Leader*, vol. 19, no. 5, Oct. 2021, pp. 467-73. *ScienceDirect*, https://doi.org/10.1016/j.mnl.2021.03.012. Accessed 28 June 2024.

Khalifa, Mohamed, and Mona Albadawy. "AI in Diagnostic Imaging: Revolutionising Accuracy and Efficiency." *Computer Methods and Programs in Biomedicine Update*, vol. 5, 2024, p. 100146. *ScienceDirect*, https://doi.org/10.1016/j.cmpbup.2024.100146. Accessed 1 July 2024.

Kocaballi, A. Baki, et al. "Envisioning an Artificial Intelligence Documentation Assistant for Future Primary Care Consultations: A Co-design Study with General Practitioners." *Journal of the American Medical Informatics Association*, vol. 27, no. 11, 26 Aug. 2020, pp. 1695-704. *PubMed*, https://doi.org/10.1093/jamia/ocaa131. Accessed 27 June 2024.

Labied, Maria, and Abdessamad Belangour. "Automatic Speech Recognition Features Extraction Techniques: A Multi-criteria Comparison." *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 8, 2021. *ResearchGate*, https://doi.org/10.14569/ijacsa.2021.0120821. Accessed 28 June 2024.

Latif, Siddique, et al. "Speech Technology for Healthcare: Opportunities, Challenges, and State of the Art." *IEEE Reviews in Biomedical Engineering*, vol. 14, 2021, pp. 342-56. *PubMed*, https://doi.org/10.1109/rbme.2020.3006860. Accessed 28 June 2024.

Lawson McLean, Aaron. "Artificial Intelligence in Surgical Documentation: A Critical Review of the Role of Large Language Models." *Annals of Biomedical Engineering*, vol. 51, no. 12, 20 June 2023, pp. 2641-42. *PubMed*, https://doi.org/10.1007/s10439-023-03282-2. Accessed 27 June 2024.

Lee, Huan-Fang, and Miao-Fen Yen. "Nurse Burnout in Taiwan." *Journal of Nursing and Women's Health*, vol. 2, no. 1, 21 Jan. 2017, https://doi.org/10.29011/2577-1450.100007. Accessed 28 June 2024.

Lee, Tso-Ying, et al. "Machine Learning-based Speech Recognition System for Nursing Documentation – a Pilot Study." *International Journal of Medical Informatics*, vol. 178, Oct. 2023, p. 105213. *ScienceDirect*, https://doi.org/10.1016/j.ijmedinf.2023.105213. Accessed 27 June 2024.

Li, Zhouxiao, et al. "Artificial Intelligence in Dermatology Image Analysis: Current Developments and Future Trends." *Journal of Clinical Medicine*, vol. 11, no. 22, 18 Nov. 2022, p. 6826. *PubMed*, https://doi.org/10.3390/jcm11226826. Accessed 27 June 2024.

Mairittha, Tittaya, et al. "Automatic Labeled Dialogue Generation for Nursing Record Systems." *Journal of Personalized Medicine*, vol. 10, no. 3, 16 July 2020, p. 62. *PubMed*, https://doi.org/10.3390/jpm10030062. Accessed 27 June 2024.

Milne-Ives, Madison, et al. "The Effectiveness of Artificial Intelligence Conversational Agents in Health Care: Systematic Review." *Journal of Medical Internet Research*, vol. 22, no. 10, 22 Oct. 2020, p. e20346. *PubMed*, https://doi.org/10.2196/20346. Accessed 28 June 2024.

Ministry of Culture. "國家語言發展報告" ["National Language Development Report"]. *Ministry of Culture*, 6 Mar. 2023, www.moc.gov.tw/ News_Content.aspx?n=167&s=95744. Accessed 20 June 2024.

Nashwan, Abdulqadir J., et al. "Charting the Future: The Role of AI in Transforming Nursing Documentation." *Cureus*, 31 Mar. 2024. *PubMed*, https://doi.org/10.7759/cureus.57304. Accessed 27 June 2024.

Ng, Zi Qi Pamela, et al. "The Role of Artificial Intelligence in Enhancing Clinical Nursing Care: A Scoping Review." *Journal of Nursing Management*, vol. 30, no. 8, 13 Aug. 2021, pp. 3654-74. *PubMed*, https://doi.org/10.1111/jonm.13425. Accessed 28 June 2024.

Novak, Laurie Lovett, et al. "Clinical Use of Artificial Intelligence Requires AI-capable Organizations." *JAMIA Open*, vol. 6, no. 2, 6 Apr. 2023. *PubMed*, https://doi.org/10.1093/jamiaopen/ooad028. Accessed 27 June 2024.

Peivandi, Sahar, et al. "Evaluation and Comparison of Errors on Nursing Notes Created by Online and Offline Speech Recognition Technology and Handwritten: An Interventional Study." *BMC Medical Informatics and Decision Making*, vol. 22, no. 1, 8 Apr. 2022. *PubMed*, https://doi.org/10.1186/s12911-022-01835-4. Accessed 27 June 2024.

Quiroz, Juan C., et al. "Challenges of Developing a Digital Scribe to Reduce Clinical Documentation Burden." *Npj Digital Medicine*, vol. 2, no. 1, 22 Nov. 2019. *PubMed*, https://doi.org/10.1038/s41746-019-0190-1. Accessed 27 June 2024.

Seibert, Kathrin, et al. "Application Scenarios for Artificial Intelligence in Nursing Care: Rapid Review." *Journal of Medical Internet Research*, vol. 23, no. 11, 29 Nov. 2021, p. e26522. *PubMed*, https://doi.org/10.2196/26522. Accessed 27 June 2024.

Shah, Megha K., et al. "Prevalence of and Factors Associated with Nurse Burnout in the US." *JAMA Network Open*, vol. 4, no. 2, 4 Feb. 2021, p. e2036469. *PubMed*, https://doi.org/10.1001/jamanetworkopen.2020.36469. Accessed 28 June 2024.

Suominen, Hanna, et al. "Benchmarking Clinical Speech Recognition and Information Extraction: New Data, Methods, and Evaluations." *JMIR Medical Informatics*, vol. 3, no. 2, 27 Apr. 2015, p. e19. *PubMed*, https://doi.org/10.2196/medinform.4321. Accessed 27 June 2024.

Van Buchem, Marieke M., et al. "The Digital Scribe in Clinical Practice: A Scoping Review and Research Agenda." *Npj Digital Medicine*, vol. 4, no. 1, 26 Mar. 2021. *PubMed*, https://doi.org/10.1038/s41746-021-00432-5. Accessed 27 June 2024.

Wang, Jesse, et al. "A Patient-centered Digital Scribe for Automatic Medical Documentation." *JAMIA Open*, vol. 4, no. 1, 1 Jan. 2021. *PubMed*, https://doi.org/10.1093/jamiaopen/ooab003. Accessed 28 June 2024.

Wang, Jixuan, et al. "PhenoPad: Building AI Enabled Note-taking Interfaces for Patient Encounters." *Npj Digital Medicine*, vol. 5, no. 1, 27 Jan. 2022. *PubMed*, https://doi.org/10.1038/s41746-021-00555-9. Accessed 27 June 2024.

Warraich, Haider J., et al. "The Digital Transformation of Medicine Can Revitalize the Patient-clinician Relationship." *Npj Digital Medicine*, vol. 1, no. 1, 20 Sept. 2018. *PubMed*, https://doi.org/10.1038/s41746-018-0060-2. Accessed 27 June 2024.

Yadav, Sankalp. "Embracing Artificial Intelligence: Revolutionizing Nursing Documentation for a Better Future." *Cureus*, 6 Apr. 2024. *PubMed*, https://doi.org/10.7759/cureus.57725. Accessed 27 June 2024.

Yen, Po-Yin, et al. "Nurses' Time Allocation and Multitasking of Nursing Activities: A Time Motion Study." *AMIA Annu Symp Proc.*, 5 Dec. 2018. *PubMed*, www.ncbi.nlm.nih.gov/pmc/articles/PMC6371290/#:~:text=Studies%20reported%20nurses%20spent%2026.2,time%20on%20documentation51%2C52. Accessed 17 June 2024.

Yu, Yen-Cheng, et al. "The Perceptions of Automated Artificial Intelligence-powered Clinical Documentation Assisted in Dentistry." *Journal of Dental Sciences*, vol. 18, no. 3, July 2023, pp. 1421-22. *ScienceDirect*, https://doi.org/10.1016/j.jds.2023.04.028. Accessed 27 June 2024.

Zhang, Jun, et al. "Intelligent Speech Technologies for Transcription, Disease Diagnosis, and Medical Equipment Interactive Control in Smart Hospitals: A Review." *Computers in Biology and Medicine*, vol. 153, Feb. 2023, p. 106517. *PubMed*, https://doi.org/10.1016/j.compbiomed.2022.106517. Accessed 27 June 2024.

---. "Intelligent Speech Technologies for Transcription, Disease Diagnosis, and Medical Equipment Interactive Control in Smart Hospitals: A Review." *Computers in Biology and Medicine*, vol. 153, Feb. 2023, p. 106517. *PubMed*, https://doi.org/10.1016/j.compbiomed.2022.106517. Accessed 17 June 2024.

Zhou, Li, et al. "Analysis of Errors in Dictated Clinical Documents Assisted by Speech Recognition Software and Professional Transcriptionists." *JAMA Network Open*, vol. 1, no. 3, 6 July 2018, p. e180530. *PubMed*, https://doi.org/10.1001/jamanetworkopen.2018.0530. Accessed 17 June 2024.