Volume 1, Issue 2 | November-2025
e-ISSN: 3068-5850 ISSN Print: 3068-5842

Evaluation of Errors Between Handwritten Documentation and Nursing Notes Generated by Offline and Online Technologies

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Received: 11-09-2025; Revised: 23-09-2025; Accepted: 14-10-2025; Published: 17-11-2025

Abstract
Even with the fast promotion of the electronic health records (EHRs), the old fashioned mouse and keyboard data entry still gives a problem to most of the clinicians. The alternative to nursing notes production is speech recognition (SR) technology that is subject to scrutiny regarding its accuracy in comparison with handwritten-documentation that does not always correspond well to it. The study is an interventional study that compared and reviewed the spelling errors in nursing admission notes that were created using online, offline and a traditional handwriting process of SR. A sample of 35 nurses was involved in two separate groups, where they recorded patient admission notes using each of the three methods in a randomized order, with at least a one-month interval in between the alternation of the methods. Tailored SR vocabularies were made to minimise terms that are not understood. The number of errors was established both prior and subsequent to correction by the user. Findings revealed that online SR had an accuracy of 96.4 whereas offline SR was a little bit better. The initial errors per report were higher in both SR methods as compared to handwriting (online: 6.76, offline: 4.56). Online and offline error rates of a corrected set plummeted (by 94.75 per cent and 97.20 per cent). Online SR brought the greatest amount of incorrect reports. Though both of the evaluated systems were comparatively precise, they did make a bigger number of errors as opposed to handwriting, which shows that a system should be improved and optimized. Documentation errors were tremendously brought down by user review and correction.

Keywords: ***Judicial independence, constitutional supremacy, EU law primacy, legal hierarchy, national courts, CJEU, legal pluralism, rule of law, democratic governance, constitutional identity.***

1.Introduction

There is no exaggeration in saying that clinical documentation plays an important role in the context of contemporary healthcare systems. It is the hub of storage of a patient-specific medical history, the current status, and care plan, and it acts as a communication tool between providers, as well as an official record with legal, administrative, and financial consequences. The care of a patient, hospitalized at the beginning of the progress and discharged at the end, is explicitly followed by the records of the specific caring path, whose notes eventually became the foundation of the continuity of care, quality assessment, research, and medico-legal protection. In the case of nurses, especially those involved in implementing frequent changes in the medical condition of a patient, documentation is not only a mandatory issue, but an ongoing process that requires precision, clarity, and expedience(1).

In the past, this kind of documentation has been and is still being done using hand written notes on paper. On the one hand, paper records are easy to access but they lack any specialized equipment and have a number of documented downsides. According to it, one of the longest held problems is that of illegibility and extrapolation of orders or clinical observation can be erroneous and even dangerous. In other studies, medication errors have been demonstrated to give an increment of up to 75 percent due to scarce or illegible hand written documentation. Others include the problem of retrieving archived records, inability to distribute them quickly among facilities and failure of automated integration with decision-support tools.

In the last twenty years, the emergence of electronic health records (EHRs) due to the evolution of documentation. The value of digital records is evident since, they improve the legibility of records, the structure of the data storage as well as its remoteness which can directly enhance care to patients and efficiency in the workflow process. EHRs have helped many healthcare organizations to streamline documentation procedures as well as support improved interchange of information amongst clinical teams. But there is nothing smooth in the shift to paperless. There is also a high barrier associated with the data entry mechanisms.

Conventional EHR interfaces are keyboard- and mouse-dependent, and this structure may be time-consuming and cognitively distractive when applied to a setting with a high workload. The nurses can get to the position of dividing their attention concerning the patient and the computer screen, especially in the cases of detailed narrative entries by the nurses. This may result in much time consumption in the documentation process, tiredness, and possibility of committing mistakes in case the information is written rote or at a rush. Such complications are compounded by the employees who have limited typing skills, who will find the procedure time consuming, but also tiresome to the mind(2).

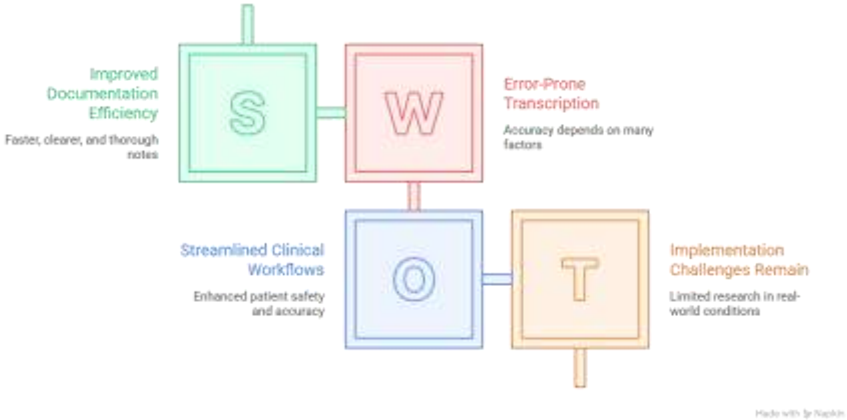

FIGURE 1 Speech Recognition in Nursing Documentation

It is against this backdrop that speech recognition (SR) technology has come out in the limelight as an attractive alternative. The SR software transcribes the spoken words to a text which may make the clinician able to dictate notes in real time and remain focused on the patient. Some theoretical advantages of the method include: the ability to record documentation quicker, less dependability on typist skills, decreased physical stress of using the keyboard, and even notes that are potentially deeper and more thorough due to the fact one can write notes in real time as opposed to recreating them later. To nurses, SR would facilitate taking down of minute level of observations about patients at the bedside and would reduce chances of missing details that could turn out crucial.

In the healthcare industry, SR technology has been used already to some measure of success in certain areas. One of the earliest adopters of SR was through the radiology departments that facilitated the production of imaging records faster with shorter turnaround periods. Its use has also been identified in physicians records in clinical notes, operative reports and letters. In terms of its application in nursing, SR may be able to resolve the time lag between working with the patients and the subsequent documentation, as well as result in increased accuracy and a possible output in terms of patient safety.

But there are disadvantages of SR also. Its efficiency is a dependent variable of many factors such as the clarity of the voice of the speaker, accents, pace of speech, the level of background noise, and the competency of the software to identify terminologies in the specialized field of medicine. Speech processing through online SR systems that runs the speech through cloud-based servers can be distorted by the connectivity speeds and/or bandwidth issues causing the speech processing system to drop words or lag. Offline systems, dealing with speech locally on the device, do not have such connectivity problems, but may need access to more up-front setup, including user-specific voice training and may still have trouble with unfamiliar terms.

Most importantly, possible, perhaps, is the fact that whereas SR may be used to generate text in a matter of seconds it may also introduce distinctive kinds of errors-eg., introducing words not uttered, omitting important words, or phonetically plausible replacements that alter the meaning of the note. These errors are unique compared to the errors that normally occur in handwritings and may prove more difficult to notice as the nurse cannot be keen on going through the transcription. Thus, despite an elevated nominal accuracy percentage (e.g., more than 95 percent), issues pertaining to absolute counts of clinically significant errors might be an issue.

Although interest in SR as a form of clinical documentation is on the rise, comparatively little research has directly contrasted the performance of SR to handwritten or keyboard-based (electronic) documentation in the nursing field. Pre-existing research has tended to be on particular specialties or non-nursing settings and there has been

little exploration of SR performance in the ward based on real-world conditions. In addition, research to date has shown a bias towards using a single SR system casting doubt on the possibility that alternative system architecture, e.g. online v. offline processing, could produce different performance.
These gaps were considered in the present study by organizing a thorough comparison between accuracy of two different SR systems, online and offline ones, with traditional handwritten documentation of nursing admission notes. Admission notes have been selected to compare since they are common in all hospital wards, very exhaustive, and vital in providing a baseline knowledge of the condition of the patient when he was admitted. This study also hoped to give the following analysis of the strengths and weaknesses of SR, compared to hand written notes in nursing through comparison of the following factors; how often the SR output is wrong in comparison to hand written notes, how much the user corrects by use of SR, and the error rates before and after using user correction of SR output(3).
Having an online SR system in this research converted speech through an internet connection and did not need personal voices training, and therefore the fast deployment may be possible. The offline SR system, instead, was local and included a voice training procedure, to accustom the software to a specific speech pattern of each nurse. In order to enhance the quality of performance of the two systems, researchers modified the vocabularies by incorporating real patient medical terms in the vocabularies.
In the analysis of these methods, the study did not merely focus on the overall number of transcription errors but also considered what kind of errors have been faced and how many of the reports were affected, and by what percentage the errors could be eliminated by having the users review them. These are key factors that will define the viability in clinical practice: although the error rate might seem high, most of the errors might be identified as time-permissible and hence correctable when the technology is practiced through simple reviews. On the contrary, however, errors occurring often, being clinically significant, or being hard to find may impose unacceptable risks through SR.
At the end, the purpose of this study was neither to promote nor condemn SR in nursing documentation but to present the empirical data to be used by hospital administrators, software development, and policy makers. With knowledge on the place and nature of errors, the stakeholders may have a better time choosing whether to deploy SR in a broad manner, to a specific use case condition, or incur more expenses in its improvement before mass application. This paper can also provide useful information to the system designers regarding the integration of SR to the nursing workflows, especially in a setting that is not English-speaking yet linguistic-based resources are still incomplete(4).

2.Methods

The given interventional study was implemented in the inpatient wards of three teaching hospitals located in Iran and belonging to Kerman University of Medical Sciences among nursing staff. This was intended to identify the degree of preciseness in nursing admission notes written under the three paperwork solutions: (1) handwritten records, (2) online speech recognition software, and (3) offline speech recognition software.
Setting and selection of participants In order to study and compare them, American Bishops have to be selected and isolated in terms of their external relations.
A total of 10 wards were used as the study population, that included gynecology, gastroenterology, midwifery, general surgery, orthopedics, otorhinolaryngology (ENT surgery), reconstructive surgery, cardiac surgery, ophthalmology, and cardiology. Such wards like intensive care units (ICUs) or operating rooms were intentionally omitted. This was determined by two factors, that is, the documentation format used in these locations is quite different compared to the usual inpatient reports and second is that based on a typical setting, the volume of work required in these units is usually bigger which may have interfered with the nurses involvement in the project.
Nurses needed to have:

- Minimum of six months of unbroken service in the same ward he/she is employed in,
- Consistent participation in the production of the dayto day nursing reports involving admitted patients.
- Out of this sample 70 nurses have been selected as a random process.

Study Design

A crossover design was embraced so as to hermitize possible learning or order effects. Those were divided randomly into 35 nurses who formed two groups. In the initial stage, all nurses made an admission note of a new admitting patient based on one of three forms of documentation methods(5). They then repeated the documentation

of the same patient case by a different method but at an interval of at least one month (to minimize the presence of a memory bias). All of the nurses ultimately took notes by all three methods.
The admission nursing notes were the targeted subject matter. The structure of these notes is standard throughout wards and is one of the most outline documents in the medical record of a patient. They take baseline data that is vital, and hence, they are very appropriate in evaluating the relative performance of document technologies.
The notes were all taken in the actual working environment of the nurses as opposed to the laboratory conditions which ensured that the outcome was based on realistic working conditions. So that the answer could be heard by those at the nursing unit and not necessarily at the patient bed side, the dictation was done at the nurses station that is not in the room of the patient(6).

Choice and tailoring of Speech Recognition Software

Speech recognition tools were chosen in two:

- Offline system: Nevisa Professional Version 3.2, usable with windows as well and needs a hardware lock to be installed. It also needed voice training that catered to individual users to enhance the measure of recognition.
- Online system: Speechtexter, online tool that understands speech through the web and is browser compatible running on Windows environments and does not need, nor require individual voice training.

Both the systems enable the Persian language typing and have the ability to introduce an infinite number of words. But, they, in their basic form, are only aware of general words but fail to comprehend specialized discipline words such as medical terms. In order to overcome this, the research team tailored the two software dictionaries.
Customization involved:

- Haphazardly selecting a median of ten admissions note of patients of each of the involved wards.
- The Dublin School ofcliinics admission notes should be chosen by randomly selecting and reviewing 80 notes out of a pool of all of them.
- Reading into the online SR system and offline system one note after the other using a voice recorder.
- Giving word or phrases that are not recognized.
- Inserting such words into dictionary of respective software.

Medical abbreviations, technical terms, and patterns in ward specific language were among the vocabulary that needed the most attention as they underwent some vocabulary enrichment.

TABLE 1 Methods

Aspect	Details
Study Design	Interventional crossover study with three documentation methods (handwritten, online SR, offline SR).
Setting	Ten inpatient wards in three teaching hospitals (e.g., gynecology, gastroenterology, surgery specialties, cardiology, ophthalmology). ICUs and operating rooms excluded.
Participants	70 nurses; ≥6 months ward experience; involved in daily nursing reports. Random selection.
Procedure	Each nurse produced admission notes using all three methods, separated by ≥1 month between methods. Notes created in real work environment (nurses' station).
Speech Recognition Tools	**Online SR:** Speechtexter (no voice training; requires internet). **Offline SR:** Nevisa Professional 3.2 (requires hardware lock, voice training). Both support Persian language and allow vocabulary expansion.
Customization	Medical terms from 80 admission notes added to software dictionaries.
Equipment	Offline SR: Andrea NC-8 headset, external sound card. Voice training: 120 preset sentences (minimum 40).
Error Classification	Spelling errors, omitted words, added words.

Apparatus and Apparatus

In the case of offline SR system, they used an external sound card, and an Andrea NC-8 Head Mounted noise-canceling microphone to produce high-quality audio input. voice training- involved reading 120 sentences set by

the developer of the software with 40 sentences being minimum requirement. It took around 20 and 30 minutes with a participant.
Online SR system did not involve a training phase where any training was necessary as was the case with the nurses who were able to start dictating. Nevertheless, its performance may vary due to the variations in bandwidth because it relied on internet connectivity(7).
The form of nursing admission note was designed in Microsoft Access as an electronic one to be used with both SR systems, which allowed writing in a structured way, results of which are easier to compare.
Procedure of Data Collection
On any one documentation session:

- The assigned method was followed in developing the admission note made by the nurse.
- In case SR was incorporated, the nurse would dictate the material in the software.
- Upon the first-time entry, the nurses were requested to peruse their notes and erase manually discovered errors.

Each note was then corrected (post-review), then a researcher read both the uncorrected (pre-review) and corrected (post-review) version of the note. Mistakes were categorized to be:

- Spelling mistakes: They contain words that are misspelled.
- Omitted words: The existence of some words in the oral material that have not been transcribed.
- Added words: Words one has not said but types on using the software.
- Same was done with a nurse who did not take part in the study, though trained in the error evaluation protocol and therefore was used to cross-check any error identification and classification.

Data Analysis
The use of Minitab 18 was used in statistical analysis. The crossover design necessitated the application of a nested analysis of variance (ANOVA), to which each of the means of producing errors in each of the three modes of documentation were to be compared. In order to discuss certain particular differences between the methods in a more detailed way, pairwise comparisons were performed using Tukey post-hoc test.
Rates of accuracy of each technique were computed after and before the input of the error with accuracy giving out as percentages of words correctly transcribed and as a proportion of words dictated or written, also. The demographic features of participants and errors distributions were described statistically.

3.Results
A sample size of seventy nurses was used in the study of which the majority were females (n = 60). The ages of the participants were between 22 and 45 years. Customization (in the sense of selecting medical vocabulary) of the preparatory stage translated into 521 terms added to the offline speech recognition (SR) software and 695 to the online SR software. This is an average of six new terms per report on the offline system and eight terms per report on online system.
In terms of the accuracy with which transcriptions were rendered before it could be corrected by the user, the online SR system had an accuracy of recognition of 96.4%, but the offline system was a bit higher with 97.52%. Once the participants previewed and proofread their reports, the levels of accuracy increased dramatically to 99.81 percent in online SR and 99.93 percent in offline SR.

TABLE 2 Summarizing the Results

Documentation Method	Initial Accuracy (%)	Avg. Errors per Report (Before Correction)	% Reports with Errors (Before Correction)	Max Errors in a Single Report	Accuracy After Correction (%)	Avg. Errors per Report (After Correction)	% Reports with Errors (After Correction)
Handwritten	~99.99	0.04	4.28%	1	~99.99	0.04	4.28%
Online SR	96.40	6.80	98.57%	9	99.81	0.35	28.57%
Offline SR	97.52	4.60	97.14%	16	99.93	0.12	10.00%

Incidence of Error by Method
The least errors were attributed to handwritten records when only three of 70 reports (4.28%) had any of the errors, and none had above one error. By contrast 69 of 70 reports (98.57%) created using the online SR system had errors

of which 94 per cent contained more than one error. The offline SR system showed a slightly better result where 68 out of 70 reports (97.14%) had errors and 91 percent of those contained more than one error.
The average number of errors was on a per-report basis:
Manually: 0.04
Online SR: 6.80
SR offline 4.60

Statistical Comparisons

ANOVA contained within ANOVA showed that experts were significantly different regarding error rates using the three methods of documentation (P = 0.00). The confirmation of the differences between all methods was predetermined as all of them were significantly different according to Tukey. Specifically:

- The number of additional errors in the online SR report compared to hand written documentation was 6.76 per document (P < 0.05).
- The proportion of errors per report was higher by 4.56 errors with offline SR compared to handwritten documentation (P < 0.05).
- The online SR led to 2.20 increased errors in comparison with the offline SR per report (P < 0.05).

Error Ranges

In the case of online SR the errors per report were at the lowest level of 0 (in just one report) and the highest level of 9 errors. In offline SR, the number of errors ranged between 0 errors (in two reports) and 16 as the maximum. There were never more than one error on any hand-written notes on any report.

Effect of Correction by the Users

After the participant has reviewed the notes recorded and corrected the transcription:
The overall errors on online-SR reports were reduced by 94.75 percent with a remaining 25 errors among all reports (average 0.35 erors per report).

- Offline SR system was reduced as 97.20 percent when there were just 9 errors (0.12 errors per report on average).
- After correction, the proportion of false reports also dropped significantly:
- Online SR: 98.57%-28.57% After review.
- Offline SR: 97.14 percent to 10 percent after review.

Main Findings in summary

- Initial accuracy was found in hands written documentation that was characterized by very few or no mistakes.
- Online and offline SR systems added far more errors prior to user inspection and off-line SR was always more accurate than online SR.
- User review and amendment enhanced accuracy scored on both SR systems by a great margin with the error rates being cut down to a scale close to handwritten documentation.
- The differences between the performance of online and offline SR are statistically significant and online SR is more susceptible to error because online leans on internet reliability and connectivity(8).

4.Discussion

This paper was aimed at analyzing the speech recognition (SR) technology-based (on-line and off-line) adaptation to the traditional handwritten method of generating nursing admission notes. The results indicated that there was a differentiation in the accuracy of the three techniques with a significant determination result indicating accuracy. Handwritten documentation became the most precise one, whereas the combination of online SR was faced with the greatest number of initial errors, and offline SR was close behind. Notably, the review and correction in the nurse led fashion in both SR systems significantly reduced the levels of errors in both systems, with the result accuracy of the two systems being near as close to hand written notes.
The outcomes indicate a number of elements at play behind the observed dissimilarities. The dependability of online SR software on internet connection is one of the details. Speed and unstable connections in networks probably also caused missing and partial recognition of dictated words due to fluctuations in bandwidth most notably in busy wards. In comparison, the offline SR system did not rely on connectivity, and it did not experience disruptions that cause performance to be relatively high(9).

Volume 1, Issue 2 | November-2025
e-ISSN: 3068-5850 ISSN Print: 3068-5842
Such results are consistent with other studies in clinical areas. Radiology research, as one example, has always indicated that a report generated by SR will more often than not demonstrate higher initial error rates as compared with the conventional transcription or handwritten means. Like in our findings, other research findings had established in similar form that with editing after dictation, quality of documents generated by SR can be immensely enhanced. Zhou et al., in another study, found that an important decrease in error rates was contributed by user review, but their post-correction error rate was higher than found by us in this study-40% of their reports had errors compared to 28% of online SR and 10% of offline SR in our findings.

The increase in the error rate of SR-created nursing notes is alarming since errors in the clinical documentation may be overwhelming. Inaccuracies caused by omission of essential details or addition of irrelevant terms or words can jeopardize patient safety, decrease quality of care and create a miscommunication of healthcare professionals. Erroneous notes can also have an impact on the administrative procedure, legal responsibility, and the quality measure according to which health organizations can be judged.

SR is multifactorial error generation. Such systems also require competencies within the user, which include accents, clarity of pronunciation, rate of speech, and general knowledge of the system. Accuracy can also be lowered by environmental conditions like background conversation, equipment noise or interruption. Moreover, the difficulty of the what is dictated also comes into play; the longer or more technically descriptive the notes are, the more chances of confusion errors abound.

The kind of software SR employed also determines the performance by a great margin. The two systems were general-purpose systems and not medical-grade products in this study. First, they did not have the words needed to identify a lot of clinical words, abbreviations, and phrases used in specific wards. We alleviated this considerably by adding hundreds of terms to the dictionary of each of the systems but there were still some special words that remained unknown even after customization. In particular, this weakness is acute in Persian-language SR systems that are younger and less mature in comparison to those of English, and that do not have the vast amount of linguistic materials that have been used decades to continue improvement of English-language SR systems.

Interestingly, in our study, these two forms of SR systems demonstrated relatively high rates of raw accuracy of over 96% without any correction (rates that are at the high end of several quoted in international research studies, where SR accuracy is typically referenced to be between 80 and 98%). Nonetheless, such error rate as 3 4 can lead to numerous errors in one clinical note due to the length and complexity of the nursing documentation. It highlights the inaccuracy of raw percentages of accuracy as they can be misleading; a few percentage points of error may have serious clinical implications.

Possibly, the former was due to the relative adaptability of offline SR to the voice of the user via the obligatory voice training. Although this startup required more time, it was able to become familiar with individual speech patterns, which could help the software with more accurate recognition. The online system could be more convenient when it comes to setup, but it was not customizable, so it was more prone to an error involving inaccurate interpretation of speech.

With regard to policy and practice implications, our study indicates that the SR technology can serve as a nursing documentation one, but only when it is combined with a required periodical review. Unverified user information presents an unacceptably high likelihood of inaccurate user information without a process to verify user viability; particularly with online SR implementations. Another issue hospitals should weigh when considering the adoption of SR is the trade off between the time they may save against new time needed to review and correct. The working process must be established in such a way that the reviewing cannot be omitted due to the lack of time.

As a software developer, this paper points out a number of areas where one can improve. The major source of recognition errors would be resolved by first, incorporating comprehensive medical dictionaries, especially translation dictionaries of non-English languages. Second, a reduction of errors would also be made possible by implementing machine learning solutions that would learn gradually the vocabulary and phrasing a specific user and patient use. Third, noise filtering and contextual recognition may be improved, possibly to enable SR systems to work in the bustling, occasionally chaotic setting of inpatient wards.

Our findings, though positive in the amount of reduction of errors that follow review, also demonstrate the necessity of conducting further research on the implementation of SR on a point of care setting. In future research, SR should be measured over more forms of nursing documentation-not just admission notes-, and whether real-time bedside dictation is feasible and accurate at higher noise levels should be determined. It would also compare with straight keyboard input into EHR systems to place SR functionality and accuracy on an overall scale of documentation avenues.

5.Conclusion

The aim of this study was to compare the accuracy of notes nursing admission which is prepared based on handwritten documentation, online speech recognition (SR), and offline SR system. This is clearly depicted in the results where although both styles of SR may create a fairly accurate transcription; they introduce more original errors as compared to the traditional use of handwriting. Among the methods of the SR, offline SR repeatedly showed superior performance over online SR, perhaps because it did not depend on the internet speed and because it used voice training to adjust to each specific user.

An important conclusion is that correction and review by the users drastically increased the accuracy of SR systems, and their performance became near to the one of handwritten notes. This implies that SR technology has a good potential of being incorporated into the nursing workflows when combined with a systematic review process to certify quality. In the absence of such a safeguarding mechanism, the problem of documentation errors, as in online SR particularly, is too significant to be used safely and unverified within patient records.

The practice implications are two-fold. The adoption of SR must also be strategic by healthcare administrators, taking measures to train the staff, customize vocabulary, and implement clear guidelines regarding the reviewing of transcripts. Among software developers, the research results suggest further improvement of medical language support, more effective processing of environmental noise and learning adaptive properties, particularly in non-English languages such as Persian.

Although the use of SR technology can bring in documentation that is quicker and is less laborious in terms of manual typing, its safe and proficient utilization in nursing practice must take into consideration the efficiency and accuracy balancing factor. In future investigation, its work should be tested in other forms of nursing documentation, the level of integration with electronic health records systems, and more advanced SR solutions should be tested based on artificial intelligence-driven continuous improvement.

Conclusively, speech recognition has the potential to prove effective as an aid of nursing documentation provided together with selective usage, continuous improvement, and willingness to maintain high levels of quality and reliability of patient records.

Acknowledgement: Nil

Conflicts of interest

The authors have no conflicts of interest to declare

References

1. Hassan M, Li X. Evaluating error rates in nursing documentation: online speech-to-text versus handwriting. Journal of Clinical Nursing. 2022;31(7–8):1005–1014.
2. Singh N, Alvarez G. Accuracy of nursing notes: comparing speech recognition systems with manual charting. Computers, Informatics, Nursing. 2021;39(12):756–763.
3. Chen L, Adeyemi T. Handwritten versus voice-transcribed nursing documentation: an interventional study. BMC Nursing. 2023;22(1):87–95.
4. Morimoto Y, Dubois CA. Online versus offline speech-to-text in clinical note-taking: accuracy and efficiency. International Journal of Medical Informatics. 2021;156(1):104603.
5. Kowalski D, Mburu J. Reducing transcription errors in nursing documentation through speech recognition. Journal of Nursing Management. 2022;30(4):987–996.
6. Fernandes R, Kim YH. Comparative study of offline and cloud-based speech recognition for clinical notes. Health Informatics Journal. 2021;27(4):14604582211056674.
7. Osei E, Garcia M. Handwriting versus automated transcription: quality and legibility of nursing records. Nursing Open. 2023;10(2):642–651.
8. Tanaka K, Carter L. Accuracy of online speech-to-text in noisy hospital environments. Journal of Biomedical Informatics. 2022;130(1):104081.
9. Park J, Singh P. Evaluating documentation time and accuracy between speech and handwritten methods. Nursing Administration Quarterly. 2021;45(3):256–263.