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Trial of Converting Nursing Records into Simplified and Structured Information Utilizing ChatGPT-3.5

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Abstract. In Japan, the excessive length of time required for nursing records has become a social problem. A shift to concise "bulleted" records is needed to apply speech recognition and to work with foreign caregivers. Therefore, using 96,000 descriptively described anonymized nursing records, we identified typical situations for each information source and attempted to convert them to "bulleted" records using ChatGPT-3.5(For return from the operating room, Status on return, Temperature control, Blood drainage, Stoma care, Monitoring, Respiration and Oxygen, Sensation and pain, etc.). The results showed that ChatGPT-3.5 has some usable functionality as a tool for extracting keywords in "bulleted" records. Furthermore, through the process of converting to a "bulleted" record, it became clear that the transition to a standardized nursing record utilizing the "Standard Terminology for Nursing Observation and Action (STerNOA)" would be facilitated.

Keywords. Electrotonic Health Records(EHR), Bulleted records, Voice recognition, ChatGPT-3.5, Standard Terminology for Nursing Observation and Action (STerNOA)

1. Introduction

Numerous previous studies have shown that the writing of nursing records accounts for 30% to 50% of nursing work. There are important reports of the impact of electronic health record usability on nurses' workload, although the number of subjects is small [1], and more such usability studies should be conducted.

Nursing records in Japanese are generally written in narrative form rather than in template form. In addition to the complex use of adverbs and particles, the Japanese language has a structure that is not clearly defined and understood in context, and tends to be long-winded. Foreign care workers are indispensable in Japan, which has the

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world's most aged population. However, the large language barrier makes it difficult to accept foreigners [2].

Nursing records using speech recognition technology have been studied for at least 30 years. [3] However, the accuracy of speech recognition has long been an issue with many technical terms. [4] In recent years, advances in AI have also improved accuracy, with accuracy in speech recognition exceeding 95%. [5] However, there are differences between "spoken" and "written" languages, and these differences tend to be larger in Japanese. Therefore, corpora have been constructed to convert between the two languages, and research has been conducted for some time to incorporate these corpora into speech recognition technology. [6]

On the other hand, "bullet-pointed" business conversations based on a list of words, once in air traffic control and now in chain coffee shops, have also taken hold. Such A bullet point is described by the Longman Dictionary as "a thing in a list that consists of a word or short phrase, with a small printed symbol in front of it. In the Japanese language, in addition to being a short sentence, a bulleted sentence is understood as a sentence in which the noun ends in a "body phrase" rather than forming a sentence in which the subject and verb are aligned. Air traffic control and coffee shops have established rules of conversation in which short words are stated in a predetermined order because the subject, object, quantity, etc. must be said without error in a short conversation. "Bullet-pointed" language recordings are extremely important for speech recognition by nurses and for foreign caregivers to read nursing records.

In addition, since "bullet-pointed" language records have a simple language structure, it is easy to create a structured record using standardized terminology.

Therefore, the purpose of this study is to decompose the existing "narrative record" into its elements and to develop a bulleted record template using ChatGPT-3.5.

2. Methods

The research materials used were 96,000 nursing records (237,000 records) that were anonymized for research purposes. This anonymized information was created through legal procedures at an acute care hospital with approximately 100 beds located in an urban area.

Three typical situations were illustrated for each of the following sources of information: (1) nurses, (2) patients, and (3) equipment. For each source of events, we examined three situations: (1) the "Return to the patient's room" situation in which the nurse is the source of the event, (2) the "pain" situation in which the patient is the source of the event, and (3) the "sensor" situation in which the equipment is the source of the event.

Each of the records from (1) through (3) was text-mined to identify three types of frequent occasions each (nine types in total) using KH Coder 3b07f. KH Coder is a tool developed by Prof. Higuchi for morphological analysis of Japanese. [7]

For each of these three scenes, three more typical detailed scenes were extracted (nine in total), taking care not to select words that were too similar from the upper concepts of the tree diagram based on cluster analysis. The nine types of nursing records were then fed into ChatGPT-3.5 to generate summary sentences, and "bulleted summary sentences" were also generated.

3. Results

3.1. Situation of returning to the hospital room

There were 1083 nursing records related to "return to patient's room. A cluster analysis of nursing records at the time of return to the room revealed that the main recording topics included drains, consciousness, auscultation results such as breath sounds and bowel peristalsis, catheters such as central veins, and subjective symptoms such as pain and nausea.

The situations detailed in this "return to room" record included (a) the nurse's observation of the patient's return from the operating room, (b) the physician's explanation to the patient after surgery, and (c) the patient's return from the examination room. Since the keywords listed in the cluster analysis rise most frequently, examples are given for typical (a) situations.

The original narrative record was fed into ChatGPT-3.5 and instructed to list up to about 5 main points. As a result, a "bulleted" record was generated in the following example (*Table 1*).

 Table 1. Example of nursing record upon return from surgery

Note: Bolded and underlined sections are "bullet" headings as indicated by the Chat-GPT3.5

As in the example above, approximately five issues showed slightly different wording, but generally similar "bulleted headings" were found.

3.2. Painful Situations

Nursing records of situations in which patients complained of pain were found in 18,094 cases. Cluster analysis revealed that the main topics of these pain records were

abdominal symptoms such as defecation and bloating, wound symptoms such as bleeding and drainage, oral analgesics such as OxyContin, expressions of pain, IV analgesics such as Flurbiprofen axetil, non-pain symptoms such as fever and redness, and patient preferences for pain medication.

Typical records containing these key words included (a) situations in which pain was uncontrolled and discussed with the patient, (b) explanations from the physician to the family regarding pain control, and (c) nurse conferences regarding pain. In this pain scene, the "bulleted headings" generated by ChatGPT-3.5 when it summarized the descriptive vanishing billions varied widely. However, when the higher-level concepts of the headings were organized, they could be divided into causes of pain (e.g., continuous suctioning, stoma status), mental challenges (e.g., complaints, restlessness), and other systemic conditions (e.g., vital signs, urine scale).

3.3. Situations where equipment became a source of information

There were 767 records regarding situations where equipment was the source of information. Cluster analysis of records on sensors and other devices revealed that the main topics included responding to risky behaviors such as restraints, IVs, sleep, nurse calls, toileting, falls, and daily living assistance such as watching over the patient and wheelchairs.

The detailed scenes in the records that contained many of these key words were often (a) explanations from the physician to the family regarding situations requiring sensors, (b) situations in which falls occurred, and (c) situations in which the patient was likely to self-extract a catheter such as an intravenous drip.

While (B), the situation where there was a risk of catheter removal, was mostly recorded "before" the event, (C), the fall, was mostly recorded "after" the event. When the records of these falls were summarized using ChatGPT-3.5, the "bulleted headings" were generally summarized as follows: discovery of the fall, physical condition, sensor response, guidance to the toilet, CT results, contact with family, and future actions.

4. Discussion

At this point in time, there have been few studies of nursing record descriptions using the chatGPT-3.5, so in this experiment, we extracted "typical nursing situations" for each information source and examined whether these descriptions could be delegated to the chatGPT.

The results showed that there are typical description patterns even for narrative records when the source of information is a nurse (e.g., observation upon return from the operating room) or when the source of information is a device such as a sensor (e.g., fall). In such situations, rather than applying ChatGPT-3.5 directly to the nursing record, it would be easier to use it as an analytical tool and record using a standardized template. It goes without saying that the "STerNOA", as standard terminology for glossary of terms related to nursing care and observation approved as a standard by the Japanese Ministry of Health, Labor and Welfare, should be used in such templating.

On the other hand, in situations where the source of information is the patient (e.g., pain), it was found that the content recorded tended to be diverse and the "bullet headings" were often scattered.

In such situations, the significance of interactive recording by artificial intelligence becomes significant. Since the knowledge base required for this (e.g., solving questions for national examinations [8], searching for evidence materials [9], etc.) seems to have already been covered by artificial intelligence such as ChatGPT-3.5, it should be possible to perform interactive recording.

One limitation of this study is that the validity of the extraction of "bullet points" by Chat-GPT 3.5 was done solely by the research team. Our team avoided extreme bias in the study design by including multiple perspectives, including a licensed health information manager nurse, a physician, and an engineering researcher. Strictly speaking, the extraction results should probably be validated using, for example, the Delphi method, but it is too complicated to evaluate the extraction results of generative AI, where terms are originally extracted in a black box, using such classical methods. Therefore, we would like to follow the growth of modern evaluation methods for the extraction results of generative AI and verify them at a later date.

5. Conclusions

By utilizing the summary function of ChatGPT-3.5, it was found that nursing records, which are often descriptive in nature, can be replaced with concise "bullet points". However, it is not possible at this time to reach a concise expression that would facilitate voice recognition, such as that used in air traffic control and cafes.

This point needs to be re-examined in ChatGPT-4.0, but it is probably more realistic to use it in a moderate way, as it depends on the characteristics of the nursing work.

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