# Information Flow in Intensive Care Narratives

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## Abstract

*Fluent patient information flow is a prerequisite for clinical decision making. Our purpose is to identify unmet information needs in the flow of Finnish intensive care narratives in order to focus the development of natural language processing methods for this domain. Our data set consists of 516 authentic electronic patient records. First, we assess statistically the amount of narratives. We find that the amount is substantial: elective admission type and high nursing intensity contribute this. Second, we perform a content analysis. We observe that notes relevant for a given topic are scattered over the narratives, headings are inconsistent, and the flow from earlier narratives is fragmented. Consequently, support for gaining topical overviews is needed. Meeting this clinical need holds the promise of making narratives better accessible throughout a patient's stay and thereby improving clinical decision making and outcomes of care.*

## 1. Introduction

In intensive care units (ICUs), clinical information needs are emphasized. Patients require continuous monitoring and observation of vital signs. As a result, a vast amount of nursing narratives is accumulated; they are recorded at all times during the whole in-patient period. Narratives are used to support clinical decision making and the continuity of care. Hence, their intelligibility and timely accessibility throughout a patient's stay [1], that is, a fluent information flow [2], is a prerequisite.

Natural language processing (NLP) is still rarely used in clinical settings[1]. Studies report clinical NLP for diagnosing [3-6], searching [7] and extracting information [8-16], as well as generating alerts [17]. Of these, however, only four are in clinical use [6, 8, 17] or trial [11], only two explicitly mention ICU narratives [11, 16], and none of them is specifically tailored for nursing narratives or Finnish. In this paper, we describe clinical NLP needs by analyzing information flow in Finnish ICU nursing narratives.

## 2. Material and Methods

The Finnish 24-bed ICU from which our data is originated has used electronic patient records since 2002. It accommodates approximately 2,000 admissions per year. In 2006, the average length of stay was 3.3 days with a standard deviation (SD) of 4.9 days. At least twelve nurses and two physicians are on duty in every shift.

Our data includes nursing narratives in 516 patient records from 2005 Jan 1 to 2006 Aug 1 with proper

[1] PubMed: (patient records) AND (natural language processing OR language technology OR decision support systems, clinical OR decision support OR decision making) AND (narrative* OR note* OR text*); published in the last 2 years, Humans, English; utilizes the MeSH hierarchy; 15 out of the returned 42 studies on 2007 Nov 12 were relevant. To ensure reliability, both HS and HL-L analyzed the studies.

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permissions. Our inclusion criterion is the length of stay at least five days, as fluent information flow is likely to be challenged with protracted in-patient periods. The narratives can be grouped into *admission documents*, *daily notes*, and *discharge documents*. Admission and discharge documents are compact patient descriptions at the time of ICU admission and discharge. They are guided by default headings. Daily notes are written during the ICU stay and stored shift-specifically. We call the file containing all daily notes of the patient a *daily document*.

The patient demographics in our data are *age* (min 6, max 88, mean 59, SD 16); *average nursing intensity* (low-high, i.e., 1-5, min 2.2, max 4.6, mean 3.2, SD 0.37); *length of stay* (min 5.0, max 58, mean 11, SD 7.3); *sex* (183 female, 333 male); *admission type* (449 emergency, 67 elective); *main ICU ICD-10 diagnostic group*[2] (group id: no. of patients, A) 1:36, 2:23, 3:8, 4:29, 5:217, 6:64, 7:42, 8:11, 9:86, B) 1:246, 2:100, 3:50, 4:120); *ICU outcome* (398 recovering, 21 in the middle of care, 29 no care outcomes, 57 dead, 11 missing); and *discharged to* (155 medical ward, 242 surgical ward, 56 other hospital, 56 dead, 1 missing).

Our first analysis aspect is the amount of narratives and patient demographics that increase the amount of daily notes. For the amount, we use descriptive statistics of the number of words in admission, daily, and discharge documents. For daily documents we consider not only the *total amount* but also seven other number-of-words variables: the *average daily amount* (1); the *amount written during the first one, two, three*, and *four days of stay* (2-5); and for patients with long enough LOS, the *amount written during the first week* and *two weeks of the stay* (6, 7). For the comparison with the demographics, we first divide the patients into five groups according to the amount of text, separately for the eight number-of-words variables. Then, we perform logistic regression. Finally, we use the Kruskal-Wallis test for the rougher granularity of diagnostic groups due to the skewed distributions. In further pairwise comparisons with the Mann-Whitney *U*, we apply the Holm variation of the Bonferroni correction. All statistical analyses are performed with SAS 9.1. For information regarding the statistical tests, see, for example, [18, pp. 71, 139-144, 225, 226].

Our second aspect is topic, headings, and information flow in narratives. This type of analysis is also performed in [19]. We use the method of content analysis – a systematic, replicable technique for compressing text into topics based on explicit coding-rules that allows for monitoring shifts and changes in content and style [20]. First, we analyze nine documents, which reflect the variability of the document length: the shortest admission, daily, and discharge document; narratives of the patient with the largest amount of text (the admission and daily documents are the longest); and narratives of the patient whose daily document is closest to the average size. Then, we study the headings in all daily documents; we apply the semi-automatic heuristic of headings being separated from the text by a colon and a space. This has the precision of 0.99 and recall of 0.90 in the three daily documents above.

## 3. Results

The overwhelming amount of narratives challenges the information flow (Table 1): The longest admission, daily, and discharge documents have approximately 7, 48, and 4 pages (A4 paper, 3 cm margins, Times font of size 12, single lines). On average, 12 pages of nursing narratives are written about a patient during the ICU in-patient period. The amount is, however, varying, as five shortest and longest daily documents illustrate (480, 590, 600, 620, and 640 words vs. 8,600, 9,600, 12,000, 12,000, and 13,000 words).

Problems of the flow are likely to increase, if the patient has a high nursing intensity or elective admission type, belongs to one of the diagnostic groups of *Tumors*, *Unclassified symptoms or abnormal clinical and laboratory findings*, and *Traumas, intoxications and extrinsic factors*, or stays long in the ICU (Table 2 and Kruskal-Wallis tests). Our interpretation of high nursing intensity increasing the amount of daily notes is that the higher the need for caring, the more things are to be documented. Contrary, more daily notes are written about elective patients especially directly after admission, even though emergency patients should have more things to be documented; the admission of elective patients is pre-arranged and their medical status is carefully checked in advance. Thus, emergency patients seem to require such intensive caring that nurses have no time for writing daily notes. The least daily notes are about patients with infections or lung diseases.

[2] Since the data has 115 groups and only few patients per group, we merge them into two granularities based on the ICD-10 tree and disease features: A) 1. *Infections*, 2. *Tumors*, 3. *Endocrinology, nutrition and metabolism*, 4. *Diseases of muscle and nervous system*, 5. *Cardiovascular diseases and problems in conduction system*, 6. *Lung diseases*, 7. *Diseases of the abdominal cavity organs*, 8. *Unclassified symptoms or abnormal clinical and laboratory findings*, and 9. *Traumas, intoxications and extrinsic factors*. B) 1. A4 & A5, 2. A1 & A6, 3. A3 & A7, and 4. A2 & A8 & A9.

**Table 1. Descriptive statistics for the amount [words] of nursing notes**

| Document type | | *n* | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Admission | | 348 | 250 | 240 | 8 | 2,100 |
| Daily | 1st day | 516 | 270 | 110 | 37 | 720 |
| | 1st 2 days | 516 | 480 | 170 | 130 | 1,290 |
| | 1st 3 days | 516 | 690 | 220 | 240 | 1,700 |
| | 1st 4 days | 516 | 880 | 260 | 290 | 2,000 |
| | 1st week | 382 | 1,500 | 360 | 660 | 2,800 |
| | 1st 2 weeks | 99 | 2,800 | 590 | 1,600 | 4,600 |
| | Total | 516 | 2,100 | 1,500 | 480 | 13,000 |
| | Daily average | 516 | 190 | 44 | 89 | 380 |
| Discharge | | 514 | 400 | 140 | 140 | 1,000 |

**Table 2. Logistic regressions with the 95 % Wald confidence limit strictly below or above one**

| Words | Granularity | Effect | Odds ratio | Confidence limit |
|---|---|---|---|---|
| 1st day | 4 | average nursing intensity | 3.041 | (1.904-4.857) |
| | | emergency vs. elective | 0.579 | (0.353-0.950) |
| | 9 | average nursing intensity | 2.688 | (1.699-4.330) |
| | | group 2 vs. 9 | 0.380 | (0.157-0.919) |
| 1st 2 days | 4 | average nursing intensity | 2.645 | (1.659-4.216) |
| | 9 | average nursing intensity | 2.401 | (1.492-3.864) |
| 1st 3 days | 4 | average nursing intensity | 6.364 | (3.890-10.412) |
| | 9 | average nursing intensity | 5.659 | (3.431-9.331) |
| | | emergency vs. elective | 0.479 | (0.344-0.976) |
| | | group 2 vs. 9 | 0.313 | (0.128-0.765) |
| | | group 6 vs. 9 | 0.441 | (0.228-0.852) |
| 1st 4 days | 4 | average nursing intensity | 6.600 | (4.023-10.828) |
| | | emergency vs. elective | 0.563 | (0.341-0.929) |
| | 9 | average nursing intensity | 6.300 | (3.799-10.449) |
| | | emergency vs. elective | 0.535 | (0.554-0.904) |
| 1st week | 4 | average nursing intensity | 7.982 | (4.282-14.877) |
| | 9 | average nursing intensity | 8.733 | (4.757-16.033) |
| | | group 6 vs. 9 | 0.340 | (0.162-0.752) |
| 1st 2 weeks | 4 | average nursing intensity | 35.046 | (7.774-157.989) |
| | 9 | average nursing intensity | 44.819 | (8.922-225.149) |
| | | group 3 vs. 9 | 0.013 | (<0.001-0.445) |
| | | group 6 vs. 9 | 0.073 | (0.013-0.412) |
| Total | 4 | average nursing intensity | 5.007 | (2.826-8.872) |
| | | length of stay | 2.880 | (2.54-3.260) |
| | 9 | average nursing intensity | 4.699 | (2.621-8.425) |
| | | length of stay | 2.889 | (2.551-3.270) |
| | | group 2 vs. 9 | 0.292 | (0.100-0.854) |
| | | group 6 vs. 9 | 0.380 | (0.170-0.851) |
| Daily average | 4 | average nursing intensity | 7.658 | (4.642-12.633) |
| | 9 | average nursing intensity | 7.070 | (4.247-11.768) |
| | | group 2 vs. 9 | 0.310 | (0.127-0.757) |
| | | group 6 vs. 9 | 0.349 | (0.180-0.679) |

Topical scattering of admission documents challenges the flow. The longest document (c. 2,100 words) and the document (c. 420 words) of the patient with the average size daily document have all 17 default headings[3]. However, each heading covers several topics, and the same topic is under multiple headings. When nurses discuss a particular topic under multiple headings, their viewpoints differ (e.g., under Pain management, nurses use intracranial pressure (ICP) when estimating analgesic actions and under Hemodynamics they discuss the effect of the heart rhythm on ICP). The shortest document (8 words) had only the patient ID, the first default heading and the phrase Previously been healthy.

[3] *Previous/other diseases and anamnesis; Reason for admission; Breathing; Hemodynamics; Diuresis; Excretion; Consciousness and mood; Nutrition; Pain management; Skin and wound care; Medical treatments; Infections; Special treatments; Rehabilitation; Belongings; Relatives; Other*

**Table 3. Topics under the most common headings in the longest daily document**

| Heading | Topics | | | |
|---|---|---|---|---|
| Hemodynamics | Artery catheter<br>Bladder training<br>Blood pressure<br>Brain computer tomography | Central venous pressure<br>Cerebral perfusion pressure<br>Diuresis<br>Electroencephalogram | Freezing therapy<br>Hemoglobin<br>ICP<br>Medication<br>Mixed venous oxygen saturation | Pain<br>Pulse<br>Relaxation<br>Ultrasonic cardiography |
| Relatives | Discussions with doctor | Mood | Phone conversations | Situation assessment |
| Diuresis | Bladder training<br>Central venous pressure<br>Fluid balance | ICP<br>Medication | Quality<br>Urinary catheter | Volume<br>Volume compensation |
| Consciousness | Cerebral perfusion pressure<br>Communication<br>Computer tomography<br>Diuresis<br>Electroencephalogram | Electroneuromyography<br>Freezing therapy<br>Hyperventilation<br>ICP<br>Medication<br>Mood | Physical therapy<br>Planning<br>Plasma sodium<br>Pupils<br>Reactions<br>Rehabilitation | Relatives<br>Saturation of jugular venous oxygen<br>Sleep<br>Tremor |
| Oxidation | Breathing exercise<br>C-reactive protein<br>Hyper-ventilation<br>ICP | Jugular bulb venous<br>Medication<br>Mucous | Saturation of jugular venous oxygen<br>Suction<br>Thorax x-ray | Tracheostomy<br>Ventilator management<br>Weaning from mechanical ventilation |
| Breathing | Breathing exercise<br>ICP<br>Jugular bulb venous | Oxidation<br>Mucous<br>Pleura drain | Saturation of jugular venous oxygen<br>Suction/trachea&mouth | Tracheostomy<br>Tremor<br>Ventilator management |

**Table 4. The amount of headings and notes in the longest daily document in four quarters**

| Heading | Frequency: shifts 1-30 | Frequency: shifts 31-60 | Frequency: shifts 61-90 | Frequency: shifts 90-120 |
|---|---|---|---|---|
| Hemodynamics | 23 | 19 | 17 | 11 |
| Relatives | 21 | 14 | 15 | 10 |
| Consciousness | 11 | 9 | 15 | 9 |
| Diuresis | 18 | 12 | 7 | 7 |
| Oxidation | 13 | 13 | 9 | 6 |
| Breathing | 9 | 7 | 10 | 5 |
| Other | 8 | 5 | 7 | 5 |
| Neurology | 5 | 5 | 2 | |
| Excretion | 3 | 3 | 3 | |
| Neurological status | 3 | 4 | | |
| Consciousness and ICP | | 2 | | |
| Consciousness and mood | 1 | | 1 | |
| Heart and blood circulation | 2 | | | |
| Infections | | | 2 | |
| Basic care | | 1 | | |
| Brain pressure | 1 | | | |
| Electroencephalogram | 1 | | | |
| Freezing therapy | 1 | | | |
| Head wound | 1 | | | |
| Pain management | 1 | | | |
| Rehabilitation and mood | | | 1 | |
| Sedation | 1 | | | |
| Situation of the head | 1 | | | |
| Skin and wound care | 1 | | | |
| Special treatments | 1 | | | |
| Treatments | 1 | | | |
| No headings | 6 | 9 | 10 | 19 |
| Column sum | 133 | 103 | 99 | 72 |
| Text amount [words] | 4,300 | 3,900 | 2,400 | 2,800 |

Topical scattering is also evident in daily documents, and inconsistent headings add to the challenges. In the 516 documents, headings are used in half of the about 18,400 shifts and they are quite well-established; the most common headings and their frequencies are *Hemodynamics* (7,800), *Consciousness* (6,900), *Relatives* (5,700), *Diuresis* (5,400), *Breathing* (4,500), *Oxidation* (3,600), *Other* (3,200), *Excretion* (590), *Hemodialysis* (370), *Pulse* (160), and *Skin* (160). However, each heading has a considerable number of synonyms and spellings. The manual analysis of the three documents (c. 480, 13,000, and 2,100 words) verifies these results. Problems related to topical scattering are evident (Tables 3 and 4) and nurses often write matters unrelated to the heading. The amount of headings and notes decreases and text gets more and text gets more telegraphic in time. Topics do not change whether headings are used or not, but notes without headings are more verbal and grammatical.

Based on the analysis of discharge documents, the flow from earlier narratives is fragmented. The three documents (c. 150, 710, and 450 words) have extremely little text from daily documents (e.g., in the shortest, the only content from the daily document was the patient's state at discharge). All default headings[4] are used, but in the shortest document, almost half of them have no notes, and in two other documents, the phrases are copied almost word to word from the admission documents. In the longest discharge document, topics under the headings are consistent. The style of the shortest document reminds a checklist (e.g., nurses describe some topics only with *OK*).

## 4. Discussion

A clear clinical need for supporting ICU information flow exists. For example, when creating an overview of the patient's ICP during the ICU in-patient period for the discharge document, a nurse may have to browse, depending on the patient demographics, as much as sixty pages of narratives. Furthermore, if trying to search the ICP notes with the heading *Hemodynamics*, the nurse faces over thirty variants of this nominative, and inflection increases the number to 140. Finally, this is not enough, because at least the headings *Diuresis*, *Consciousness*, *Oxidation*, and *Breathing* may contain notes related to ICP. Partial, personalized structuring and standardization of narratives contribute to their content, information access, and intelligibility [21-23]. However, the support must retain a narrative expressive power and ease of producing; substituting entirely structured data for narratives may lead to a significant information loss [24, 25], weaker support to individualized care [26, 27], and clinicians spending more time on formatting data [28, 29].

Our results are consistent with previous studies and supplement them by addressing Finnish ICU nursing narratives. By analyzing 70 patient records from Finnish surgical, neurological, maternity, and children's wards, [21] shows that nursing narratives are detailed descriptions of the care process and evaluating their content is exhausting and time-consuming. Further, based on the analysis of 35 Thai patient records from a medical-surgical ward, crucial information is lacking from nursing narratives in terms of topics and sufficiency of notes; narratives have inconsistencies, irrelevant notes, and time-wise gaps; and unsuitable default headings lead to topical scattering, duplicated information, and increased documentation time [22]. Moreover, [23] analyzes admission documents, care plans and discharge documents of 66 patients from Norwegian medicine and cardiopulmonary units and concludes that broad default headings help nurses improve the completeness, structure, and content of discharge documents, but the headings should differentiate between various patient demographics. Finally, [19] compares headings with their content in 43 different types of nursing narratives from a US hospital and finds that the headings and their content are inconsistent.

The practical significance of this study lies in a foundation that we have created for building NLP tools to support producing and using ICU nursing narratives. We have not only identified unmet information needs but also described task-specific constraints, which can be utilized in domain-tailored NLP tools. Because of the international similarity of clinical decision making in ICUs [30], the information needs that we have identified may also be internationally applicable.


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