Latent Content Analysis on ICU Survivor Photoscripts: A Computational Model

Tiffany Chu

Supervisor: Dr. Fuchsia Howard

COGS 402: Research in Cognitive Systems

Facilitator: Christopher Mole

December 8, 2023

Abstract

This project aims to analyze intensive care unit (ICU) survivorship discourse using quantitative natural language processing (NLP) tools on qualitative data. Addressing the prevalence of post-intensive care syndrome (PICS) among discharged patients is necessary for supporting their reintegration into society. This computational design is used to supplement qualitative Photovoice research, providing an unbiased perspective and revealing information within the text that may be overlooked. Latent Dirichlet Allocation (LDA) – an unsupervised machine learning algorithm, was integrated into the design of a universal topic model which revealed abstract themes within textual data. Additionally, the process involved programming metrics to assess the model’s performance, which included computing coherence scores, measuring semantic similarity among words within topics, and perplexity values, indicating the model's predictive capability. This model found themes of PICS and gratitude in ICU survivorship discourse from a Photovoice study. Combining Photovoice research with computational methods allows us to pinpoint areas for improving post-ICU patient care within healthcare systems.

Keywords: Photovoice, Post-Intensive Care Syndrome (PICS), Latent Dirichlet Allocation (LDA), Topic Modelling

Introduction

Once patients are discharged from the ICU, they are expected to recover at home and reintegrate into society, however, their health concerns are often left unaccounted for. This is evidenced by statistics showing that in most survivors discharged from an intensive care unit (ICU), up to half will suffer new or worsening physical, cognitive, and psychiatric complications, termed post-intensive care syndrome (PICS) (Mikkleson, 2022). Additionally, the mortality rate after hospital readmission in Canada was found to be 19% at 30 days (Van Walraven, 2011), and readmission to acute inpatient care within one month of discharge is at 8.5% in BC (Zuckerman et al., 2016). Readmission due to discharge complications is not unfamiliar and can be avoided. Our goal is to identify challenges people experience after hospitalization that might contribute to an unplanned hospital readmission in the future. Analyzing critical illness survivorship experiences can guide the development of healthcare delivery and services for different contexts. This project expands upon an ICU survivorship Photovoice study by contributing a computational model for data analysis, it is designed to provide an objective and quantified interpretation of the collected information.

Photovoice

To understand and improve the lived experiences and challenges of recently discharged patients, studies often interview past patients on their transition from the hospital (Abbasinia et al., 2019). However, some aspects of critical illness recovery can be difficult to articulate. An emerging methodology known as photovoice allows participants to advocate for themselves, empowering them to visually document and share their experiences and through photography. Photovoice involves participants creating or taking photos after being given a question prompt, and then coming together to discuss their photos over multiple months. By using photography to depict their experiences during and after critical illness, participants are given an outlet to express and discuss their struggles, recovery process, support systems, and achievements. This participatory research method gathers new insights and perspectives that aims to prompt discussion, raise awareness, and drive social change (Barry and Christian, 2021). Through Photovoice research, researchers identify pitfalls in the medical system which may contribute to PICS and high readmission rates, which are then translated into actionable knowledge and policy development.

Natural Language Processing

Natural Language Processing (NLP) methods can be applied to photovoice to compute the evidence showing the lack of outpatient support, this can be done alongside traditional methods to analyze textual data (Marder, 2022). NLP methods are useful for asking whether researchers have been measuring and looking for the right information. For instance – have we been distracted by a tendency to focus on aspects of hospitalization that are less relevant for understanding readmission and recovery? Computational tools are a valuable complement to photovoice studies, providing a quantitative approach to analyzing qualitative data.

Qualitative research immensely contributes to primary care, yet faces criticism due to the lack of consensus on evaluating its quality and robustness (Leung, 2015). However, improving the assessment of qualitative research is necessary for advancing patient care, refining health services, shaping policies, and managing health administration. To avoid the subjectivity and biases inherent in language/text-based assessments conducted by clinicians and researchers, many researchers suggest supplementing traditional clinical assessments with computational analyses. This approach aims to overcome these limitations by offering a more nuanced analysis of language, thereby uncovering information that might otherwise remain unnoticed (Marder, 2022).

Motivation

The motivation behind this research project stems from a critical need to understand and improve the experiences of ICU survivors beyond their inpatient care. The diverse backgrounds of ICU patients often involve complex challenges and potential health inequities that might not be adequately captured through conventional assessments (Abbasinia et al., 2019). Tailoring outpatient care to accommodate the diverse contexts and backgrounds of individuals is crucial in mitigating structural vulnerabilities that worsen post-intensive care syndrome (Howard, et al, 2022). Photovoice sessions offer an avenue for these survivors to express their unique experiences both visually and verbally. Integrating NLP tools for Photovoice research analysis can identify prevailing themes that encapsulate the diverse perspectives of participants, suggesting ways to support the transition from hospital to home in future ICU survivors.

Through this computational text analysis, we hope to answer: “What are the predominant themes and challenges experienced by ICU survivors during their post-hospitalization recovery, as revealed through survivorship discourse?”.

The hypothesis driving this question comes from the belief that clear topics will emerge through the computational analysis of Photovoice transcripts from ICU survivors, reflecting the support and challenges encountered during their post-ICU recovery. These emergent themes that provide insight on the nuanced difficulties experienced by ICU survivors, contributing to our understanding of their unique post-hospitalization journeys.

Methods

Photovoice Design

Five participants met the eligibility criteria of having received care in an ICU in BC for over 48 hours in the past five years. They met weekly beginning in 2023, dedicating two hours per session to discuss photographs related to prompts regarding their hospital-to-home transition experiences. An example question was "What did you and your family need at home, at first and/or ongoing?". The dataset being analyzed is a transcription of multiple discussions around these questions and their associated photos, spanning a total of 10 hours.

This collection of in-depth discussions is qualitative material to be analyzed by both the researchers and myself. While the research team conducts their analysis of the data, I am independently analyzing the NLP quantitative results without prior knowledge of their findings. This approach ensures that my interpretations of the data remain unbiased and uninfluenced by their analyses.

Computational Model Design

To analyze the transcripts of post-ICU participants engaged in Photovoice sessions, I chose the method of topic modelling for content analysis. Topic modelling, a natural language processing technique, learns from the co-occurrences of words to uncover abstract topics that best characterize the text collections. I used Latent Dirichlet Allocation (LDA) to create my topic model. LDA is a statistical algorithm used in NLP and text mining, it uses a Bayesian approach – probabilistically assigning text to topics, revealing the underlying thematic structure within a corpus of text. As an unsupervised machine learning technique, LDA doesn't rely on labelled data, rather, it identifies patterns within the data, generating rules to learn topics within a corpus. From the input corpus (photovoice transcripts), LDA topic modelling generates co-occurrence patterns of words across documents, which is how it estimates parameters and iteratively updates topic-word and document-topic distributions. While this method doesn't generate explicit predictions, its strength is in organizing and extracting themes in volumes of textual data, outputting clear topics and their associated words. This process will be programmed in a Google Colab notebook, so code can be written and executed on the cloud and tested with different datasets. The process is visualized in *Figure 1.*

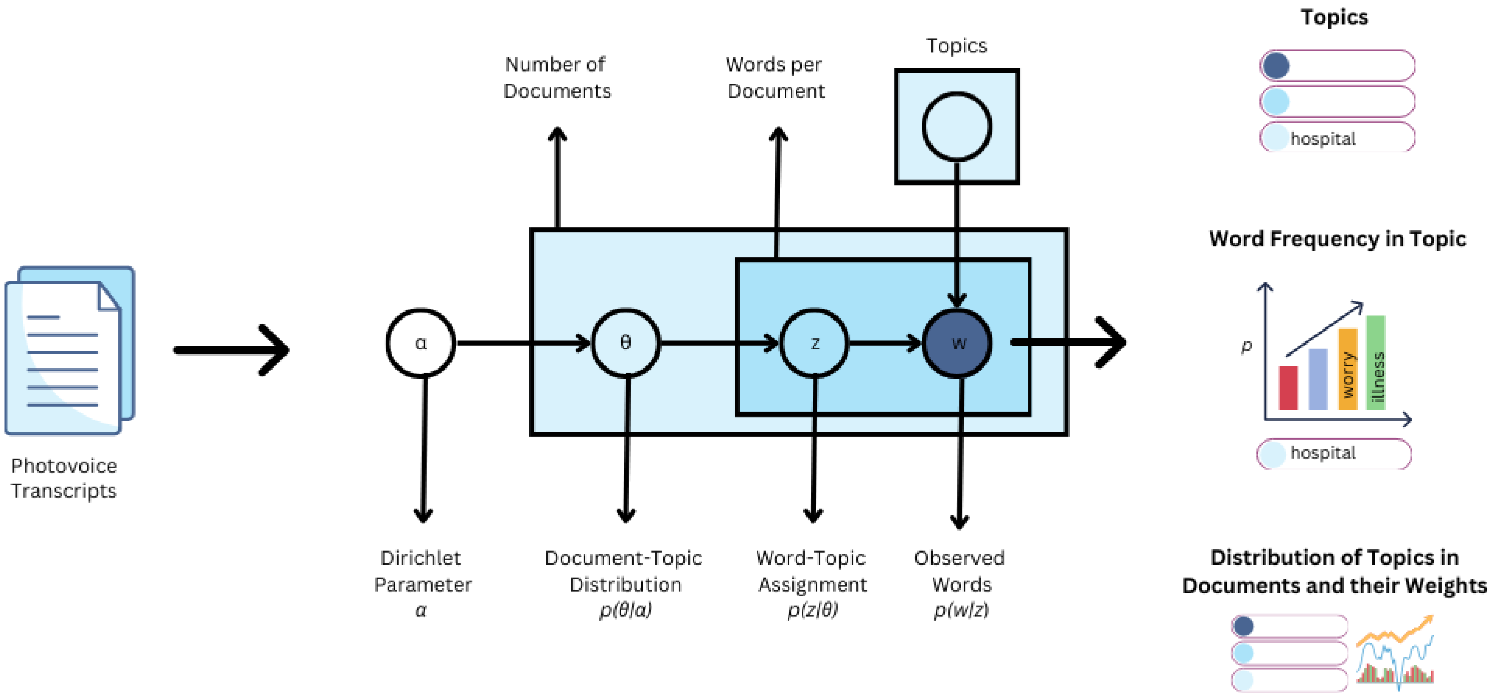

Figure 1: Schematic of LDA Topic Modelling – a theoretical overview

Implementation

The complete code is attached and linked, it works with any textual dataset in a .docx or .json format. This was made entirely using the programming language Python for simplicity and readability. Seven libraries were used in this project: NLTK, Numpy, Gensim, Spacy, Sklearn, pyLDAvis, and Matplotlib, the first three are general purpose tools for natural language processing, streamlining the statistical process for LDA topic modelling, and the latter four were used specifically to visualize the data. The following is a concise overview of the programming methodology, I have provided a more detailed explanation which is available in the code comments on Colab.

1. ***Preprocessing the Data***

The initial step involves data preprocessing – cleaning up text to make it computer-readable. These functions mainly consisted of eliminating stopwords, which carry little information or value. For example, stopwords such as "this", "a", "and", or "it" were removed.

2. Lemmatization

Lemmatization refers to deriving the base form of words, simplifying variations like "running" or "ran" to their root, "run.". This function outputs a lemmatized version of the transcripts.

3. Bigrams and Trigrams Model

Constructing a bigrams and trigrams model captures pairs or triplets of words that frequently co-occur in the same order. Bigrams are two words frequently occurring together and Trigrams are 3 words frequently occurring. For instance, terms like "Nurse Aide" are treated as bigrams to prevent double counting and to preserve contextual meaning that arises from paired or triplet words. Some words only make sense when combined, another example, "the Covid-19 Pandemic" when read together, provides contextual understanding and enhances the model's accuracy and relevance in analyzing the textual data.

4. Word-to-ID Mapping

This function creates a dictionary that assigns unique IDs to words. This step is crucial in converting textual data into a format suitable for computational analysis. Each distinct word is represented by a numeric ID, turning text into numerical data to be machine-interpretable. In the transcripts, the word “idea” is represented with ID 0.

5. Bag of Words Model

Bag of Words or BoW is a feature extraction method that represents text as a collection of word occurrences. Each text is transformed into a list of tuples, where each tuple contains a word's ID and the frequency of that word in the text. For example, a tuple (5, 2) indicates that the word represented by ID 5 occurs twice in the text.

6. Training the Model

To train my topic model, I make settings to determine how the model behaves. These parameters are standard and can easily be edited to accommodate different datasets. Some settings include: specifying the number of topics I want the model to identify, adjusting the amount of training (or iterations), and other parameters that control the model's output.

7. Visualizing Topic Models

The last step involved writing functions that visually represented the output, this was so topics generated by this model are easily interpreted and understood by the layman. I used a range of libraries to offer graphical representations and summaries of the topics discovered in the corpus. Most are interactive so an audience can easily explore and select different topics to view their weightage.

Results

The following figures are visualizations of this topic model, revealing a subset of the overall topics and their corresponding words. A comprehensive summary of the outcomes is presented in the next section. These visuals highlight the most prominent topics, making it easier to derive valuable insights and interpretations from the generated topic model.

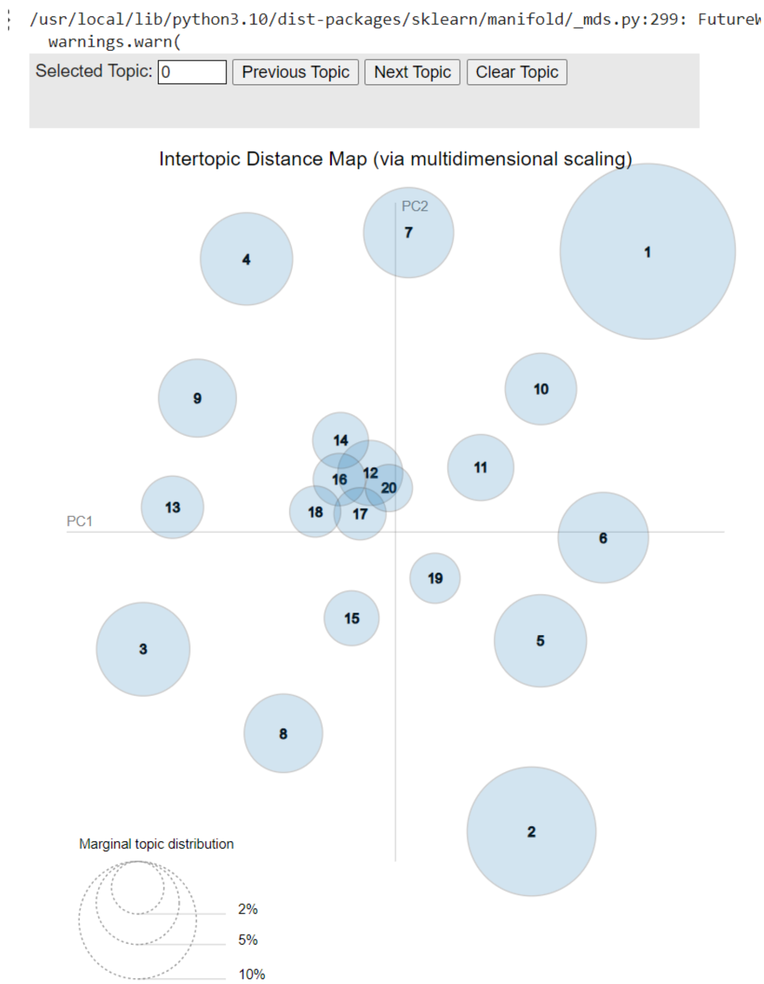

Figure 2. Intertopic Distance Map.

The visual representation showcases the 20 topics within a distance map in descending order, providing an interactive experience in the notebook. In this visualization, the size of the topic circles indicates the prevalence of a theme in the text, and its weightage can be compared using the "marginal topic distribution" on the bottom left. The distance from the center signifies uniqueness, farther circles indicate that these topics do not significantly overlap with others. Notably, smaller circles at the center contain similar words that may lack substantial meaning. I removed the inner six in my interpretation.

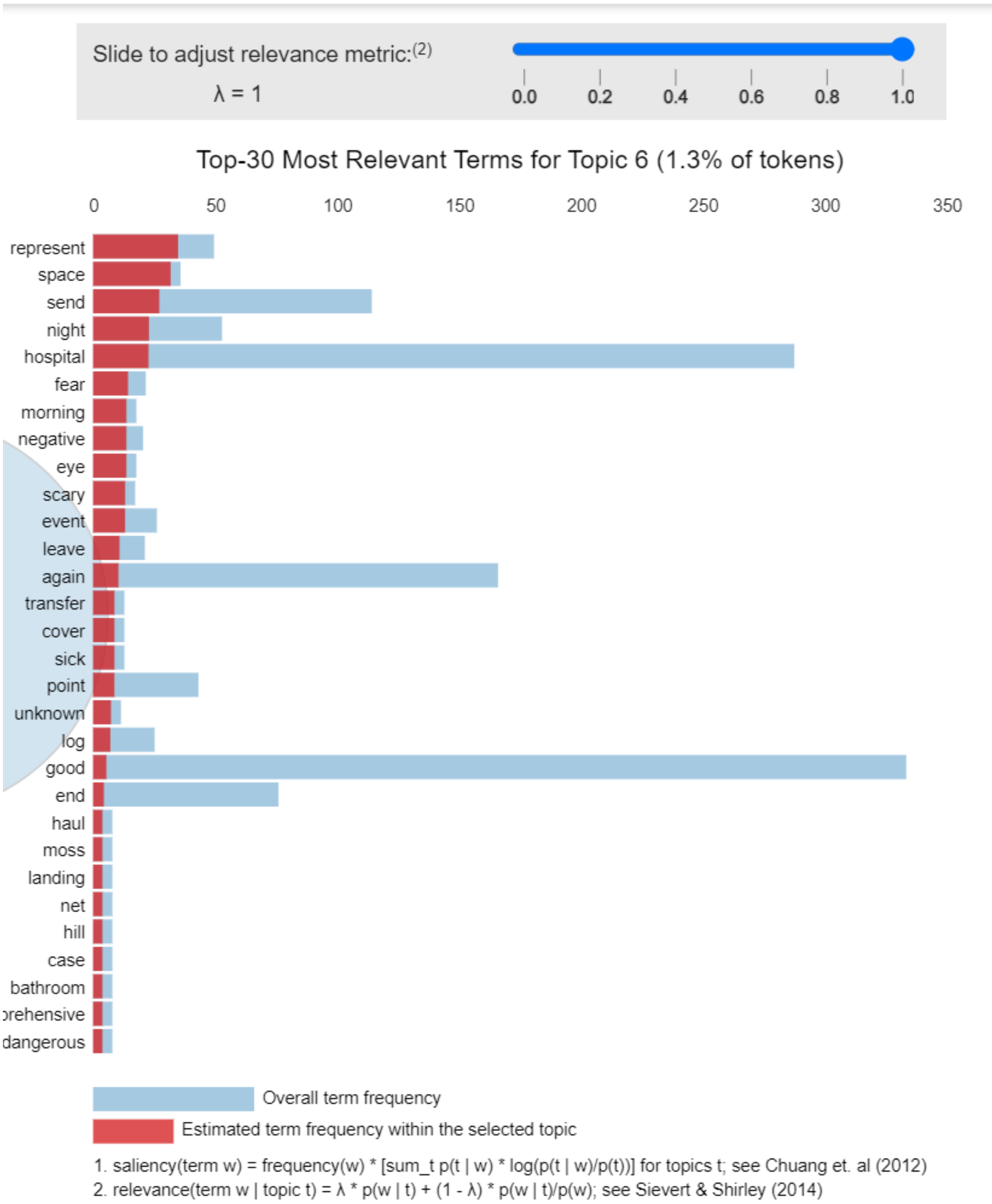

Figure 3. Relevant Terms for Specific Topics

This figure shows the result of clicking on a bubble, revealing the saliency of words and their estimated relevance to the respective topic. Included are parameters for fine-tuning the display and the information presented. For example, adjusting the relevance slider allows the display of words based on their frequency rather than their calculated perceived importance – typically, this slider is kept at a value of 1.

```
topics = lda_model.show_topics(formatted=False)

#Generating word clouds for the topics
generate_wordclouds(lda_model, topics)
```

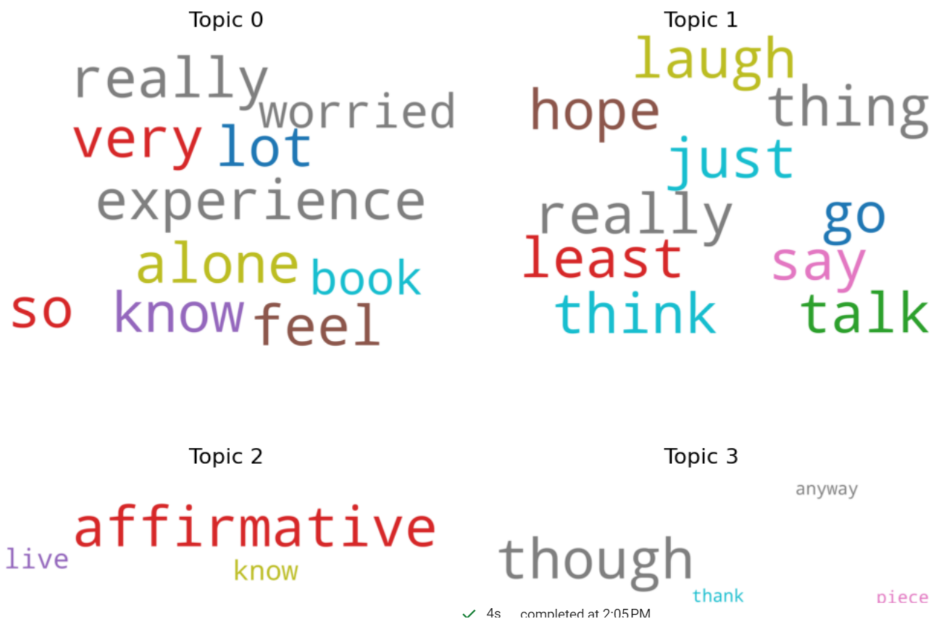

Figure 4. World Cloud Visualization

This visualization is a word cloud of the first and second topics, the keywords are in a larger font. The first topic appears to be about emotions concerning the participants' experience. The second seems more positive and likely relates to the self-advocacy aspect of Photovoice.

```
    dominant_topic, perc_contrib, keywords, text = row
    print(f"{document_no}, {dominant_topic}, {perc_contrib}, {keywords}, {text}")

Document_No, Dominant_Topic, Topic_Perc_Contrib, Keywords, Text
0, 13, 0.4472000002861023, want, idea, expertise, downstairs, gut, afterwards, field, eating, restaurant, can,
1, 11, 0.2223999947309494, just, come, then, have, thank, really, say, guy, laugh, thing,
2, 19, 0.49950000643730164, think, photo, cause, thank, really, say, guy, laugh, thing, good,
3, 13, 0.4472000002861023, want, idea, expertise, downstairs, gut, afterwards, field, eating, restaurant, can,
4, 10, 0.4666999876499176, take, time, thank, really, guy, say, laugh, thing, much, good,
5, 6, 0.44290000200271606, point, road, restaurant, gut, afterwards, field, expertise, eating, lunch, downstairs
6, 15, 0.4657999873161316, kind, bit, actually, thank, really, thing, laugh, guy, say, much,
7, 11, 0.557699978351593, just, come, then, have, thank, really, say, guy, laugh, thing,
8, 6, 0.44290000200271606, point, road, restaurant, gut, afterwards, field, expertise, eating, lunch, downstairs
9, 19, 0.49950000643730164, think, photo, cause, thank, really, say, guy, laugh, thing, good,
```

Figure 5. Topic Weightage

This chart displays the percentage distribution of each topic, indicating their significance in representing the text. The words on the right are example words in that specific topic.

Evaluating the Model

To evaluate the quality and effectiveness of my topic model I used two metrics to assess my topic modelling results:

Perplexity Score: -25

Perplexity is a measure of how well the model predicts a sample. Lower perplexity values (5 to 50) indicate better performance. This model produced a perplexity value of -25, indicating that the model, on average, is making relatively good predictions about unseen data. It is calculated over the log of probabilities, hence its negative value.

Coherence Score: 0.766

The coherence score, measures the interpretability, or semantic similarity between words within a topic. This model has a coherence score of 0.7661 indicating a moderate level of interpretability in the topics generated by the model. It can be interpreted as decently understandable, however, the words within a topic might not make sense together and they also overlap with other topics. Higher coherence scores (1 to 3) generally imply more coherent topics.

Discussion

Out of the 20 topics generated by the model, 6 were excluded from the discussion as they failed to meet the criteria of having at least 10 relevant words. The topics contained words like “next, hello, okay, yeah, same, okay, hm” due to the text being a transcription of a discussion rather than a formal document.

The top 3 meaningful topics identified were characterized by cohesive and closely related words with high significance:

1. "Alone, validation, crazy, worry" - Implies a challenging adjustment after being discharged from the hospital, indicating a negative impact on mental health. Centers

around the theme of loneliness and difficult emotions that surface after a traumatic event.

2. "Dangerous, terrified, fearful, apprehensive" - Suggests that transitioning to life outside the hospital may be physically demanding as illness causes cognitive and physical weakness, showing that this topic represents the challenges due to illness-induced weakness.
3. "Gratitude, wisdom, happiness, and reason" - Indicates gratitude for life after surviving a difficult experience, reflecting the participants' mental and physical endurance during and after recovery.

To interpret their implications for the healthcare system and the health of recently discharged patients I initially sought themes that were evident across various visualizations of the topic model, this was to cross-validate the information I derived. Then, I connected these themes with existing literature on post-hospitalization challenges (from the introduction), aligning them with the three primary symptoms of PICS: poor mental health, worsened physical health, and cognitive decline. A critical illness and/or hospitalization is a traumatic event that leaves many unable to cope or reintegrate smoothly into society, and this is evident in the topics the model provided – confirming my initial hypothesis. Interestingly, the model also unveiled a notable theme centered around an appreciation for life and acknowledgment of positive events, adding a surprising dimension to the findings. Through this computational analysis, it is strongly suggested that the post-ICU transition is extremely turbulent. Although major differences in experiences exist – common themes surrounding the universality of PICS are clear in the photovoice discussions.

Limitations

Vague

The primary challenge with this topic model lies in its vagueness. This limitation arises from the difficulty in consolidating related terms into coherent topics due to subtle differences or infrequent co-occurrences among terms. Over half of the topics lack specificity or depth, leading to those topics having words that do not form a distinct or meaningful theme.

Lack of Context

Some topics were excluded as they had no meaning since LDA topic models like this cannot comprehend context or nuances. There exist supervised algorithms or pre-trained models like

BERT, that could replace or validate this model, however, I specifically chose unsupervised ML to avoid biasing the themes and further contributing to the subjectivity prevalent in qualitative research.

As well, human interpretation is crucial for understanding the model's output, allowing for a subjective analysis. While this model represents a diverse participant group, their voluntary involvement might introduce a self-selection bias, limiting the generalizability of this project. However, I argue that this possibility should not influence this study's outcome, as the primary goal is to identify post-ICU challenges, which can be later validated by confirming with recently discharged patients.

Broad and vague topics are difficult to interpret and therefore hardly affect decision-making for policymakers. So I recommend that this should be a supplement to the researchers' actual analysis and not a standalone analysis.

Conclusion

The findings from this project reveal that major symptoms of PICS align with feelings of anxiety and depression, offering insight into the often neglected phase of transitioning out of the hospital. Analyzing survivor narratives through a computational model enables researchers to pinpoint overlooked areas in post-ICU patient care, which could potentially improve patient experiences and outcomes by informing healthcare policies and practices of these pitfalls. This project advocates for patient-centered care by acknowledging the unique needs and perspectives of ICU survivors. It emphasizes the significance of patient narratives in shaping healthcare decisions. By using NLP methods to quantify the challenges of post-ICU journeys, this model serves to validate qualitative photovoice analysis by offering presumably similar results. Overall, the project's significance supports the prevalent experience of PICS in post-ICU Photovoice discourse.

References

Abbasinia, Mohammad, et al. "Patient Advocacy in Nursing: A Concept Analysis." Nursing Ethics, 2019, https://doi.org/10.1177/0969733019832950.

Barry, Wayne, Christian Beighton, and SAGE Research Methods Complete A-Z List. Using Photovoice in Participatory Educational Research. SAGE Publications Ltd, London, 2021.

Howard, A. F., et al. "Health Equity: A Priority for Critical Illness Survivorship Research." Critical Care Explorations, vol. 4, no. 10, 2022, pp. e0783-e0783.

Leung, Lawrence. “Validity, reliability, and generalizability in qualitative research.” Journal of family medicine and primary care vol. 4,3 (2015): 324-7. doi:10.4103/2249-4863.161306

Marder, Stephen R. "Natural Language Processing: Its Potential Role in Clinical Care and Clinical Research." Schizophrenia Bulletin, vol. 48, no. 5, 2022, pp. 958-959.

Mikkelsen ME, Netzer G, Iwashyna TJ: Post-Intensive Care Syndrome. UptoDate [Internet], 2022.

Schmidt, Elizabeth K., et al. "Scoping Review of Self-Advocacy Education Interventions to Improve Care." OTJR: Occupation, Participation and Health, 2019, https://doi.org/10.1177/1539449219860583.

van Walraven C, Jennings A, Forster AJ. A meta-analysis of hospital 30-day avoidable readmission rates. J Eval Clin Pract 2012;18:1211-1218.

Zuckerman RB, Sheingold SH, Orav EJ, et al. Readmissions, Observation, and the Hospital Readmissions Reduction Program. N Engl J Med 2016;374:1543-1551.