Chief Complaints and Survival of Heart Failure Patients at Critical Care Units

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Abstract

The chief complaint (CC) is a short description of the main reason(s) why the patient seeks medical attention. Despite its somewhat subjective nature, we aimed to explore the effect of single CCs on patient survival in critical care units (CCU) in heart failure patients.

We prepared a dataset of 1,548 admission reports from 798 patients (median age 74 years) originating in the MIMIC-III database. The dataset contained 162 "expired" events (patients who died). We identified 48 common keywords in CCs and organized them into ten keyword topics. Keywords with more than 50 occurrences were further analyzed: using CCU hospitalization duration and discharge status, we built Kaplan-Meier plots for data dichotomized by specific keywords in CCs. The separating effect of each CC group was demonstrated by hazard ratio accompanied by p-value (Gehan-Breslow-Wilcoxon test) and χ^2. Furthermore, we built multivariate Cox models to consider interactions.

Significant stratification by CC was found with shortness of breath - hazard Ratio (HR) 0.75, p 0.016, $\chi^2$6.45, and hypotension - HR 1.90, p 0.001, $\chi^2$10.17. However, the influence of age over 74 years was the most important factor - HR 1.95, p 0.001, χ^2 10.28.

1. Introduction

Heart failure (HF) is a leading cause of morbidity and mortality worldwide, particularly among patients admitted to critical care units (CCU). Understanding these patients' chief complaints (CC) and survival outcomes is crucial for improving clinical management [1] and patient prognosis.

Several studies demonstrated the importance of early symptom recognition in heart failure management, for example, the prognostic value of symptoms such as dyspnea, fatigue, etc., in connection to patient outcomes [2], [3].

Automated analysis of CCs is complicated by some level of subjectivity from the patient's side or by the medical staff's usage of abbreviations, acronyms, or synonyms. Furthermore, considering the fast pace of CCU, typographical errors are inevitable. However, steps to standardize CCs have been taken in the past, as suggested and evaluated by clinicians [4].

This paper aims to explore the chief complaints presented by heart failure patients in CCUs and analyze their effect on survival rates, providing insights into potential areas for further research.

2. Method

2.1. Data

In our study, we used the MIMIC-III dataset [4], containing 58,976 CCU admissions from 46,520 patients. Using admission information, we isolated only admissions with the keywords "HF" or "HEART FAILURE" in the diagnoses field. We paired each of their admission with a discharge summary and extracted whether the patient had expired and the length of stay at the CCU. We automatically removed admission records missing the chief complaints field or those unrelated to heart failure; we also removed records where we could not assess sex or obesity level. Finally, our dataset consisted of 1,548 records from 798 heart failure patients.

Table 1. Admission statistics. Admission data were collected from 798 patients.

Data parameter	Value
Admissions count	1548
Age	74 (median)
Female	766
First-time hospitalization	794
Obese	69
Congestive heart failure	1180
Expired status	162

 ISSN: 2325-887X DOI: 10.22489/CinC.2024.077

2.2. Building a Dictionary

Next, we created a dictionary from the most common chief complaints. The dictionary was organized into topics ("Pain," "Breathing," "Swelling," etc.). Each topic contained single or grouped keywords. Cases of such a single keyword are SWEAT or CHEST PRESSURE. Keyword groups are used when single keywords are abbreviated as SOB and SHORTNESS OF BREAT (with intentionally missing letters). Groups are also used for keywords that are close in meaning and sometimes for terms that are a bit farther away but are still related, e.g., DOE and DYSPNEA. Table 2 shows clinical features related to admissions. Keyword processing was performed in Python 3.10 [5] using Numpy [6] and Pandas [7] packages.

2.3. Data Analysis

In keywords or groups with more than 50 occurrences, we examined the univariate effect on patient survival in CCU using Kaplan-Meier [7] plots. Next, we evaluated Hazard ratios (HR) with 95% confidence intervals(CI), including the Gehan-Breslow-Wilcoxon test, in GraphPad Prism 9.5.1 software (GraphPad Software, LLC, MA, USA). We also examined features when they entered Cox-proportional hazards regression analysis [8].

3 Results and Discussion

3.1. Dictionary Results

Table 2 shows occurrences for defined keywords and keyword groups in the "chief complaint" field. Seven keywords/groups having more than 50 occurrences (Tab. 2, bold) were selected for further analysis.

3.2. Survival - Univariate Analysis

Figure 1 shows how these seven features – extracted from the chief complaint text field – affect patient survival in CCU. Two of these seven chief complaints remain significant:

- Keyword group related to shortness of breath and dyspnea (HR 0.75, 95%CI 0.55-1.02, p-value 0.011, Chi-square 6.45)
- Hypotension (HR 1.90, 95%CI 0.96-3.74, p-value 0.001, Chi-square 10.17)

Only the age ≥ 74 years was significant regarding demographic and clinical features (HR 1.95, 95% CI 1.43-2.65, p-value 0.001, Chi-square 10.28).

Table 2. Keywords and thier occurences in admisions. Bold keywords/groups have 50 occurences or more.

Topic	Keywords	Count
Pain	**Chest pain, angina**	**80**
	Chest pressure	1
	Abdominal pain	39
	Heel pain	1
	Flank pain	0
	Foot pain	4
	Leg pain	3
	Arm pain	4
Breathing	**Sob, doe, dyspnea, shortness of breat**	**689**
	Cough	35
	Hemoptysis	4
	Wheez	2
	Resp	**101**
Temp.	**Fever**	**53**
	Chill	4
Blood pressure	**Hypotension**	**89**
	Hypertension	15
	Dizzines	7
Digestion /Secretion	Vomit	18
	Nausea	24
	Diarrhea	12
	Melena	12
	Hematemesis	3
	Hematuria	2
	Anuria	1
	Diurese	0
	Urin	9
Swelling	**Swelling, edema**	**60**
	Redness	1
	Diaphoresis	0
	Sweat	0
Weakness	**Weakness, fatigue**	**68**
	Somnolence	4
Any bleeding	Blood, bleed	37
Responsivity	Unconscious, nonresponsive, non-responsive, unresponsive	8
Weight	Weight gain	13

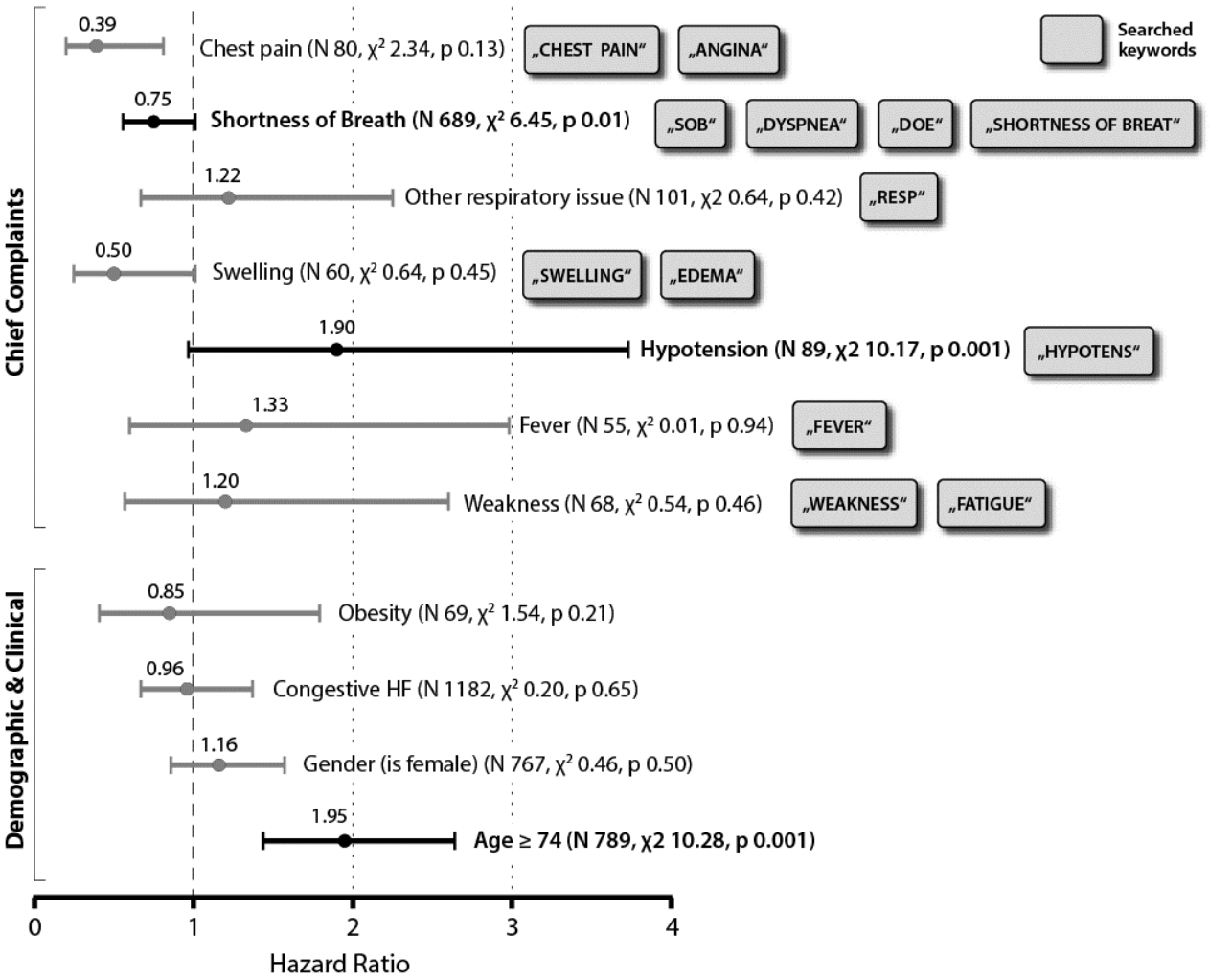

Figure 1. Hazard ratios after survival analysis show the effect of single features on survival at CCU. Significant features are **bold**.

Fig.2 shows significant stratification by the best of chief complaint keywords – "hypotens", describing the presence of hypotension (systolic blood pressure dropped below 90 mmHg or diastolic blood pressure dropped below 60 mmHg). When hypotension is present in the chief complaints, the chance of surviving the CCU stay is nearly twice as low. However, this keyword is less "subjective" than the others since it is probably based on measuring the blood pressure with some device.

Interestingly, the keyword group with issues related to shortness of breath (Fig.1, second row) leads to stratification with the opposite hazard ratio (having some shortness of breath lowers the risk of death). This could be explained by the behavior of patients with higher self-awareness and more sensitivity to worsening symptoms. This probably helps to capture worsening at the earlier stage, and – consequently – clinicians can apply proper treatment while it is more effective. Considering the number of occurrences in this keyword group, it could be valuable to analyze included keywords separately.

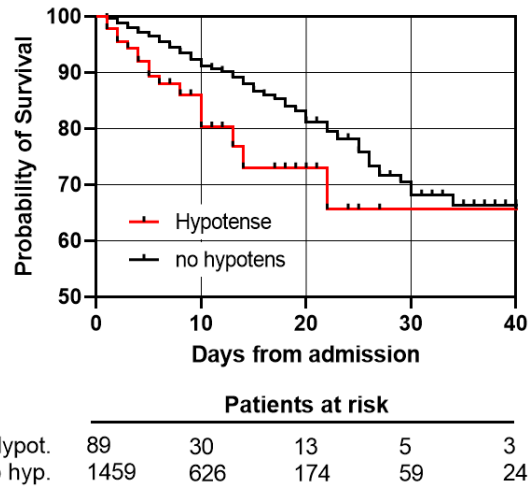

Figure 2. HF admissions by hypotension (Chi-square 10.17, HR 1.90, 95%CI 0.96-3.74, p 0.001)

3.3. Survival – Multivariate Cox model

In addition to the univariate analysis, we provided a multivariate approach using the Cox proportional-hazards approach. This approach was applied twice: once for all features with more than 50 occurrences, including demographical & clinical features and all keywords, and second, when manual backward feature reduction was made, leaving only significant features by p-value.

The Cox model based on all features resulted in only one significant feature: the age ≥ 74 years; the Akaike information criterion (AIC) was 2,099. However, when non-significant features were – iteratively - removed, two features remained in a model (Fig.2), both significant: age ≥ 74 years (HR 1.95, 95%CI 1.42-2.72, p 0.016) and hypotension (HR 1.88, 95%CI 1.08-3.06, p < 0.0001) with AIC 2091.

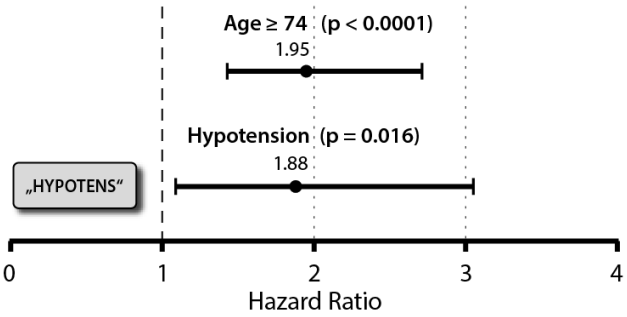

Figure 2. Cox proportional-hazards model after iterative manual feature reduction by p-value. Hypotension was extracted from the Chief complaint field of the text report.

3.4. Notes on Obesity

Obesity (BMI ≥ 30) was not a significant marker of survival in our data, and there are at least two explanations. The first might be connected to the "obesity paradox" [9], although its existence is under scrutiny [10]. The second was revealed during further data exploration, showing the median age at admission of obese patients of 56 years and 75 years of those non-obese. This difference was significant (p-value < 0.00001, Mann-Whithney-U test). This 19-year gap emphasizes the importance of body weight regulation. Consequently, the median age of death at CCU for obese and non-obese was 73 and 78 years, respectively (but non-significant, p 0.087).

4. Conclusion

This study analyzed chief complaints in the MIMIC-III database, focusing on heart failure patients. Our results showed that only the keyword group focused on shortness of breath and hypotension was significant in univariate examination. However, neither of these chief complaint keywords was as strong a survival predictor as age.

Acknowledgments

The research was supported by the Czech Technological Agency grant number FW06010766 and the project RVO:68081731 by the Czech Academy of Sciences.

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