PatientPro

GPT-powered Medical Insights from Electronic Health Records

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ECE1786 Project Final Report

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1 Introduction

High-quality medical research necessitates the extraction and interpretation of information from patient electronic health records (EHRs) [1], which may include doctors' notes, medical imaging results, and surgical reports. To serve research purposes, relevant EHR information is first extracted and consolidated in structured datatables, and then encapsulated in singular metrics calculated using defined algorithms. For example, a medical researcher interested in estimating ICU mortality may compute the APACHE-II score [2] for a patient admitted to the ICU for respiratory failure, by creating a datatable from their EHR with the required data points including age, body temperature, and organ failure history. This task is inherently time-consuming and labour-intensive, as these records often consist of freeform text. In light of recent breakthroughs in LLMs for performing text-related tasks, this project explores the capabilities of GPT models to automate the extraction and tabulation of relevant information from textual EHRs in order to enable medical metric computation.

2 Illustration

PatientPro's high-level architecture is illustrated in **Figure 1**. For a detailed view, see **Figure 2**.

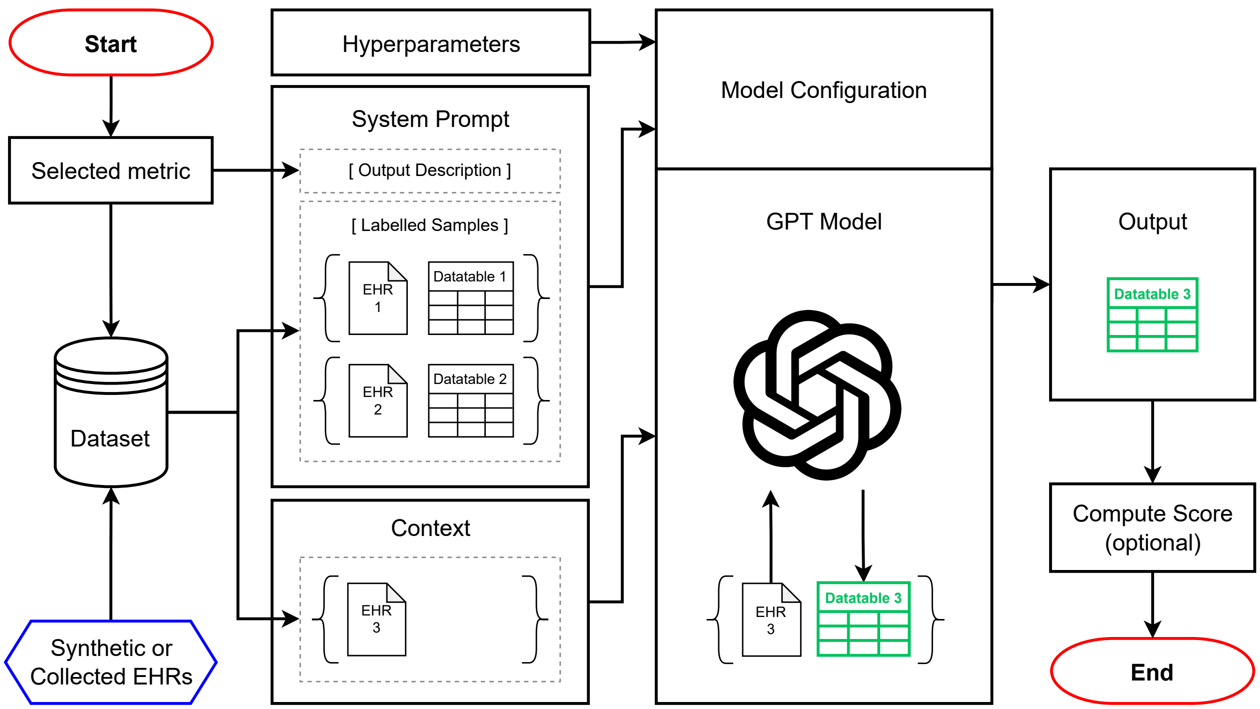

Figure 1: PatientPro's high-level system architecture

3 Background & Related Work

The use of NLP powered by LLMs to process and interpret EHRs is relatively new and rapidly gaining popularity. Previously, most literature described the development of more "traditional" ML models for building blocks of clinical NLP tasks such as Named Entity Recognition (NER), such as Spark NLP's NER model [3] which uses a CNN-BiLSTM architecture to produce tags for entities such as biomarkers or drug dosages in EHRs, to be used in downstream clinical tasks. LLMs can address these complex tasks directly. Newer developments include specialty LLMs trained on clinical corpora, such as GatorTron [4], which was trained on >82 billion words of de-identified clinical text, and evaluated on five clinical NLP tasks, including clinical concept extraction and medical relation extraction. This exploration focuses on accelerating medical research with the capabilities of GPT models.

4 Data & Data Processing

Data collection was PatientPro's greatest challenge, as EHRs are classified as Protected Health Information (PHI) and are not readily available. Access to online EHR datasets involves several steps, most notably credentialed repository access, which greatly obstructed progress due to delayed responses from administrators. However, data scarcity was anticipated early on, and the project proposal included contingency plans for using synthetic EHR generation to populate the dataset (Phase I). Later on, we gained access to the MIMIC-III dataset [5] on the PhysioNet online repository and used real data thenceforth (Phase II).

4.1 Phase I: Synthetic EHRs

4.1.1 Selected Metric: Centor Score

In Phase I of the project, there were no restrictions to the selected metric since the EHRs were being generated based on the metric rather than extracted from a dataset. We selected Centor Score [6], a measure of the likelihood of streptococcal pharyngitis in patients with sore throat symptoms. This was an appropriate starting point since it only examines five factors, including both quantitative information (e.g. temperature) and qualitative information (e.g. lymph node condition), so as to give a simple but holistic insight into the system's capabilities.

4.1.2 Data Collection

A total of **10** synthetic records were generated for the test set, (+3 for few-shot prompting). In order to mitigate hallucination, several seed records i.e. handwritten EHRs were drafted and given to the model for reference when generating the synthetic records. Both the seed records and generated records were verified by a subject matter expert to ascertain the authenticity of the synthetic data. See **Appendix A** for a sample synthetic EHR.

4.2 Phase II: MIMIC-III Dataset

4.2.1 Data Collection

MIMIC-III [5] is a massive online collection of datasets of de-identified free-text clinical notes. We selected the "noteevents" table, their collection of **2083180** freeform text records from ICU admissions, and filtered our selection to physician's notes, a total of **141624** records of about 1500 tokens each. These records had sufficiently similar formats to provide sufficient information to compute ICU metrics, while accounting for the varied writing styles of different physicians. See **Appendix A** for a sample EHR from MIMIC-III.

4.2.2 Selected Metric: qSOFA Score

In contrast to Phase I, the metrics selected for Phase II were chosen based on the information available in MIMIC-III. The first metric selected was qSOFA score [7], an estimation of mortality from sepsis based on three data points. Similar to Centor score, this was selected for its mixture of quantitative and qualitative factors. A total of **30** records (+3 for few-shotting) were extracted.

4.2.3 Selected Metric: NEWS Score

To prove the generalizability of results, and challenge the system further, we selected the NEWS Score [8] metric, a general measure of degree of illness, which considers seven data points, more than 2x that of qSOFA score, including a categorical data point (state of alertness), which had not been tested before. A total of **28** records (+3 for few-shotting) were extracted.

The following table (**Table 1**) summarizes the metrics and the data points they target in an EHR.

Metric	Data Points	Data Type
Centor Score	Age	Integer
	Tonsil swelling	Boolean
	Swollen cervical lymph nodes	Boolean
	Temperature	Float
	Cough present	Boolean
qSOFA Score	Altered mental status	Boolean
	Respiratory rate	Integer
	Systolic blood pressure	Integer
NEWS Score	Respiratory Rate	Integer
	Oxygen Saturation (%)	Integer
	Supplemental Oxygen	Boolean
	Temperature	Float
	Systolic Blood Pressure	Integer
	Heart Rate	Integer
	AVPU Score (Consciousness)	Character

Table 1: Selected metrics and the data points they target in a given EHR

5 Architecture & Software

A more detailed view of the system architecture is visible in **Figure 2**.

5.1 Architecture Description

The system architecture is straightforward. The prompt in the main flow describes the schema for the output, a list items to extract from the EHR, and several other directions such as avoiding information from previous visits on record. The hyperparameters are selected according to PatientPro's objectives, i.e., to favour consistency over creativity (temperature was set to 0). The system has an option to few-shot the prompt with up to three labelled samples. Finally, the output of the system is the datatable. We also included an option to compute the actual metric score.

The generation submodule only applies to Phase I and was replaced by MIMIC-III after access was obtained. The prompt in the generation submodule includes seed records and simply requests the GPT model to produce a number of similar EHRs with varied information. The synthetic records then populate the dataset in the main system flow.

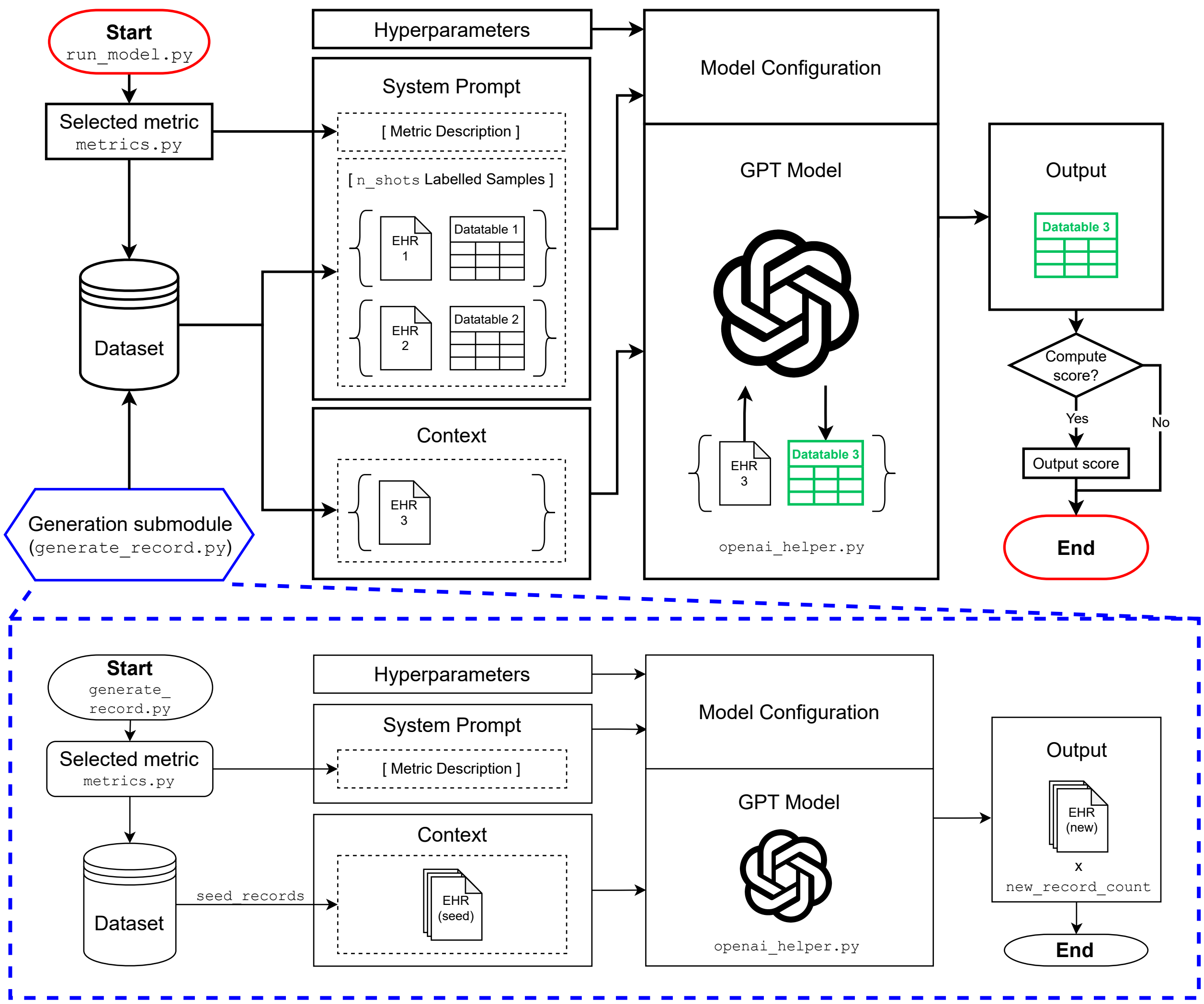

Figure 2: PatientPro's detailed system architecture

5.2 Software

The project was developed entirely in Python and can be ran in a virtual environment, provided that the user has an OpenAI API Key.

6 Comparison

The generated datatables are expected to match exactly with the expert-verified labels, due to the sensitive nature of medical data. Any hallucination or erroneous reporting whatsoever presents a risk to the patient and compromises the healthcare provider's integrity, therefore, the metric for success is a strict binary pass/fail. If any of the fields in the generated datatable do not match those in the labels, it is considered a failure.

7 Quantitative Results

7.1 Phase I

For the synthetic EHRs, PatientPro was able to extract and tabulate data for the Centor Score metric with a success rate of **90%** in direct and 1-shot mode, which improved to **100%** in 2 and 3-shot mode (see **Table 2**).

Test EHR	Direct (0-shot)	1-shot	2-shot	3-shot
sr_0.txt	PASS	PASS	PASS	PASS
sr_1.txt	PASS	PASS	PASS	PASS
sr_2.txt	PASS	PASS	PASS	PASS
sr_3.txt	PASS	PASS	PASS	PASS
sr_4.txt	PASS	PASS	PASS	PASS
sr_5.txt	FAIL	FAIL	PASS	PASS
sr_6.txt	PASS	PASS	PASS	PASS
sr_7.txt	PASS	PASS	PASS	PASS
sr_8.txt	PASS	PASS	PASS	PASS
sr_9.txt	PASS	PASS	PASS	PASS

Table 2: Results for generating Centor Score datatables

7.2 Phase II: qSOFA Score

The next metric tested was qSOFA score (**30** records). After several iterations of prompt engineering, PatientPro was able to extract and tabulate data for this metric with a 27/30 or **90%** success rate in direct mode. See **Table 3** for details.

Test EHR	Result	Test EHR	Result	Test EHR	Result
q2.txt	PASS	q24537.txt	PASS	q414226.txt	PASS
q49.txt	PASS	q24822.txt	PASS	q443913.txt	PASS
q54.txt	PASS	q64045.txt	PASS	q574369.txt	PASS
q79.txt	PASS	q80092.txt	PASS	q576902.txt	PASS
q94.txt	PASS	q140914.txt	PASS	q589715.txt	FAIL
q137.txt	PASS	q337779.txt	PASS	q663091.txt	FAIL
q174.txt	PASS	q365094.txt	PASS	q669120.txt	FAIL
q176.txt	PASS	q367858.txt	PASS	q675818.txt	PASS
q183.txt	PASS	q372279.txt	PASS	q690115.txt	PASS
q186.txt	PASS	q400812.txt	PASS	q723757.txt	PASS

Table 3: Results for generating qSOFA Score datatables

7.3 Phase II: NEWS Score

The final metric tested was NEWS Score (**28** records). The final accuracy for NEWS score was 25/28 or **89%** in direct mode. See **Table 4** for details.

Test EHR	Result	Test EHR	Result	Test EHR	Result	Test EHR	Result
n552.txt	PASS	n22330.txt	PASS	n55038.txt	FAIL	n112897.txt	PASS
n3437.txt	PASS	n26798.txt	PASS	n94649.txt	PASS	n116755.txt	PASS
n3451.txt	PASS	n34189.txt	PASS	n95424.txt	PASS	n120359.txt	PASS
n5738.txt	PASS	n41117.txt	PASS	n97101.txt	PASS	n127888.txt	PASS
n14824.txt	PASS	n41519.txt	PASS	n102186.txt	PASS	n129756.txt	PASS
n16543.txt	FAIL	n44324.txt	PASS	n102219.txt	FAIL	132739.txt	PASS
n22248.txt	PASS	n50392.txt	PASS	n105043.txt	PASS	n133448.txt	PASS

Table 4: Results for generating NEWS Score datatables

8 Qualitative Results

8.1 Phase I

The results in **Table 2** illustrate the benefits of few-shot prompting, as the accuracy increased when examples were included in the prompt. However, the perfect accuracy should be interpreted with caution. Despite efforts to make the synthetic EHRs as realistic as possible, they remained overly brief, simplistic, and organized, thus not fully representative of real EHRs. Lower, more realistic scores of 89-90% were achieved on the real data.

It should also be noted that the system was few-shotted only in Phase I, with latter metrics evaluated only in direct mode. The costs in Phase II skyrocketed as the real EHRs were substantially longer than the synthetic ones (a single run of 30 records costs an estimated $10-15 USD).

8.2 Phase II: qSOFA Score

Closer examination of the results can give greater insight into the system's errors. **Table 5** indicates exactly which data points the model extracted incorrectly. It is observed that the model made two errors on identifying an altered mental state (both a false positive and a false negative), and one error in reading systolic blood pressure. Upon inspection of the record (q663091.txt), it was revealed that there were multiple readings for this value, and the model was confused on which value to report.

Record	altered_mental		systolic_bp		Score	
	generated	reference	generated	reference	generated	reference
q589715.txt	False	True	–	–	1.0	2.0
q663091.txt	–	–	98.0	104.0	–	–
q669120.txt	True	False	–	–	3.0	2.0

Table 5: Errors in generated tables for qSOFA Score metric

8.3 Phase II: NEWS Score

Similar to the previous section, **Table 6** illustrates the errors made by the system for extracting relevant information for the NEWS Score metric. For this metric, PatientPro is able to extract all information successfully except for the AVPU Score, a quick measure of patient consciousness which classifies the alertness of the patient in one of four categories (Fully **A**lert, **V**erbal-Only, **P**ain-Only, **U**nresponsive) based on their response to various stimuli. It appears that the system has a bias towards the "Verbal-Only" category, which is likely due to alertness tests involving some level of conversation, which is misclassified by the system. As level of consciousness is notoriously difficult to ascertain, this was expected from the system.

Record	AVPU		Score	
	generated	reference	generated	reference
n16543.txt	V	P	–	–
n55038.txt	V	A	6.0	3.0
n102219.txt	V	A	4.0	1.0

Table 6: Errors in generated tables for NEWS Score metric

9 Discussion & Learnings

9.1 Overall Performance

PatientPro performed quite well ($\geq$**89%** success rate) on all tests for all metrics. Although our synthetic records did not give us entirely reliable results, they illustrated the advantages of multiple example-based learning by showcasing higher accuracy with 3-shot prompting in comparison to direct mode. Moreover, the system proved to successfully extract qualitative information such as an altered mental state or AVPU score most of the time, which was an anticipated point of great struggle. The generalizability of the system was also proved on real data by analyzing multiple metrics of varying degrees of complexity and number of data points. Overall, the project was a success and, with further refinements, can potentially accelerate medical research as intended.

9.2 Challenges

The incorrectly classified qualitative data points in both metrics for Phase II may be explained by conflicts between the model's knowledge and the in-context knowledge provided in the prompt. For example, the model may have a slightly different understanding of what an altered mental state is than the medical consensus on the idea.

One challenge that was not anticipated was the difficulty in handling the presence of multiple values for a single field in the same EHR. The system struggles to identify the correct one to report. This error was mostly reduced by including a request in the prompt to avoid reporting information from the HPI (History of Present Illness) section, and only report the earliest value it sees, but unfortunately was not foolproof.

Another unanticipated obstacle was the cost to run the system for multiple EHRs. This was greatly underestimated in Phase I as the system was only handling short synthetic EHRs. The few-shot modes became unfeasible with the real EHRs due to budget constraints, but similar improvements in accuracy are expected given a larger budget.

9.3 Potential Improvements

Experimenting with a model fine-tuned on the MIMIC-III dataset can address the issue of discerning multiple values, and potentially correct the misclassification of categorical data (altered mental state, AVPU Score). However, this would introduce a laborious task of manually labelling sufficient data to fine-tune a model. Another improvement may be to explore standardization or reformatting of the EHRs prior to analysis. If this can be automated, it has the potential to boost accuracy further for a relatively low-cost effort, otherwise, it would introduce the same issue of manual work.

10 Individual Contributions

10.1 Soliman's Contributions

Data:

- Gained access to TCAIREM Health Data Nexus
- Contacted authors of three Health Data Nexus datasets
- Labelled 10 records for qSOFA Score metric
- Labelled 28 records for NEWS Score metric

Code/System Architecture:

- Designed and implemented Metric class for total modularity of system
- Drafted initial prompts and implemented qSOFA metric subclass
- Drafted initial prompts and implemented NEWS metric subclass
- Designed project data infrastructure (directories, file name convention, data label template)
- Implemented testing functionality (runs on entire test set, reports accuracy & mistakes)

Deliverables:

- Took the lead on drafting project deliverables
- Made both presentations
- Drew all diagrams

10.2 Mohamed's Contributions

Data:

- Gained access to MIMIC-III Dataset
- Contacted subject matter expert for labelling and synthetic record verification
- Selected and labelled 20 records for qSOFA Score metric
- Created 10 synthetic records for CENTOR metric

Code/System Architecture:

- Designed initial system architecture
- Designed & implemented synthetic record creation
- Implemented core functionality of system (code for creating prompt, specifying output, learning and logging mode, calling OpenAI, initial testing functionality)
- Drafted initial template for all prompts
- Drafted and engineered prompt for Centor Score

Deliverables:

- Completed individual share of all deliverables

11 References

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A Appendix

The following is a synthetically generated EHR:

Patient: Lucas Miller
Age: 8
Date of Visit: 19/10/23
Chief Complaint:
Patient presents with a sore throat
History of Present Illness
Patient began complaining of throat soreness yesterday morning. Pain was initially mild but has worsened, causing difficulty with swallowing and affecting speech. The patient has been experiencing a low-grade fever and a persistent dry cough since last night. There is no reported radiating pain, and the patient denies any chills or respiratory distress. No known contact with sick individuals or recent upper respiratory infections reported by family.
Physical Examination:
Vitals: HR: 98BPM, BR: 16BPM, BP: 115/75 Temp: 37.6°C (99.7°F)
General Appearance: Appears somewhat uncomfortable but alert.
ENT (Ears, Nose, Throat): Throat showcases moderate erythema, tonsils enlarged and erythematous (Grade 3), without significant exudate. Oral cavity without lesions, uvula midline.
Lymph Nodes: Frontal and preauricular lymph nodes are slightly enlarged and tender on palpation, no lymphadenopathy.
Respiratory: Lung fields clear upon auscultation. No wheezing or signs of respiratory distress observed.
Assessment and Plan:
8 YOM presenting with sore throat, mild fever, and concerning lymphatic inflammation, with a persistent cough. Likelihood of viral etiology; however, bacterial pharyngitis to be considered. Observation and symptomatic care recommended.
Plan
• Acetaminophen as needed for fever and discomfort. Encourage increased fluid intake and rest.
• Continue monitoring symptoms closely for the next 48 hours. No antibiotics prescribed at this time, given the likely viral cause.
• Patient and parents instructed to keep in touch if symptoms escalate or do not resolve within the suggested timeframe.

The following is a real EHR from the MIMIC-III Dataset:

SICU
HPI:
62yM w/BOOP and significant TBM s/p R thoracotomy &
tracheobronchoplasty ([**6-22**]) in SICU until [**6-27**], then found on flr to
have temp, increasing SpO2 requirements, phlebitis from R PICC
w/partial right basilic vein thrombus) & BAL resistant Pseudomonas tx
SICU bc rapid hypotensive afib and resp distress (SaO2 90)
Chief complaint:

PMHx:
Chronic asthma/chronic bronchitis, BOOP, steroids: prednisone 20mg
daily (recent taper from 30mg), Severe tracheobronchomalacia, -
Y-stent placement [**Date range (1) 7182**], repeat Y-stent placement [**2129-3-7**],
Pneumonia: pseudomonas infection recently, CAD, CABG, [**2120**]; complicated
by unknown infection, myocardial infarction, [**2126**], Herpes zoster, Left
shoulder surgery, Depression
Current medications:
24 Hour Events:
EKG - At [**2129-7-10**] 02:00 PM
pt became diaphoretic and there was a question of changes on his
telemetry - cardiology fellow (Dr. [**Last Name (STitle) 4167**] up to evaluate ekg and
reported no changes from prior ekg
Allergies:
Bactrim Ds (Oral) (Sulfamethoxazole/Trimethoprim)
Nausea/Vomiting
Latex
Anaphylaxis;
Iodides (Topical) (Iodine/Sodium Iodide)
Unknown;
Shellfish Derived
Anaphylaxis; ”r
Last dose of Antibiotics:
Meropenem - [**2129-7-10**] 08:00 PM
Infusions:
Other ICU medications:
Heparin Sodium (Prophylaxis) - [**2129-7-10**] 03:00 PM
Other medications:
Aspirin 81’, Lipitor 10’,Avodart 0.5’,Lisinopril 2.5’,Isosorbide ”DN”
20”’,nitrolingual spray 0.4 prn,Prednisone 5’
Singulair 10’,Spiriva,Albuterol”,[**Doctor First Name 877**] 180’,Astelin nasal spray”
Flonase 2sprays”,mucinex 600”,mucamyst [**Hospital1 **],Calcium + vitamin D daily
Fosamax 70mg qFru,Hycosamine 125’,Protonix 40mg”,Flomax ,Docusate
Clonazepam 1mg qAM, qPM,Fluoxetine 40mg po qAM,Trazadone 100mg, 2tabs
qhs,Wellbutrin SR 450mg daily,Ambien 10mg po qhs,Lyrica 75mg 2tabs
daily,Hydrocodone/APAP 500/5mg 1-2 tabs 4x/day IC 10 phen - CNR liquid
qua” 1 tsp q4hrs PRN, protosol-HC 2% PRN, Carmol 40% lotion for feet
Ciclapirox 8% to toes, Floradil [**Hospital1 **]
Flowsheet Data as of [**2129-7-11**] 08:12 AM
Vital signs
Hemodynamic monitoring
Fluid balance
24 hours
Since [**32**] a.m.
Tmax: 36.5
C (97.7
T current: 36.5

C (97.7
HR: 87 (70 - 95) bpm
BP: 92/60(67) 83/45(56) - 116/75(85) mmHg
RR: 20 (14 - 24) insp/min
SPO2: 95%
Heart rhythm: A Flut (Atrial Flutter)
Wgt (current): 84.3 kg (admission): 87.3 kg
Height: 70 Inch
Total In:
2,997 mL
581 mL
PO:
1,440 mL
500 mL
Tube feeding:
IV Fluid:
1,557 mL
81 mL
Blood products:
Total out:
1,764 mL
685 mL
Urine:
1,764 mL
685 mL
NG:
Stool:
Drains:
Balance:
1,233 mL
-104 mL
Respiratory support
O2 Delivery Device: Nasal cannula
SPO2: 95%
ABG: 7.46/46/99.[**Numeric Identifier **]/33/7
Physical Examination
General Appearance: No acute distress
HEENT: PERRL
Cardiovascular: (Rhythm: Regular)
Respiratory / Chest: (Expansion: Symmetric)
Abdominal: Soft
Neurologic: (Awake / Alert / Oriented: x 3), Moves all extremities
Labs / Radiology
438 K/uL
8.1 g/dL
78 mg/dL
0.7 mg/dL

33 mEq/L
5.2 mEq/L
14 mg/dL
95 mEq/L
135 mEq/L
24.2 %
13.7 K/uL

WBC
18.0
16.2
16.5
13.7
Hct
30.3
27.0
25.3
24.2
Plt
397
353
417
438
Creatinine
0.7
0.9
0.7
0.7
0.8
0.7
Troponin T
0.06
0.06
0.07
0.06
TCO2
34
Glucose
98
87
94
91
93
85
97
78
Other labs: PT / PTT / INR:15.8/72.4/1.4, CK / CK-MB / Troponin

T:47/6/0.06, Differential-Neuts:80.2 %, Lymph:13.3 %, Mono:4.8 %,
Eos:1.6 %, Lactic Acid:1.7 mmol/L, Albumin:2.9 g/dL, LDH:246 IU/L,
Ca:6.6 mg/dL, Mg:1.6 mg/dL, PO4:3.5 mg/dL
Assessment and Plan
ALTERATION IN NUTRITION, ATRIAL FIBRILLATION (AFIB), BOOP,
Assessment and Plan: 62yM with TBM s/p tracheobronchoplasty readmitted
to SICU w/ respiratory distress (SaO2 90) w/ hemothorax on heparin gtt
s/p evacuation, repeated hypotensive rapid afib
Neurologic: Dilaudid prn pain. Minimize sedatives. Klonopin for
anxiety. On bupropion
Cardiovascular: Hypotension: hypovolemia vs. medication (metoprolol,
detrol) vs. adrenal insufficiency. Cont AFib w/ episodic RVR despite
cardioversion [**7-5**]. ?Afib from resp distress. Amio gtt, dig,
metoprolol. Attempting digoxin PO to d/c amio. Per cards cs -
cardioversion in 4 weeks if unstable, start coumadin as soon as stable
per surgery. Episodic RVR and diaphoresis- CE and 12lead EKG nL. Check
digoxin level. Aspirin.
Pulmonary: Tolerating nasal cannula. Aggressive pulmonary toilet.
Pseudomonas positive cultures from BAL ([**6-22**]) - on [**Last Name (un) **]/tobra/-vanc. F/U
recent BAL [**7-5**]. s/p thoracentesis to R (blood, non-infected)
Gastrointestinal / Abdomen: Regular. Reglan + lidocaine nebs for
hiccups. No thorazine d/t long QTc.
Nutrition: KVO. Metabolic alkalosis, hyperkalemia.
Renal: Monitor u/o. Cr 0.7. Check FENa.
Hematology: Hct 30.3¿27¿23.2¿24.
Endocrine: RISS, goal BS¡ 150. On a prednisone taper (5mg) for BOOP.
R/o adrenal insufficiency.
Infectious Disease: WBC 13.8¿20.2¿17¿13. On Meropenem/tobramycin for
pseudomonas in BAL.
Lines / Tubes / Drains: PIV, L PICC, Foley.
Wounds: Right thoracotomy
Imaging: CXR [**7-11**]
Fluids: KVO
Consults: Thoracic, IP, Cardiology, EP
Billing Diagnosis: Atrial Fibrillation, BOOP, Hypotension, Hemothorax
ICU Care
Nutrition:
Glycemic Control: Regular insulin sliding scale
Lines:
PICC Line - [**2129-7-5**] 11:43 AM
Prophylaxis:
DVT: Boots, SQ UF Heparin
Stress ulcer: PPI
VAP bundle:
Comments:
Communication: Patient discussed on interdisciplinary rounds Comments:

Code status: Full code
Disposition: ICU
Total time spent: 35 minutes

B Permissions

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Final Report	Yes	Yes
Source Code	Yes	Yes