

# SmartTriage: A system for personalized patient data capture, documentation generation, and decision support

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## Abstract

Symptom checkers have emerged as an important tool for collecting symptoms and diagnosing patients, minimizing the involvement of clinical personnel. We developed a machine-learning-backed system, SmartTriage, which goes beyond conventional symptom checking through a tight bi-directional integration with the electronic medical record (EMR). Conditioned on EMR-derived patient history, our system identifies the patient’s chief complaint from a free-text entry and then asks a series of discrete questions to obtain relevant symptomatology. The patient-specific data are used to predict detailed ICD-10-CM codes as well as medication, laboratory, and imaging orders. Patient responses and clinical decision support (CDS) predictions are then inserted back into the EMR. To train the machine learning components of SmartTriage, we employed novel data sets of over 25 million primary care encounters and 1 million patient free-text reason-for-visit entries. These data sets were used to construct: (1) a long short-term memory (LSTM) based patient history representation, (2) a fine-tuned transformer model for chief complaint extraction, (3) a random forest model for question sequencing, and (4) a feed-forward network for CDS predictions. In total, our system supports 337 patient chief complaints, which together make up > 90% of all primary care encounters at Kaiser Permanente.

**Keywords:** Symptom checker, natural language processing, clinical decision support, Electronic Medical Record, health care, deep neural networks, transformers, decision trees, random forests

## 1. Introduction

In recent years, there has been a broad proliferation of online symptom checkers and medical triage solutions as many patients seek web-based medical guidance prior to engaging with their health care provider (White and Horvitz, 2009; Semigran et al., 2015; Chambers et al., 2019; Dunn, 2020). A typical symptom checker functions by asking patients a sequence of questions and generating a set of possible conditions and treatment options. Symptom checkers vary by their operational range – some target specific populations (e.g. pediatrics) or disease states (e.g. influenza), while others have broader scopes (e.g. low acuity primary care) (Kellermann et al., 2010; Price et al., 2013; Buo; Ada; Inf; Bab; Med).

The need for high quality symptom checkers grew with the COVID-19 pandemic, which caused a significant decrease in utilization of primary and urgent care (Gelburd, 2020). Suddenly, many millions of people are seeking diagnostic assistance online and up to 90% of primary care visits have shifted to virtual care. The transition to (in some cases) majority virtual care represents an opportunity for greater

symptom checker usage and an imperative for tight integration into the health care operational workflow.

Symptom checkers with actionable outcomes can provide a host of benefits. Computer assisted triage of low acuity patients can decrease clinician patient load, while decision support for ordering of appropriate laboratory testing (including COVID-19 testing, (Greenhalgh et al., 2020; Judson et al., 2020)), medications, and imaging studies, can eliminate unnecessary visits. With advanced decision support and documentation assistance, patient visits themselves are enhanced as the clerical load (e.g. documentation, coding, ordering) is decreased.

Obtaining maximal benefit from symptom checkers requires a tight integration with the Electronic Medical Record (EMR). An integrated system can utilize knowledge gleaned directly from the patient and can also leverage historically relevant patient medical information. In addition, symptom checker output that is manipulable and represented in appropriate locations within the EMR can help facilitate clinical workflow and improve quality of care.

In this paper we present SmartTriage, a symptom checker that is tightly integrated with the EMR and which has a broad scope covering 337 presenting chief complaints. We use machine learning to bootstrap question sequencing and decision support predictions through training on two novel data sets. The first data set contains nearly one million patient generated free-text reasons-for-visit entries, each of which is mapped to a discrete chief complaint. The second data set is a collection of 25 million patient encounters including progress notes as well as discrete diagnoses and orders.

Three machine learning models enable SmartTriage. Our chief complaint extraction model (CC model) uses a fine-tuned bi-directional transformer neural network (BERT) to process patient free-text reason-for-visit entries (Devlin et al., 2019a). A collection of over 3000 random forest models were trained to produce highly informative question sequences (QS model). Finally, a feed-forward network was created to produce clinical assessments (Assessment model), taking into account all historical data and all questions answered. The CC and the Assessment models use a long short-term memory (LSTM) based patient history representation (Hochreiter and Schmidhuber, 1997). In this paper we also emphasize the role of medical history on the model performance, as it is valuable but often unutilized information source about the patient.

SmartTriage has been piloted in a single urgent care facility and is currently being piloted across the Kaiser Permanente Southern California Region in virtual visits (phone, video) as a pre-visit symptom checker. Details about the production integration can be found in Appendix B.

## 2. Methods

### 2.1. Content authoring

Clinical concepts from the UMLS are by their nature very detailed and clinically focused (Bodenreider, 2004). The level of detail often implies that multiple concepts exist to capture the same idea in different contexts. Figure 1 shows three concepts derived from a clinical narrative including the phrase “c/o pain after eating.” The concepts describe gastric contents backing up into the esophagus - “Heartburn” as the sign or symptom, “Gastroesophageal reflux” as the finding on exam, and “reflux” as a pathological process in general. Although there are context clues in medical notes, clinicians will often use these phrases or variants to imply the same idea, and our NLP engine will produce one or more of these concepts for the same span of clinical text.

In order to prepare a high quality training data set for our QS and Assessment models, we employed many man-hours of clinical review to collapse all of the items found by our NLP engine into meaningful “main idea” groups. In large part, the groups contained perfectly synonymous concepts; in some cases, however, we grouped items that were not perfectly synonymous but implied the same concept. Figure 1 shows the three UMLS concepts “Heartburn”, “Gastroesophageal reflux” and “reflux” grouped together into a container “Acid reflux” concept. Our pilot system contains more than 3K distinct SmartTriage Content Management System (ST-CMS) concepts.

SmartTriage is both patient and provider facing, and thus we had the dual challenge of authoring our grouped concepts such that they would be understandable to patients as questions and to providers as clinical concepts. An example of authored patient and provider facing content can be seen in the “Example SmartTriage Session” portion of Figure 1. Here we combine a canned phrase with patient friendly language to inquire about the symptom, and serve back to the EMR an appropriate clinical phrase and sense (positive or negative) to capture the patient’s response.

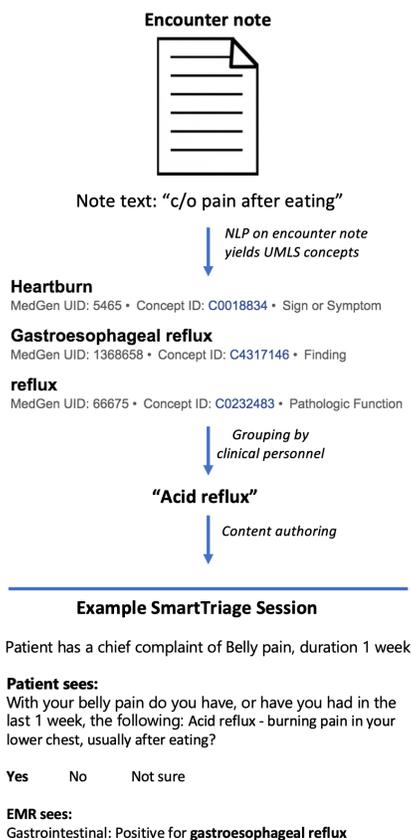


Figure 1: Diagram of concept life cycle. Extracted raw UMLS concepts are further processed and grouped into a single ST-CMS concept. For each ST-CMS concept we author separate physician and patient-friendly descriptions.

Showing questions to patients and bringing patient answers into the EMR to be placed into a progress note requires tagging each question/concept with metadata describing how it should be displayed to patients and where it should go in the clinical note. Figure C.1 shows the system we built to manage all of our content called the Content Management System (CMS), including concept groupings, patient facing text, provider facing text, and question metadata. Groupings are managed by establishing a parent-child “synonym” based relationship with functionality to add, remove, and change the parent. Each concept may have a range of response types, from simple yes/no to multi-select to free text, and

the CMS allows that to be configured. Authoring questions may include pre-text (a stem), the question itself, and post-text, all of which are editable. Metadata or question “attributes” control where in the clinician documentation the patient responses will go and how the patient’s response is meant to be interpreted by the ML components of the SmartTriage system, a parameter called “response evaluation type.” Finally, the CMS creates a preview of the question as it would be seen by the patient for validation of phrasing and question configuration.

## 2.2. Chief Complaint and Assessment models

The neural networks used in the Chief Complaint and Assessment models were implemented using TensorFlow 2.3 (Abadi et al.). For all models we used Adam optimizer (Kingma and Ba, 2015). Model architecture are schematically represented in Figure D.2. Medical history component uses the same architecture for both assessment and chief complaint models but are trained separately with each model.

**Medical history input cleaning** Medical history input data was limited to items occurring at least 5000 times in the Encounters data set.

**Chief Complaint model target cleaning** The discrete chief complaints selected by clinical personnel were further manually reviewed and grouped into 337 discrete chief complaints which were used as targets for the chief complaint model as well as inputs for the Question Sequencing and Assessment models.

**Assessment model target cleaning** For each target value  $t$  and chief-complaint  $c$ , the Bayesian lift of  $t$  appearing given  $c$  was calculated, i.e.  $\text{lift}[t|c] = \frac{\mathbb{P}[t|c]}{\mathbb{P}[t]}$ . Targets with a value  $\text{lift}[t|c] \leq 2$  were filtered out.

**Assessment model loss weighting** Loss for each output layer was weighted differently by performing a random search, limited to 10 combinations, over a 5% sample of the data, where each of the loss terms ( $\mathcal{L}_{\text{diag}}$ ,  $\mathcal{L}_{\text{med}}$ ,  $\mathcal{L}_{\text{lab}}$ , and  $\mathcal{L}_{\text{img}}$ ) was weighted by  $w \in \{0.5, 0.9, 1.0, 2.0, 3.0\}$ . The different weight combinations were sorted by the PR-AUC of all four output types, and the combination with highest rank in its worst performing output type was selected. The highest performing weighting function found was  $\mathcal{L} = 3 \cdot \mathcal{L}_{\text{diag}} + \mathcal{L}_{\text{med}} + 0.9 \cdot \mathcal{L}_{\text{lab}} + 0.9 \cdot \mathcal{L}_{\text{img}}$ .

### 2.3. Question Sequencing model

**Data cleaning** Similarly to the assessment model, question selection uses Bayesian lift to filter the target prediction. For ICD-10-CM diagnoses we calculated the Bayesian lift that a diagnosis  $t$  given the chief-complaint *c.i.e.*  $\text{lift}[t|c, a, s] = \frac{\mathbb{P}[t|c]}{\mathbb{P}[t]}$ . Target with  $\text{lift}[t|c, a, s] \leq 2$  were filtered out. Furthermore, for every cohort of chief complaint, age-bin, and sex, we filtered out diagnoses and concepts that appeared fewer than 100 times. For each cohort, we further limited the input to the 1000 most-common concepts, and limited the prediction targets to the 50 most-common diagnoses (note that the assessment model, which is used for the final differential diagnosis prediction, does not have this limit).

**Training ML question sequencing** We use the encounter data set (Section A.2) to train the ML question sequencing model. For maximal interpretability, appropriateness, and ability to handle large feature spaces ( $> 1000$  features per model) we chose to train a random forest model for each combination of chief complaint, age-bin, and biological sex. The models were trained independently using ST-CMS concepts and assertions (derived from NLP on progress notes) as features and relevant ICD-10-CM diagnoses as labels. ICD-10-CM diagnoses was chosen as a prediction target because they offer a broad proxy for patient disease states and are coded by medical professionals for every encounter in our data set. However, ICD-10-CM also introduce some bias as coding behaviors may be influenced by reimbursement dynamics and compliance to certain standard of care guidelines (e.g. a patient with cough and other upper respiratory issues may be coded as R05 or J06.9 depending on whether the treating physicians wants to prescribe antibiotics). The random forest models are trained with 100 estimators, feature subsampling of 10%, and a max depth of 15. The model was implemented using sci-kit learn 0.23 (Pedregosa et al., 2011) RandomForestClassifier algorithm.

**Selecting next ML question** At inference time we take a vote from the random forest using Algorithm 1. For every tree in the forest we traverse the nodes until we find a ST-CMS concept for which there is no assertion and extract the relevant question  $q_i$ . For each question we calculate a weight,  $w_{q_i}$  that is the number of trees that are split on a concept asked by  $q_i$ . The candidate question is validated using two rules. First, we check in the knowledge base (KB) if there is another question that should be asked

(for example, for chief complaint “foot problem” before asking “How long have you had ankle pain?” we check for the presence of “ankle pain”). If the answer to the prerequisite question is asserted as “absent” then the weight of the target question is set to 0. If the answer to the prerequisite question is asserted as “certain” then the question will not be modified. If the prerequisite question has not been answered then an additional boolean flag decides if the prerequisite question is first asked (e.g. question “How long have you had ankle pain?” is replaced by “Do you have ankle pain?”) or if the question can be asked without changes. We then sum the weights of all questions that are mapped to the same prerequisite. Second, we check candidate questions for “inappropriate” questions (e.g. some insomnia sequences that include sleep apnea may result in questions related to coughing that physician subject matter experts decided should not be asked). The highest weighted question at the conclusion of all ML and rule-based steps is then asked.

## 3. Results

### 3.1. Data sets

SmartTriage is built on historical EMR data from two novel data sets. The first is based on a collection of patient reasons-for-visit entries and the second is based on a collection of primary care encounters. Figure A.1 shows how the data sets were acquired.

When a patient schedules an appointment online they are prompted to enter a free-text reason-for-visit. At the time of the encounter, a discrete chief complaint is chosen by the intake personnel. The combination of patient entered text, the discrete chief complaint(s), and 1 year of patient history from the EMR form the Patient-Reason for-Visit data set, which contains 907,170 encounters involving 595,692 unique patients (see Appendix A.1).

During a primary care encounter a progress note is typically generated containing the patient’s history of present illness, past medical history, a review of systems, a physical exam, and an assessment and plan. The encounter may also result in a set of discretely coded outcomes such as ICD-10-CM codes for diagnoses, medication prescriptions, and laboratory or imaging orders. We use an in-house developed natural language processing (NLP) engine (Torii et al., 2015; Fan et al., 2013) to extract Unified Medical Language System (UMLS) clinical concepts from progress notes (Bodenreider, 2004). The UMLS

**Algorithm 1:** Random forest voting**Input** : Feature set  $X$ , random forest  $F$ **Output:** Question candidates  $Q$  and their weights  $W$ 

```

1 Initialize  $Q, W \leftarrow \emptyset$ 
2 foreach Decision tree  $e \in F$  do
3   | Traverse  $e$  using features  $x \in X$  until
   |   reaching node  $n$  that is either a leaf
   |   node or cannot be split using  $X$ 
4   | if  $n$  is not a leaf node then
5   |   | Let  $q$  be question to obtain feature
   |   |    $x$  that splits  $n$ 
6   |   |  $Q \leftarrow Q \cup \{q\}$ 
7   | end
8 Initialize  $\tilde{Q} \leftarrow \text{unique}(Q)$ 
9 foreach  $\tilde{q}_i \in \tilde{Q}$  do
10  |  $w_{\tilde{q}_i} \leftarrow \sum_j \delta(q_j, \tilde{q}_i)$ 
11  |  $W \leftarrow W \cup \{w_{\tilde{q}_i}\}$ 
12 end
13 return  $\tilde{Q}, W$ 

```

concepts were then further processed using our content authoring process (see 2.1) and mapped to patient and physician facing text. The extracted discrete concepts, encounter outcomes, and 1 year of patient history from the EMR form the Encounters data set, which contains 25,047,535 encounters involving 4,110,052 unique patients (see Appendix A.2).

### 3.2. Machine learning components

There are three machine-learning-based components in SmartTriage. In order of operation, the Chief Complaint (CC) model takes patient history as well as a patient entered free-text reason-for-visit and generates predictions for the discrete chief complaint. The Question Sequencing (QS) model uses the discrete chief complaint, patient history, and patient responses, to interactively ask a series of questions with discrete response choices. Finally, the Assessment model employs all of the collected information to generate predictions for diagnoses as well as medication, laboratory, and imaging orders.

### 3.3. Chief complaint extraction

**Architecture** A feed-forward neural network was constructed to combine pre-trained free-text embeddings with patient age (discretized into age groups,

see groups in Table A.1), biological sex, and patient medical history. As multiple discrete chief complaints can be extracted from a given patient-generated reason-for-visit, the output of the model is a one-vs-rest classification for 337 chief complaints. We compared several different text embedding approaches and layer size parameters, for detailed results see Table 1. The best performing embedding was a custom fine-tuned BERT model, Chief Complaint (CC) BERT, which was trained on a portion of the CC data set (anonymous citation). For detailed network architecture see Figure D.2.

The CC model utilizes patients medical history from encounters over the preceding 365 days. The history is composed of 4 different channels: previous diagnoses (1,497 distinct values), prescriptions (1,278), procedures (758), and chief complaints (954). Data from each historic encounter were placed in the four channels and channels with no relevant information were filtered out. Each channel contained the last 8 encounters with relevant information sorted in ascending order by the encounter date. We zero padded channels in cases where there were data from fewer than eight encounters. We used a single layer LSTM to combine medical history into a fixed sized representation (see Figure 2a) Pham et al. (2017); Rajkomar et al. (2018). The outputs of the recurrent layers and the demographic embeddings were then combined with the pre-trained free-text embeddings.

**Text embedding** We compared 6 different text embedding models (see Table 1). Pre-trained models for text embeddings were obtained from three publicly available sources: BERT-base (Devlin et al., 2019b), BioBERT (Lee et al., 2019), and Clinical BERT (Alsentzer et al., 2019). In addition, we fine-tuned a MD BERT model starting with Clinical BERT, using both the masked language model and the next sentence prediction task with 100 million sentence pairs extracted from patient progress notes (from encounters unrelated to the Chief Complaint Dataset). We also fine-tuned Chief Complaint (CC) BERT on the training portion of the CC Dataset, starting from MD BERT, using the masked language model prediction task. To generate BERT-based embeddings, we mean-pooled the last 4 layers, yielding an embedding size of 3,072.

As a baseline, we also trained a version of the CC model using TF-IDF embeddings. Pre-processing before TF-IDF vectorization included: (1) transforming the text to lowercase; (2) removing standard English

Table 1: Chief complaint model performance using various text embeddings

	PR AUC	ROC AUC	nDCG
TF-IDF baseline	0.4365±0.0002	0.9203±0.0008	0.7070±0.0002
BERT base	0.4210±0.0004	0.9248±0.0007	0.6970±0.0003
BioBERT	0.4194±0.0017	0.9245±0.0005	0.6962±0.0009
Clinical BERT	0.4254±0.0011	0.9248±0.0003	0.6998±0.0010
MD BERT	0.4411±0.0006	<b>0.9260±0.0003</b>	0.7102±0.0003
CC BERT	<b>0.4451±0.0005</b>	0.9254±0.0004	<b>0.7132±0.0004</b>

language stop-words; (3) replacing all numbers with the generic “#” symbol. The Penn Treebank (PTB3) tokenizer implemented in NLTK (Bird et al., 2009) was used to tokenize the text, and unigrams and bigrams were then computed. TF-IDF vectors were created consisting of values for the 50,000 most common n-grams, with at most 0.5 document frequency in the training set.

For each model, we generated 5 estimates by training in 5-fold cross validation. Resulting average and standard deviation micro Precision Recall Area Under the Curve (PR AUC), micro Receiver Operating Characteristic Area Under the Curve (ROC AUC), and Normalized Discount Cumulative Gain (nDCG) values can be found in Table 1 (Zhang and Zhang, 2009; Järvelin et al.). In terms of PR AUC and nDCG the best performing embedding was CC BERT, with statistical significance ( $p < 0.001$ ). MD BERT performed slightly better than CC BERT in terms of ROC AUC, though the difference between the methods was not statistically significant.

Finally, for the model that used CC BERT embeddings we performed hyper-parameter tuning to identify proper dropout rate and size for the feed-forward layer after concatenating patient text, demographic embedding, and medical history embedding, see Table D.1. We found that while increasing the layer size somewhat improved performance, the improvements were minimal for layers larger than 500 units, thus we used the 500 unit layer with dropout of 0.5 in our final product.

**Medical history contribution** We examined the effect of including patient medical history on CC model performance by training models with up to 1 year of patient history. We found that both PR AUC and nDCG increase slightly with inclusion history (PR AUC without history 0.432, with one year history 0.445, nDCG without history 0.705, with history

0.713; see Figure 2) by training a baseline model without the medical history input and embedding layers. The impact of history was skewed, however, which was revealed by looking at PR AUC changes achieved for complaints containing free-text terms with prevalence greater than 1% (73 terms total). For each of these terms we bucketed chief complaints containing the relevant term and compared the PR AUC and nDCG of both models. For 71 of the groups the model with history over-performed in terms of PR AUC, and 66 of the groups over-performed in terms of nDCG. The highest impact of patient history was seen in free-text reason-for-visit containing words relating to previous encounters, such as “follow”, “appointment”, “visit”, and “check” (see Figure 2), where improvement is measured as  $\frac{\text{Metric with history}}{\text{Metric without history}}$ .

**Subjective reviewer evaluation** Because our system produces chief complaints that are then presented back to patients, we needed to ensure that only appropriate chief complaints are predicted. To do this we performed a manual review on predictions for 275 patient generated reason-for-visit. We employed 3 reviewers which were presented with the patient text and SmartTriage generated chief complaint predictions. The reviewers were presented up to 5 predictions with a minimum model output score of 0.05. They were prompted to holistically evaluate the helpfulness of the predictions with the following scoring rubric (Very helpful = 1, Helpful = 2, A little helpful = 3, Not helpful = 4). The average rating over all patient reason-for-visit was  $1.7 \pm 0.8$  with root mean square inter-reviewer disagreement of 0.5. Of the 825 reviews (275 x 3) only 20 were marked as “Not helpful” (see Figure 2 for full breakdown). We also observed model performance as a function of text length (Figure 2), where we found that the score deteriorates for reasons > 100 character long. One explanation for the deterioration is that long patient

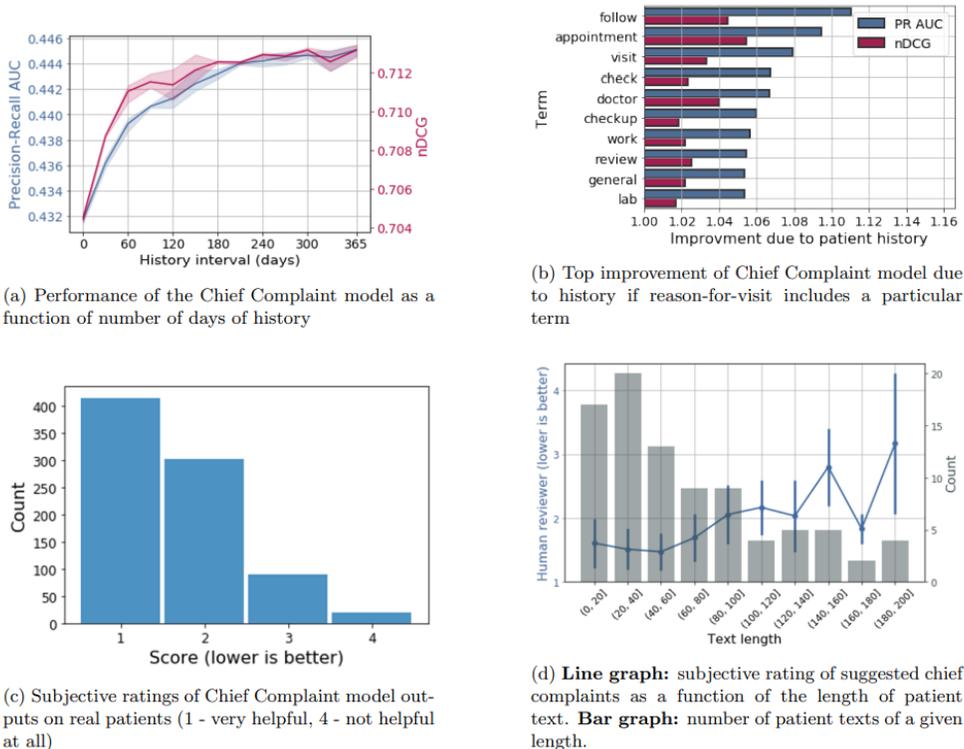


Figure 2: Chief Complaint model performance

reason-for-visit often contain multiple potentially unrelated complaints.

### 3.4. Question sequencing

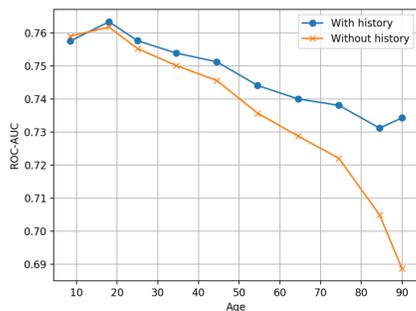
Question sequencing occurs after the chief complaint is established. By asking a series of structured and ML-derived questions, SmartTriage captures patient data that can be used to help generate the progress note. Patient responses are also fed as inputs to the assessment model. All questions and answers displayed to the patient are mapped to ST-CMS concepts (see Section 2.1). Questions may be multi-select, single-select, yes/no, drop-down (for duration questions), and free-text. Each answer has an assertion associated with it that is typically drawn from {"certain", "absent", "unsure"}. For duration and severity questions the assertions are ordinal (number of days for duration and integer-scale between [0,10] for severity).

Individual questions in SmartTriage are required to be interpretable and appropriate. Interpretable means that we can explain why each question was asked based on previous answers and patient medical

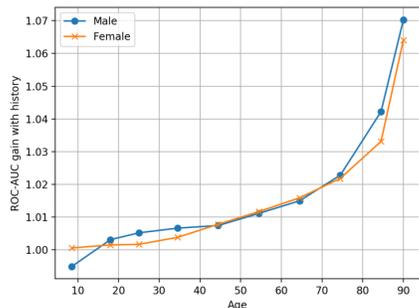
history. Appropriate means that SmartTriage should not ask questions whose answers could be inferred either from patient history or from the set of previous patient responses. To satisfy the appropriateness requirement we use a combination of rules and machine learning, both of which have available information on the chief complaint, previously answered questions, patient demographics, and 6-months worth of patient medical history (previous chief complaints, diagnoses, laboratory results, and medications; note that this is different from the CC and the Assessment models that use 1 year worth of patient medical history).

**Architecture** Schematic of the QS algorithm is presented in Figure D.1. At every step the asserted ST-CMS concepts (features) are used to infer additional asserted concepts via a rules engine. For the full set of 337 covered chief complaints, the initial rule-driven questions are stereotyped to collect a thorough chief-complaint-relevant history of present illness (HPI) with relatively minimal hard-coded branching to cover biological sex differences, timing variations, problem locations, etc. For a subset of 269 chief complaints, after the rule-based HPI

questions are exhausted ML-derived questions are asked. The ML questions are subject to additional “fixer” rules, and can extend the question sequence up to a set number of total questions.



(a) ICD-10-CM prediction ROC-AUC as a function of patient age with and without historical data



(b) Ratio of ROC-AUC with and without history as a function of patient age split by biological sex

Figure 3: Question sequencing performance evaluated on ICD-10-CM prediction task.

**Medical history contribution** We trained the random forest models with and without patient medical history. Both models achieved a very similar micro ROC AUC with respect to ICD-10-CM predictions (0.747 with history vs. 0.737 without history, 1.3% difference). However, we found that patient medical history disproportionately affects performance for older patients, with up to 7% higher performance for patients older than 90 years old, see Figure 3. We also compared the effect of history as a function of biological sex, and found that both male and female patients have a similar dependence on age, see Figure 3. To understand better what drives the benefit provided by history, we examined the ratio in ICD-10-CM prediction micro ROC AUC with and without history for different

chief complaints. We found that chronic conditions tend to have the highest improvement when including patient medical history information (e.g. “blood sugar problem” and “diabetes care management” improved by  $\sim 20\%$ ; “hypothyroidism”, “carpal tunnel syndrome”, and “chronic pain” by  $\sim 15\%$ ). Among acute diseases the “bronchitis” and the “pneumonia” chief complaints had the highest benefit from patient history at  $\sim 10\%$ . Overall, medical history was more impactful with older patients because they had more available patient medical history and a larger chronic disease burden.

### 3.5. Patient assessment

The Assessment model is the final ML model in the SmartTriage workflow, and it uses all of the collected information to predict the encounter diagnoses (1,240 distinct values) as well as medications (122), laboratory (291), and imaging (208) orders.

**Architecture** Inputs to the Assessment model are comprised of the discrete chief complaint, patient demographic data, answers from the QS model, and patient medical history. The Assessment model itself is a feed-forward neural network (Figure D) with an LSTM based patient history embedding (Figure D). Each of the inputs is embedded separately, and then the embeddings are concatenated together. The combined embedding is passed through seven ReLU dense layers of size 1024 with skip connections. The representation returned from the second layer is used by the four one-vs-rest logistic regression output layers. Comparisons of different model types and architectures are available in Table 2.

After a patient session with SmartTriage, the patient’s responses and history are provided to the Assessment model and diagnoses, medications, labs and imaging orders are inferred. These inferences are fed back into the EMR and appear as decision support suggestions in the clinician workflow we designed for SmartTriage. If a clinician agrees with a particular diagnosis suggested, they may toggle it and the diagnosis will automatically be added to the set of current encounter diagnoses. We do not currently support direct ordering of medications, labs, or imaging studies but that functionality is planned to be implemented in the near future.

**Medical history contribution** The impact of patient medical history on the quality of the Assessment model is depicted in Table 3. To generate these results, models with different periods of medical his-

Table 2: Comparison of assessment model PR AUC, ROC AUC, and nDCG with different model types

Metric	Target	Logistic regression	1 hidden layer	7 hidden layers
PR AUC	Diagnoses	0.258	0.428	<b>0.432</b>
	Medications	0.165	0.317	<b>0.325</b>
	Labs	0.178	0.264	<b>0.265</b>
	Imaging	0.068	0.187	<b>0.190</b>
ROC AUC	Diagnoses	0.894	0.977	<b>0.979</b>
	Medications	0.946	0.988	<b>0.989</b>
	Labs	0.925	0.943	<b>0.944</b>
	Imaging	0.792	0.871	<b>0.875</b>
nDGC	Diagnoses	0.513	0.596	<b>0.597</b>
	Medications	0.210	0.234	<b>0.235</b>
	Labs	0.254	0.274	<b>0.275</b>
	Imaging	0.110	<b>0.124</b>	<b>0.124</b>

Table 3: Comparison of assessment model PR AUC, ROC AUC, and nDCG with different lengths of patient medical history

Metric	Target	No history	180 d	365 d
PR AUC	Diagnoses	0.400	0.427	<b>0.432</b>
	Medications	0.274	0.312	<b>0.325</b>
	Labs	0.209	0.258	<b>0.265</b>
	Imaging	0.105	0.174	<b>0.190</b>
ROC AUC	Diagnoses	0.978	<b>0.979</b>	<b>0.979</b>
	Medications	0.988	0.988	<b>0.989</b>
	Labs	0.933	0.943	<b>0.944</b>
	Imaging	0.854	0.869	<b>0.875</b>
	Diagnoses	0.582	0.595	<b>0.597</b>
nDGC	Medications	0.229	0.233	<b>0.235</b>
	Labs	0.262	0.272	<b>0.275</b>
	Imaging	0.115	0.122	<b>0.124</b>

tory were trained (no history, half a year of history, and a full year of patient history). Across the board, the assessment model incorporating patient medical history information outperformed the model lacking such information, with a lift of 8.0%, 18.6%, 26.7%, and 80.9% in PR-AUC for diagnoses, medications, labs, and imaging respectively.

#### 4. Discussion

Here we have demonstrated SmartTriage, an automated system for engaging with patients virtually as a pre-visit questionnaire in order to provide documentation and decision support to their caregivers. Be-

cause SmartTriage was fully developed in-house, we were able to address two large short-comings of conventional symptoms checkers: (1) inability to utilize patient historical information and (2) lack of integration with an EMR. SmartTriage currently encodes up to a year of historical patient medical data, which includes demographic information, previous encounters, diagnoses, medications, procedures, laboratory results, and more. This information is used to avoid asking questions whose answers are already known (e.g. age, previous diagnoses), and uplifts the performance of all ML components utilized in SmartTriage. The ML components include the natural language understanding model for obtaining a chief complaint, the question sequencing model, and the assessment model for providing decision support.

Integrating with an EMR is crucial as it allows direct feedback from health care providers, and helps avoid unnecessary repetition for patients and gaps in continuity of care. SmartTriage’s EMR integration provides assurance that there is an easily understood record of the patient’s interactions with the system while supporting clinicians in their task of generating documentation, orders, and diagnoses. Further discussion of the production integration is available in Appendix B. Figure B.3, B.4 depict our main EMR integration, with a specially built activity that allows for manipulation of each reported patient response (Figure B.3a) and clinical decision support (CDS) elements (Figure B.4). Figure B.3b shows what our documentation assistance looks like, with text writ-

ten directly into the current progress note. The patient view of smart triage can be seen in Figure B.2.

To create our pilot version of SmartTriage, we bootstrapped the system by using historical clinical encounters as a proxy for patient interactions – we extracted patient reportable symptoms from clinical notes and employed the symptoms to stand in for possible answers. While we were able to obtain good decision support performance and clinically relevant question sequences, we recognize that the responses provided by patients may differ significantly from those in our training set in terms of interpretation (how the patient interprets the authored question) and overall question density (how many positive and negative examples are generated compared to the statistics found with NLP on clinical notes). We plan to continually retrain the system utilizing patient provided responses as more and more patients go through SmartTriage.

Although the ML components of SmartTriage were trained on healthcare data specifically from Southern California, the SmartTriage system itself would likely operate effectively in other health systems or regions. A significant effort was made to create comprehensive history of present illness rule-based (non-ML) questions to support documentation capture and quality of care. The chief complaints chosen for the initial version of SmartTriage are high frequency, primary care related, and typically have common, high evidence diagnostic and therapeutic outcomes. Considering the large volume of training data employed to generate the ML components of SmartTriage, tailoring the ML models to other systems or region specific populations would likely best be accomplished by fine-tuning on top of the existing trained models.

As the name implies, SmartTriage is meant to be a system for triaging patients. Our initial pilots and short-term roll-outs are an intermediate step to collecting the necessary ingredients for making high-quality triage decisions possible. By providing questionnaires to patients who have a forthcoming visit with a health care provider, we ensure that their data are appropriately reviewed, allowing us to learn how SmartTriage’s decision support performs in real encounter situations. Currently, all patients going through SmartTriage see a medical professional within 24 hours. Furthermore, as part of the EMR activity we developed, we ask caregivers to indicate what the most appropriate venue of care would have been for the visit, including self-care, a phone or video visit, an in-person primary care visit, urgent care, or

the emergency department. The triage and decision support feedback will allow us to continually improve the SmartTriage system and ultimately position it as a tool for getting the right kind of care for the right kind of patient at the right time.

## Ethics

This work was done as part of a quality improvement activity as defined in 45CFR §46.104(d)(4)(iii) – secondary research for which consent is not required for the purposes of “health care operations” – and as such ethical approval was not needed.

## Data availability

Additional derived statistics about the data are available from the corresponding author upon reasonable request. Raw patient data used to generate the models is not publicly available.

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## Appendix A. Data sets

### A.1. Reason-for-visit data set

We developed a Patient-Reason-for-Visit data set consisting of patient-generated reason-for-visit free-text entries, discrete chief complaints, demographic information, and patient historical information. The data set was constructed similarly to (anonymous citation) but with the addition of one year of historical information for each encounter. The data set was collected from Kaiser Permanente patients in Southern California who booked a Primary Care Physician appointment through our web portal, between February 2018 and June 2020.

Patient medical history contained four information types: previous chief-complaints (954 distinct values), medications (1,276), diagnoses (1,497), and procedures (758). Medical history was limited to encounters that took place at most 365 days prior to the current visit. For each information source, the last 8 encounters containing relevant information were kept. The mean number of historic encounters with previous chief-complaint information is 5.8, where the mean number of chief-complaints per historic encounter was 1.5. For historic diagnoses the mean number of encounters with relevant information was 6.4, and the mean number of diagnoses per encounter was 2. For medication information there were 3.6 encounters on average, where each encounter contained 2 medications on average. For procedures the mean number of historic encounters was 4.2, with 1.6 relevant procedures on average.

Of the 1,296,210 encounters retrieved, there were 1,139,585 unique text entries that were assigned 2,050,851 chief complaints (of which 2,362 were unique). A subset of encounters had very generic patient text or non-specific chief complaints, and we used simple string matching to remove such examples. The resulting data set consisted of 907,170 encounters for 586,254 members. There were 708,782 unique free-text entries mapped to a total of 1,250,749 discrete chief complaints, 1,701 of which were unique. For our model development, we chose to classify a subset of 337 high frequency chief complaints. The median reason-for-visit text was 34 characters long, with a median word count of 6 (4 without stop words). For the reason-for-visit entries with additional free-text comments added by intake personnel, we cropped out comments to enforce the 50 character limit imposed by the web portal.

Among the patients in the final chief complaint data set, 335,476 (57%) were female while 250,778 (43%) were male. The average age was 49 years old. A full breakdown by age and sex can be found in Tables A.1 and A.2.

The data set was split into a training set of 816,357 encounters and 90,813 test encounters such that the two sets do not share the same patients or exact sentence matches.

### A.2. Encounter data set

To create the content for our platform we employed a strategy that leveraged our organization’s large patient membership. The primary input knowledge source was a set of 25,047,535 historical primary care encounters with chief complaints, clinical notes and patient demographics. Our output data source consisted of the resulting ICD10 diagnoses, laboratory orders, imaging studies, and medications that were associated with the encounters.

The clinical notes we extracted are largely unstructured text documents that contain roughly the same general categories of information - why the patient was being seen, a brief medical history, a review of systems and symptomatology, a focused physical exam, an assessment, and a plan. To access these critical elements of the patient’s presentation we processed all of the notes to extract clinical concepts using an in-house developed NLP engine. The engine incorporates, among other sources, the UMLS (Unified Medical Language System) terminology.

Each note yielded between 10-200 (or more) medical history items, symptoms, physical exam findings, and some elements of patient social and family history. The NLP engine assigns every item a probability that it is present (positive) or absent (negative) and identifies the section in the note that the item came from. For the purposes of Smart-Triage we limited ourselves to considering items from the Chief Complaint (CC), History of Present Illness (HPI), Review of Systems (ROS), and Physical Exam (PE) sections, and only considered positive or negative items where the classification probability was  $\geq 90\%$ .

The resulting 25 million encounter records annotated 4,110,052 patients with unique 2,900 chief complaints and 24,472 ICD-10-CM diagnose codes. Tables A.3 and A.4 show the full breakdown of HPI, medical history records, and clinical concepts by gender and age group.

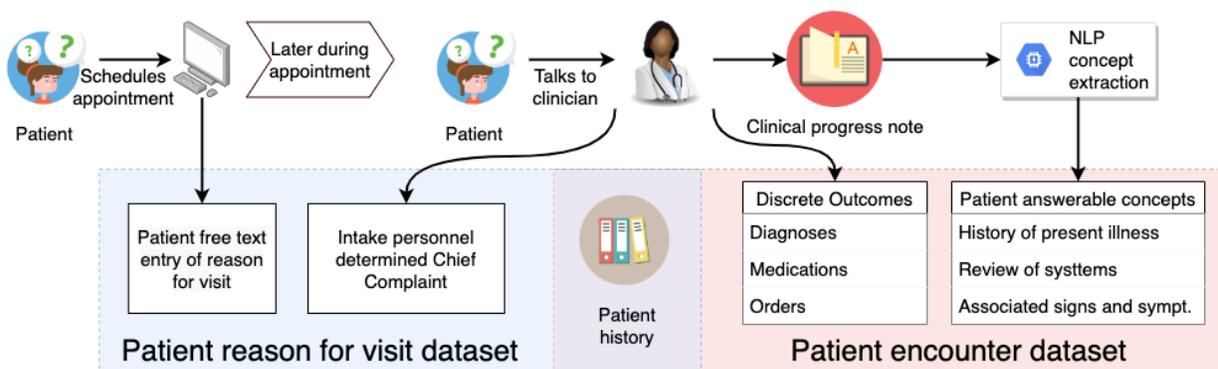


Figure A.1: Diagram depicting how the patient reason-for-visit and patient encounter data sets are acquired. For the patient reason-for-visit data set, a free-text reason is entered when the appointment is scheduled. At the time of the encounter intake personnel choose a discrete chief complaint from a structured list. For the patient encounter data set, we combine discrete outcomes coded by the physician with NLP extracted concepts from clinical progress notes. Both data sets are further bundled with patient history elements including previous chief complaints, diagnoses, medications, laboratory results, and orders.

Table A.1: Age distribution of patients in the reason-for-visit data set. Percentage of total in parenthesis.

Age group	# patients	# encounters
0 - 1	15,050 (2.5%)	28,037 (3.1%)
2 - 15	49,356 (8.3%)	81,108 (8.9%)
16 - 20	14,178 (2.4%)	19,306 (2.1%)
21 - 29	98,496 (16.5%)	144,646 (15.9%)
30 - 39	121,733 (20.4%)	184,205 (20.3%)
40 - 49	89,399 (15.0%)	136,482 (15.0%)
50 - 59	81,047 (13.6%)	120,824 (13.3%)
60 - 69	75,059 (12.6%)	113,470 (12.5%)
70 - 79	37,867 (6.4%)	58,310 (6.4%)
80 - 89	11,347 (1.9%)	17,580 (1.9%)
90+	2,160 (0.4%)	3,202 (0.4%)
Total	595,692	907,170

Table A.2: Biological sex distribution of patients in the reason-for-visit data set. Percentage of total in parenthesis.

Biological sex	# patients	# encounters
Female	335,476 (57.22%)	534,940 (58.97%)
Male	250,778 (42.78%)	372,230 (41.03%)
Total	586,254	907,170

Table A.3: Age segmented statistics for the encounters data set

Age Group	Historical	UMLS Concepts	Severity & Duration	HPI Concepts	Total
2 - 15	18368(15.71%)	75458(64.53%)	21715(18.57%)	1398(1.20%)	116939
16 - 20	33699(18.25%)	113872(61.67%)	35489(19.22%)	1589(0.86%)	184649
21 - 29	47743(20.48%)	138151(59.25%)	45572(19.55%)	1684(0.72%)	233150
30 - 39	56880(21.25%)	155805(58.22%)	53195(19.88%)	1755(0.66%)	267635
40 - 49	65236(22.22%)	168297(57.33%)	58240(19.84%)	1794(0.61%)	293567
50 - 59	69826(22.63%)	176086(57.07%)	60807(19.71%)	1828(0.59%)	308547
60 - 69	72559(23.51%)	174957(56.69%)	59299(19.21%)	1823(0.59%)	308638
70 - 79	65289(23.19%)	161833(57.48%)	52653(18.70%)	1755(0.62%)	281530
80 - 89	49265(21.82%)	134266(59.45%)	40657(18.00%)	1641(0.73%)	225829
90 +	31415(20.09%)	96605(61.77%)	26882(17.19%)	1492(0.95%)	156394

Table A.4: Biological sex segmented statistics for the Encounters data set

Biological sex	Historical	UMLS Concepts	Severity & Duration	HPI Concepts	Total
Female	286842(22.63%)	729148(57.53%)	242815(19.16%)	8517(0.67%)	1267322
Male	223438(20.14%)	666182(60.04%)	211694(19.08%)	8242(0.74%)	1109556

## Appendix B. Production integration

SmartTriage is currently being piloted across the Kaiser Permanente Southern California Region in virtual visits (phone, video) as a pre-visit symptom checker. If the pilot is successful, SmartTriage will likely be rolled out widely throughout our health care organization, impacting millions of patients. To enable production deployment, we had to build multiple interfaces with existing enterprise systems. A high-level interaction diagram is presented in Figure B.1.

**ETL process for patient history** Rather than directly query the EMR, we maintain a local copy of the discrete patient history information for members in our geographic region. We refresh our copy (~ 500 million rows) as a nightly extraction process.

**Encounter start notification** We extract all new appointments every hour and send email notification 24 hours prior to the appointment. If the patient does not engage within 3 hours of the appointment, we send a text message to their mobile device.

**Webapp API** We implemented a custom REST API to communicate with the enterprise web UI service. When the patient clicks on the link in the email or text message they are redirected to the enterprise patient authentication service, and then presented with the patient view of SmartTriage (Figure B.2).

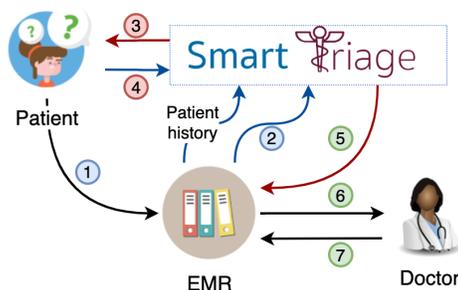


Figure B.1: Interaction overview diagram for SmartTriage. 1-2. Appointment is created, SmartTriage extracts all new appointments once per hour. 3-4. SmartTriage interacts with patient to obtain encounter specific information. 5. SmartTriage inserts patient assessment back into the EMR. 6. Provider views patient information and assessment 7. Further actions by the provider and feedback on SmartTriage are recorded.

**Inputting data back into the EMR** We leverage existing SOAP APIs to send the patient data back into the EMR.

**Provider facing interface** We implemented a custom UI in the EMR for the clinicians to interact with the SmartTriage data, integrate into patient chart, and provide feedback to the SmartTriage system (see Figure [B.3](#), [B.4](#)).

**Daily reporting** A daily reporting job is used to extract clinician feedback and collect data for re-training of the machine learning models.

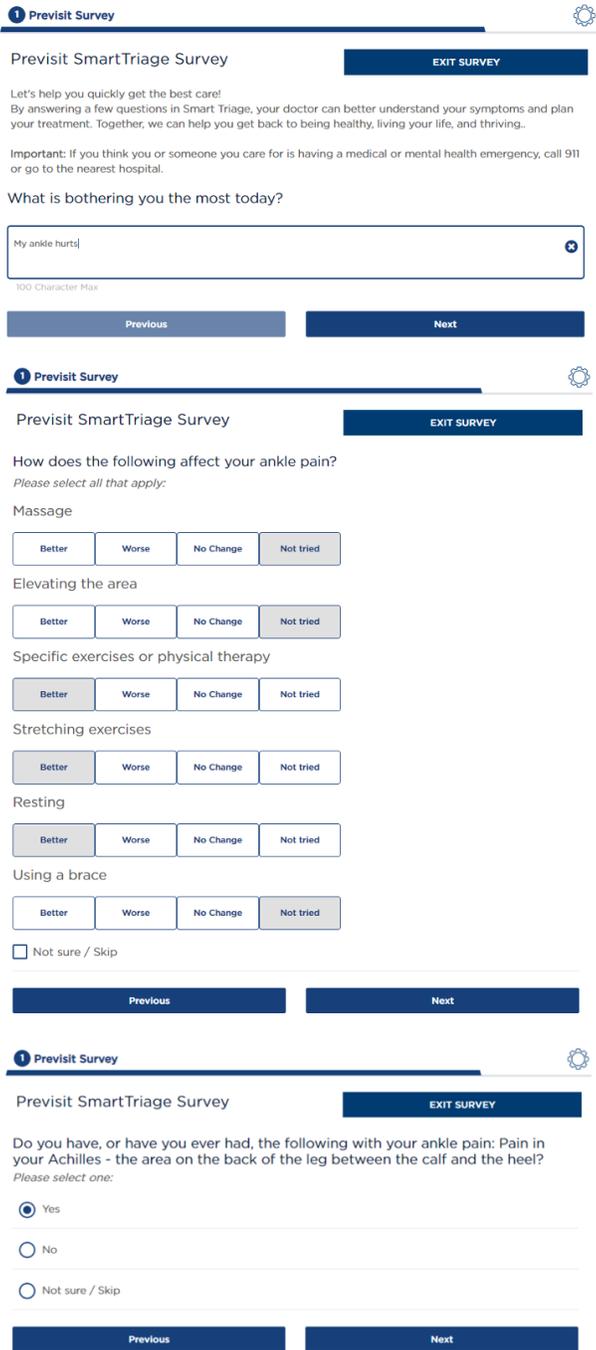
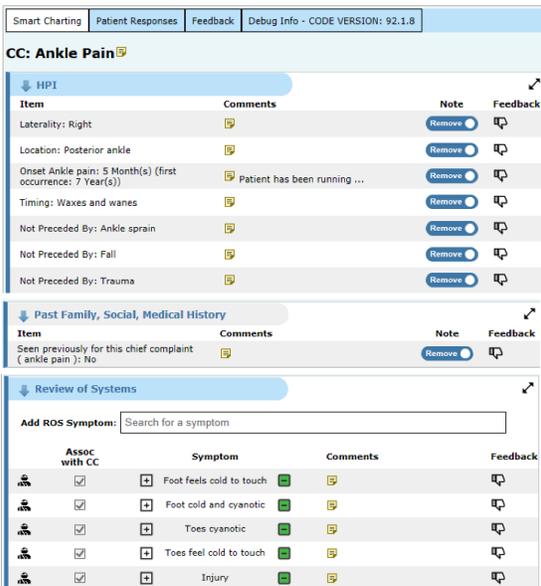


Figure B.2: Screen shots from the patient view of smart triage.

(a) 

Smart Charting Patient Responses Feedback Debug Info - CODE VERSION: 92.1.8

**CC: Ankle Pain**

**HPI**

Item	Comments	Note	Feedback
Laterality: Right		Remove	
Location: Posterior ankle		Remove	
Onset Ankle pain: 5 Month(s) (first occurrence: 7 Year(s))	Patient has been running ...	Remove	
Timing: Waxes and wanes		Remove	
Not Preceded By: Ankle sprain		Remove	
Not Preceded By: Fall		Remove	
Not Preceded By: Trauma		Remove	

**Past Family, Social, Medical History**

Item	Comments	Note	Feedback
Seen previously for this chief complaint ( ankle pain ): No		Remove	

**Review of Systems**

Add ROS Symptom:

	Assoc with CC	Symptom	Comments	Feedback
<input checked="" type="checkbox"/>	<input type="checkbox"/>	Foot feels cold to touch		
<input checked="" type="checkbox"/>	<input type="checkbox"/>	Foot cold and cyanotic		
<input checked="" type="checkbox"/>	<input type="checkbox"/>	Toes cyanotic		
<input checked="" type="checkbox"/>	<input type="checkbox"/>	Toes feel cold to touch		
<input checked="" type="checkbox"/>	<input type="checkbox"/>	Injury		

(b) **Smart CC:**  
Ankle Pain

**Smart HPI:**  
**Laterality:** Right  
**Location:** Posterior ankle  
**Onset Ankle pain:** 5 Month(s) (first occurrence: 7 Year(s)) **(Patient has been running a lot)**  
**Timing:** Waxes and wanes  
**Not Preceded By:** Ankle sprain, Fall, Trauma, Foot injury, Rolled ankle  
**Severity:** Moderate  
**Alleviated by:** Exercise, Stretching, Resting  
**Quality:** Staying the same, Shooting, Sharp, Tender  
**Patient Comment:** Practicing for my 10K and I might have overused. Do I need to slow down?

**Smart PFSH:**  
**Seen previously for this chief complaint ( ankle pain ):** No

**Smart ROS:**  
**Associated with Ankle Pain:**  
**Constitutional:** Negative for Injury.  
**Skin:** Negative for Abnormal sensation of foot, Altered sensation toes, Ankle feels hot to touch, Ankle erythema, Erythematous calf, Foot feels hot to touch, Foot erythema.  
**Cardiovascular:** Negative for Foot feels cold to touch, Foot cold and cyanotic, Toes cyanotic, Toes feel cold to touch.  
**Musculoskeletal:** Positive for **Achillodynia**, **Heel pain**. Negative for Foot pain, Edema, Calf pain, Calf swelling, Inability to walk on affected side, Limited range of motion secondary to pain.  
**Neurological:** Negative for Numbness.

Figure B.3: Provider view of SmartTriage. (a) The EMR activity is what the clinician sees when they open the patient’s encounter. Each discrete piece of captured data is actionable. (b) The EMR note is dynamically generated by the data in the EMR activity. Positive symptoms are in red.

Smart Triage Identified Clinical Conditions			
Clinical Condition	Likelihood	Enc Dx	Feedback
ACHILLES TENDINITIS, RIGHT LEG [M76.61]	56%	<input type="radio"/> Add	
PAIN IN RIGHT ANKLE AND JOINTS OF RIGHT FOOT [M25.571]	30%	<input type="radio"/> Add	
ACHILLES TENDINITIS, UNSPECIFIED LEG [M76.60]	25%	<input type="radio"/> Add	
PAIN IN RIGHT FOOT [M79.671]	12%	<input type="radio"/> Add	
ACHILLES TENDINITIS, LEFT LEG [M76.62]	10%	<input type="radio"/> Add	

Common Medication Orders			
Medication	Relevance	Order	Feedback
Meloxicam	16%		
Ibuprofen	9%		
Naproxen	7%		
Acetaminophen	1%		

Common Lab Studies			
Lab	Relevance	Order	Feedback
URIC ACID	4%		
ERYTHROCYTE SEDIMENTATION RATE, AUTOMATED	1%		

Common Imaging Studies			
Image	Relevance	Order	Feedback
XR, RIGHT ANKLE 3 OR MORE VIEWS	30%		
XR, RIGHT FOOT 3 OR MORE VIEWS	9%		
XR, RIGHT CALCANEUS 2 OR MORE VIEWS	4%		
XR, BILAT FEET WT BEARING 3 OR MORE VIEWS EA	2%		
XR, RIGHT ANKLE WT BEARING 3 OR 4 VIEWS	1%		

Figure B.4: Provider view of SmartTriage’s Assessment activity. Recommendations for encounter diagnoses, medications, labs, and imaging studies are provided. Diagnoses can be directly added into the current encounter.

## Appendix C. Content management system

The screenshot shows the 'Severity of PAIN' content management page. At the top, there are navigation links: Dashboard, Validation, ML Rules, ROS Load, and Admin. The page title is 'Severity of PAIN' with an 'Edit Name' link. Below the title, it shows 'STCMS Concept ID: 24343' and 'Last Updated: 07/04/2020 09:51 AM'.

The main content is divided into three sections:

- Attributes:** This section contains various configuration options. 'Authoring Status' includes Draft, QA, Needs Revision, and Finalized. 'Use in ST?' and 'Split Question?' have Yes/No options. 'Filter' is set to 'Both' (Male/Female). 'Response Evaluation Type' is 'Translation\_SEVERITY'. 'KPHC Component Type' is 'HPI'. There are buttons for 'Lock', 'Unlock', 'Delete', and 'Copy'.
- Question:** This section shows the question stem: 'Are you experiencing...'. It includes fields for 'Translated Concept' (your pain), 'Clinical Name' (Pain), and 'Post Text' (defaults to concept name). There are 'Add' buttons for new questions and captions.
- Responses:** This section shows a table of response options. The table has columns for CMS ID, Concept, Clinical Name, Translated, Filter, Sure, Excl, Repeats, and Del. The data is as follows:
 

#	CMS ID	Concept	Clinical Name	Translated	Filter	Sure	Excl	Repeats	Del
4	22974	not sure		Not sure / Skip	M F B	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
3	14009	C0278140   Severe pain   severe pain	Severe	Severe	M F B	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2	14008	C0278139   Moderate pain   moderate pain	Moderate	Moderate	M F B	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
1	14007	C0278138   Mild pain   mild pain	Mild	Mild	M F B	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

On the right side, there is a 'Note Samples' section with 'Preview', 'Change Log', and 'Export' buttons. The preview shows a sample question: 'How would you rate the severity of your pain?' with a 'Please select one:' prompt and radio buttons for Mild, Moderate, Severe, and Not sure / Skip.

Figure C.1: Screen shot of the content management system. Concepts can be grouped according to synonymy and authored for the patient (“Translated concept”) and EMR (“Clinical name”). UI components are built-in to help author meta-data for both the question as it appears to the patient (question type, stem, etc.) and as it appears to the EMR (component type, system name or header name when applicable, etc.). The assertion status determines how the answer(s) to the question is/are formulated when sent to the ML models.

## Appendix D. Machine Learning Component Architecture

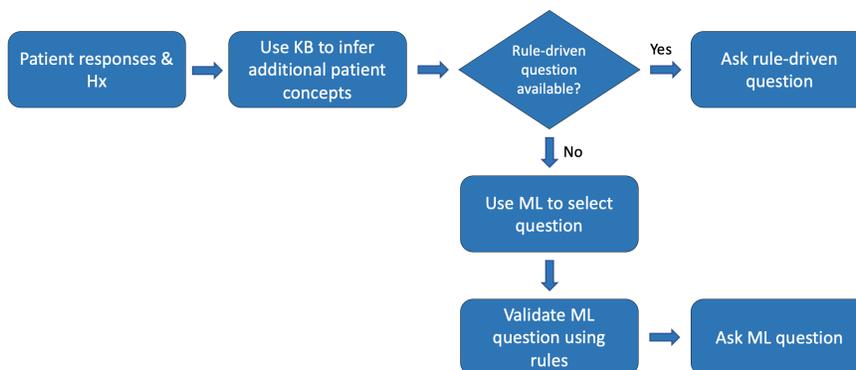


Figure D.1: Schematic of a single round in the question selection process.

Table D.1: Chief complaint model performance on validation set comparing hyperparameters

Hidden layer size	Dropout rate	PR AUC	ROC AUC	nDCG
100	0.0	0.4356±0.0034	0.9242±0.0002	0.7086±0.0015
100	0.3	0.4311±0.0026	0.9263±0.0003	0.7045±0.0016
100	0.5	0.4084±0.0050	0.9245±0.0001	0.6897±0.0036
500	0.0	0.4423±0.0005	0.9226±0.0015	0.7105±0.0007
500	0.3	0.4535±0.0005	0.9307±0.0006	0.7169±0.0003
500	0.5	0.4508±0.0009	0.9326±0.0003	0.7151±0.0003
1000	0.0	0.4407±0.0001	0.9230±0.0013	0.7103±0.0001
1000	0.3	0.4505±0.0007	0.9325±0.0002	0.7152±0.0001
1000	0.5	<b>0.4549±0.0001</b>	0.9344±0.0001	<b>0.7172±0.0001</b>
2000	0.0	0.4406±0.0003	0.9246±0.0008	0.7104±0.0001
2000	0.3	0.4447±0.0006	0.9330±0.0022	0.7123±0.0002
2000	0.5	0.4535±0.0005	<b>0.9351±0.0004</b>	0.7169±0.0003

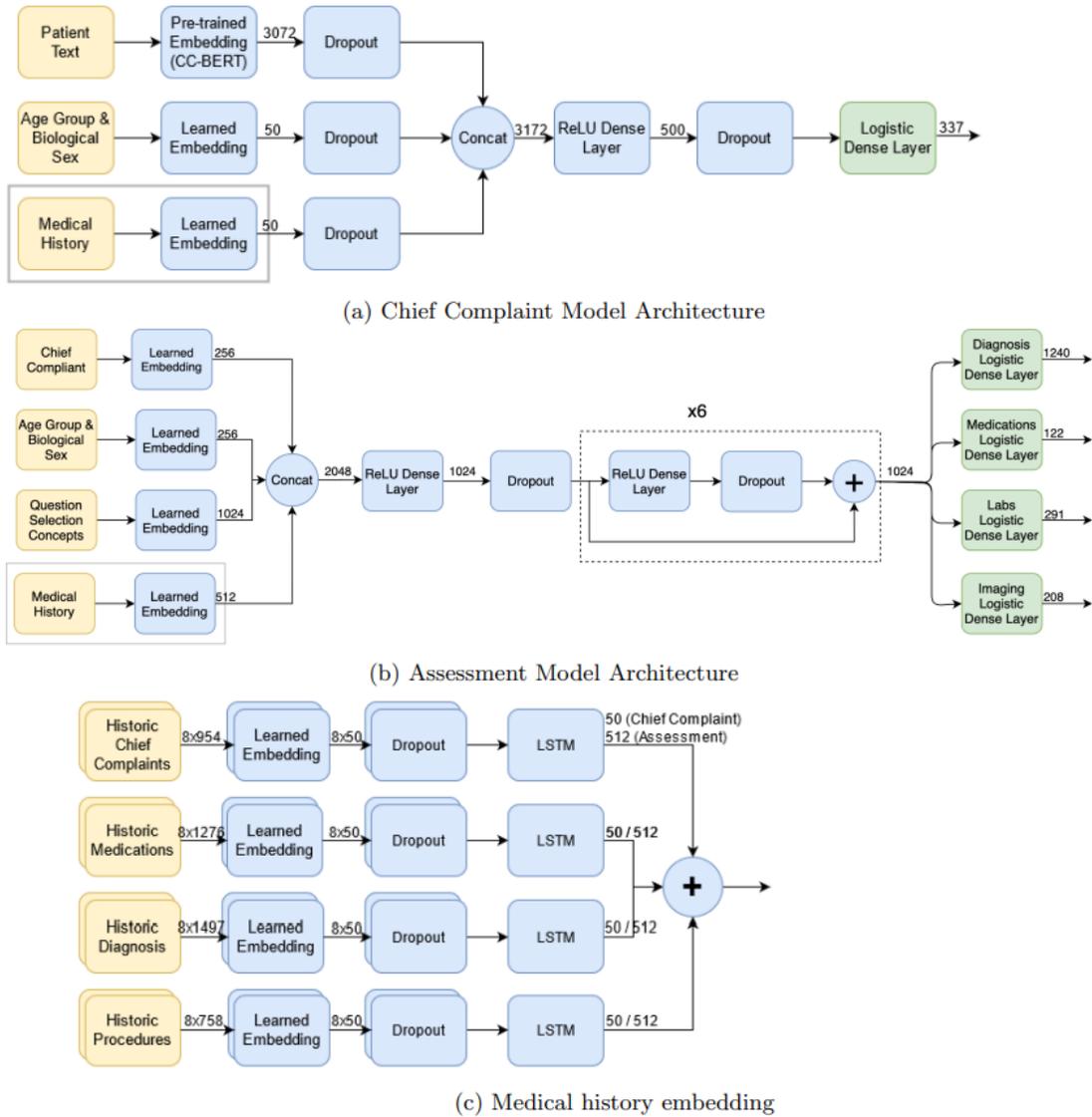


Figure D.2: Neural network components of SmartTriage **a.** Chief Complaint Model Architecture **b.** Assessment Model Architecture **c.** Medical history embedding