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## A Datasheet for Datasets

### A.1 Motivation

- **For what purpose was the dataset created?**

We created EHRXQA to provide a valuable resource for advancing machine learning applications in multi-modal question answering systems on structured electronic health records (EHRs) and chest X-ray images. As an affiliated dataset, we created MIMIC-CXR-VQA to provide a benchmark for medical visual question answering systems.

- **Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?**

The authors of this paper.

- **Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.**

This work was (partially) supported by Microsoft Research Asia, Institute of Information & Communications Technology Planning & Evaluation (IITP) grant (No.2019-0-00075, RS-2022-00155958), National Research Foundation of Korea (NRF) grant (NRF-2020H1D3A2A03100945), and the Korea Health Industry Development Institute (KHIDI) grant (No.HR21C0198), funded by the Korea government (MSIT, MOHW).

### A.2 Composition

- **What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?**

EHRXQA contains natural questions and corresponding SQL/NeuralSQL queries (text). MIMIC-CXR-VQA contains the image ID of the MIMIC-CXR dataset and their related natural questions.

- **How many instances are there in total (of each type, if appropriate)?**

In EHRXQA, there are about 46.2K instances (16,366 image-related samples, 16,529 table-related samples, and 13,257 image+table-related samples). In MIMIC-CXR-VQA, there are about 377.4K instances.

- **Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set?**

We will provide all instances in our GitHub repository for EHRXQA<sup>9</sup> and MIMIC-CXR-VQA<sup>10</sup>.

- **What data does each instance consist of?**

EHRXQA contains (Question, SQL/NeuralSQL, Answer) pair for each instance. MIMIC-CXR-VQA contains (Question, CXR image ID, Answer) pair for each instance.

- **Is there a label or target associated with each instance?**

The answer (label) is provided for each question.

- **Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.**

No.

- **Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)?**

No.

- **Are there recommended data splits (e.g., training, development/validation, testing)?**

See [Appendix B.2.2](#) and [Appendix C.3.3](#).

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<sup>9</sup><https://github.com/baeseongsu/ehrxqa>

<sup>10</sup><https://github.com/baeseongsu/mimic-cxr-vqa>

- **Are there any errors, sources of noise, or redundancies in the dataset?**  
Questions are created by filling the slots in the templates with pre-defined values and records from the database. Thus, some questions can be grammatically incorrect but not critical (e.g., verb tense).
- **Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?**  
EHRXQA depends on three open-source databases: MIMIC-IV<sup>11</sup>, MIMIC-CXR<sup>12</sup> and Chest ImaGenome<sup>13</sup> which are accessible via PhysioNet<sup>14</sup>. MIMIC-CXR-VQA depends on two open-source databases: MIMIC-CXR and Chest ImaGenome.
- **Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)?**  
No.
- **Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?**  
No.
- **Does the dataset relate to people?**  
Yes.
- **Does the dataset identify any subpopulations (e.g., by age, gender)?**  
No.
- **Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)?**  
No. The source datasets are already de-identified.

### A.3 Collection process

- **How was the data associated with each instance acquired?** To collect diverse questions, we constructed question templates and their associated query (SQL, NeuralSQL) by analyzing existing resources (for image, medical VQA datasets, and for table, table-based EHR QA datasets). Then, we sampled QA samples from source databases (MIMIC-IV, MIMIC-CXR, Chest ImaGenome) for each question template.
- **What mechanisms or procedures were used to collect the data (e.g., hardware apparatuses or sensors, manual human curation, software programs, software APIs)?**  
We mainly used Excel, Google Sheets, and Python to collect, process and label the data. In addition, we used OpenAI's ChatGPT (GPT-4) to generate paraphrases for each question template.
- **If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?**  
When it needs random sampling such as data splitting, patient sampling, CXR image sampling for each (question, answer) pair, we fixed the random seed and randomly selected a fixed number of samples from the larger set.
- **Who was involved in the data collection process (e.g., students, crowd workers, contractors) and how were they compensated (e.g., how much were crowd workers paid)?**  
The data collection and construction process, which included SQL/NeuralSQL labeling, was performed exclusively by the authors of the study. No crowd workers were involved due to the sensitive nature of the data and the specialized knowledge required for query labeling.

<sup>11</sup><https://physionet.org/content/mimiciv/2.2/>

<sup>12</sup><https://physionet.org/content/mimic-cxr/2.0.0/>

<sup>13</sup><https://physionet.org/content/chest-imagename/1.0.0/>

<sup>14</sup><https://physionet.org/>

- **Over what timeframe was the data collected?**

The EHRXQA and MIMIC-CXR-VQA datasets were constructed in 2023. They were built using data from the MIMIC-CXR and MIMIC-IV databases. The MIMIC-IV data was collected between 2008 and 2019, and the MIMIC-CXR data was collected between 2011 and 2016.

- **Were any ethical review processes conducted (e.g., by an institutional review board)?**

N/A.

- **Does the dataset relate to people?**

Yes.

- **Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?**

N/A.

- **Were the individuals in question notified about the data collection?**

N/A.

- **Did the individuals in question consent to the collection and use of their data?**

N/A.

- **If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses?**

N/A.

- **Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted?**

The dataset does not have individual-specific information.

#### A.4 Preprocessing/cleaning/labeling

- **Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)?**

N/A.

- **Was the “raw” data saved in addition to the preprocess/cleaned/labeled data (e.g., to support unanticipated future uses)?**

N/A.

- **Is the software that was used to preprocess/clean/label the data available?**

Preprocessing, cleaning, and labeling are done via Excel, Google Sheets, and Python.

#### A.5 Uses

- **Has the dataset been used for any tasks already?**

No.

- **Is there a repository that links to any or all papers or systems that use the dataset?**

No.

- **What (other) tasks could the dataset be used for?**

Our dataset is designed to promote research in question answering systems related to structured electronic health records (EHRs), chest X-ray (CXR) images, or a combination of both.

- **Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses?**

N/A.

- **Are there tasks for which the dataset should not be used?**

N/A.

## A.6 Distribution

- **Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created?**  
No.
- **How will the dataset be distributed?**  
The datasets will be released at <https://github.com/baeseongsu/ehrxqa> and <https://github.com/baeseongsu/mimic-cxr-vqa> upon publication.
- **Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?**  
The dataset is released under MIT License.
- **Have any third parties imposed IP-based or other restrictions on the data associated with the instances?**  
No.
- **Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?**  
No.

## A.7 Maintenance

- **Who will be supporting/hosting/maintaining the dataset?**  
The authors of this paper.
- **How can the owner/curator/manager of the dataset be contacted(e.g., email address)?**  
Contact the first authors ([seongsu@kaist.ac.kr](mailto:seongsu@kaist.ac.kr) & [kyungdaeun@kaist.ac.kr](mailto:kyungdaeun@kaist.ac.kr)).
- **Is there an erratum?**  
No.
- **Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?**  
If any corrections are required, our plan is to upload an updated version of the dataset with comprehensive explanations for the changes. Furthermore, as we broaden our QA scope, we will consistently update the dataset with new QA templates/instances.
- **If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were the individuals in question told that their data would be retained for a fixed period of time and then deleted)?**  
N/A
- **Will older versions of the dataset continue to be supported/hosted/maintained?**  
Primarily, we plan to maintain only the most recent version of the dataset. However, under certain circumstances, such as significant updates to our dataset or the need for validation of previous research work using older versions, we will exceptionally preserve previous versions of the dataset for up to one year.
- **If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?**  
Contact the authors in this paper.

## B Preliminary

### B.1 Uni-modal data resources

For our research, we utilize the dataset under the PhysioNet license, ensuring compliance with the required credentials and permissions. The following are the data resources we utilize:

- MIMIC-IV: Available at <https://physionet.org/content/mimiciv/2.2/>
- MIMIC-CXR: Available at <https://physionet.org/content/mimic-cxr-jpg/2.0.0/>
- Chest ImaGenome: Available at <https://physionet.org/content/chest-imagenome/1.0.0/>

### B.2 Uni-modal EHR QA datasets

#### B.2.1 Table-based EHR QA

☑ **Template construction for MIMIC-IV** Given the structural similarities between the MIMIC-IV and MIMIC-III databases, we successfully adapted the original MIMIC-III question templates from the EHRSQL dataset for use with MIMIC-IV. Our methodology involved a comprehensive analysis of the question templates associated with both the MIMIC-III and MIMIC-IV database schemas to identify similarities and discrepancies. Through this comparative study, we were able to pinpoint the discrepancies between the question templates designed for MIMIC-III and those compatible with MIMIC-IV. While a substantial portion (*i.e.*, 165 templates) of the question templates from MIMIC-III could be seamlessly adapted to MIMIC-IV, we identified several question templates that were unique to each database, as presented in [Table B1](#). For instance, MIMIC-IV provides information about microbiology test names, a feature absent in MIMIC-III. Taking these differences into account, we have assembled a collection of 174 question templates specifically designed for MIMIC-IV.

Table B1: We present a comparative analysis of template suitability between MIMIC-III and MIMIC-IV. This includes question templates from EHRSQL, indicating their applicability to MIMIC-III and/or MIMIC-IV. Checkmarks (✓) and crosses (✗) are used to denote compatibility and incompatibility, respectively.

No.	Question Template	MIMIC-III	MIMIC-IV
21	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} was transferred to ward ward_id on the current hospital visit?	✓	✗
22	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} received a procedure on the current hospital visit?	✗	✗
23	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} received a procedure_name procedure on the current hospital visit?	✗	✗
29	What was the [time_filter_exact1] ward of patient {patient_id} [time_filter_global1]?	✓	✗
46	What was the name of the allergy that patient {patient_id} had [time_filter_global1]?	✗	✗
47	What was the name of the substance that patient {patient_id} was allergic to [time_filter_global1]?	✗	✗
49	What was the organism name found in the [time_filter_exact1] {test_name} test of patient {patient_id} [time_filter_global1]?	✗	✓
51	What was the name of the microbiology test that patient {patient_id} [time_filter_exact1] received [time_filter_global1]?	✗	✓
78	When was patient patient_id's [time_filter_exact1] {test_name} test [time_filter_global1]?	✗	✓
85	Has_verb patient patient_id received a {procedure_name} procedure in other than the current hospital [time_filter_global1]?	✗	✗
98	Has_verb patient {patient_id} had any allergy [time_filter_global1]?	✗	✗
101	Has_verb patient {patient_id} had any {test_name} test result [time_filter_global1]?	✗	✓
103	Has_verb there been any organism found in the [time_filter_exact1] {test_name} test of patient {patient_id} [time_filter_global1]?	✗	✓
137	Count the number of patients who stayed in ward {ward_id} [time_filter_global1].	✓	✗
153	Count the number of patients who received a {test_name} test [time_filter_global1].	✗	✓
180	What are_verb the top [n_rank] frequent microbiology tests that patients had [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?	✗	✓

Continued on next page

Table B1: We present a comparative analysis of template suitability between MIMIC-III and MIMIC-IV. This includes question templates from EHRSQL, indicating their applicability to MIMIC-III and/or MIMIC-IV. Checkmarks (✓) and crosses (✗) are used to denote compatibility and incompatibility, respectively. (Continued)

No.	Question Template	MIMIC-III	MIMIC-IV
176	What are_verb the top [n_rank] frequent microbiology tests [time_filter_global1]?	✗	✓
178	What are_verb the top [n_rank] frequent microbiology tests that patients had [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?	✗	✓
180	What are_verb the top [n_rank] frequent microbiology tests that patients had [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?	✗	✓

☑ **SQL annotations** Following a similar approach to the template construction, we utilize the EHRSQL SQL templates and adapt them for MIMIC-IV. Due to the structural similarities between MIMIC-III and MIMIC-IV, we can seamlessly map the schema from MIMIC-III to MIMIC-IV without altering the SQL query logic significantly. This enables the efficient conversion of SQL queries from MIMIC-III to MIMIC-IV, thus reducing the time and effort required to adapt the queries for the new database. While most of the schema information (*i.e.*, table and column names) remains the same, there are minor modifications introduced in MIMIC-IV compared to MIMIC-III, as presented in [Table B2](#). Therefore, we annotate the corresponding SQL queries for 174 question templates.

Table B2: Column-wise schema mapping from MIMIC-III to MIMIC-IV

MIMIC-III schema	MIMIC-IV schema
d_icd_diagnoses.icd9_code	d_icd_diagnoses.icd_code
d_icd_diagnoses.short_title	d_icd_diagnoses.long_title
d_icd_procedures.icd9_code	d_icd_procedures.icd_code
d_icd_procedures.short_title	d_icd_procedures.long_title
diagnoses_icd.icd9_code	diagnoses_icd.icd_code
procedures_icd.icd9_code	procedures_icd.icd_code
prescriptions.startdate	prescriptions.starttime
prescriptions.enddate	prescriptions.stoptime
charevents.icustay_id	charevents.stay_id
inpuvents_cv.icustay_id	inpuvents.stay_id
inpuvents_cv.charttime	inpuvents.starttime
outpuvents.icustay_id	outpuvents.stay_id
icustays.icustay_id	icustays.stay_id
transfers.icustay_id	transfers.transfer_id

☑ **Other implementation details** We use the fundamental template grammar from EHRSQL, including key components like the operation value slot, condition value slot, and time filter slot. Each slot has an associated natural language expression and a corresponding SQL pattern. For a complete list of time templates, operation values, and condition values, please refer to the comprehensive listing detailed in the original EHRSQL paper.

## B.2.2 Image-based EHR QA: MIMIC-CXR-VQA

☑ **Preprocessing** Our dataset is preprocessed following these steps:

### 1. Image selection

- (a) We filter out images captured from frontal view positions (*i.e.*, PA, AP).
- (b) Per study, we select one representative CXR image based on the earliest study datetime.
- (c) When multiple images in a study share the same study datetime, we choose the image whose dicom ID is alphabetically first.

### 2. Outlier removal

- (a) We cap the maximum number of consecutive studies per patient at 20.
- (b) We eliminate images missing bounding boxes for any anatomical locations.
- (c) We discard images with widths exceeding three standard deviations from the mean for each anatomical location.
- (d) To maintain uniformity between the gold and silver datasets' object and attribute pools, we eliminate six attributes (*i.e.*, “*aortic graft/repair*”, “*artifact*”, “*bronchiectasis*”, “*diaphragmatic eventration (benign)*”, “*pigtail catheter*”, “*skin fold*”) and one object (*i.e.*, “*left arm*”) that are exclusively present in the silver dataset.
- (e) We also exclude the object “*right arm*” due to its association with the object “*left arm*”, which is not present in the gold dataset.

### 3. Label refinement

- (a) To enhance the precision of label assignments, we employ three types of CXR ontology used in Chest ImaGenome: (i) parent-to-child (object) relationships; (ii) parent-to-child (attribute) relationships; (iii) possible relationships (object-attribute).
- (b) For parent-to-child (object) relationships, we propagate the presence of attributes from a child object to its parent object. For instance, if the left middle lung zone (a child object) is labeled with pneumonia (an attribute), then the left lung (its parent object) must also be labeled with pneumonia.
- (c) For parent-to-child (attribute) relationships, we propagate the presence of a child attribute to its parent attribute. For example, if lung cancer (a child attribute) is present in the left lung (an object), then lung opacity (a parent attribute) must also be present in the same object.
- (d) For possible relationships (object-attribute), we exclude any relationships between an object and its associated attributes that are not allowed by the ontology. For instance, according to this ontology, the object ‘left lung’ cannot be associated with the attribute ‘clavicle fracture’.

### 4. Dataset split

- (a) From the *silver* dataset in Chest ImaGenome, which is machine-generated, we divide it into a 95:5 ratio, with 95% serving as the training image pool and 5% as the validation image pool. These image pools consist of 164,398 training images and 8,653 validation images.
- (b) The *gold* dataset, which is human-labeled, is used as the test image pool, consisting of 500 test images.
- (c) During the splitting process, we also balance the distribution between abnormal images (*i.e.*, studies with at least one attribute present) and normal images (*i.e.*, studies without any attributes).
- (d) Note that each image in image pools represents 563 relationships between 36 anatomical locations (*i.e.*, objects) and their associated attributes (a total of 68), indicating the presence or absence of an attribute for an object.

☑ **Question template construction - *argument*** In our template, we designate five primary arguments, represented as  $\{\dots\}$ :  $\{\text{object}\}$ ,  $\{\text{attribute}\}$ ,  $\{\text{category}\}$ ,  $\{\text{viewpos}\}$ , and  $\{\text{gender}\}$ . When an argument is required to appear more than once in a question template, each time with a unique value, we append an index to it, like  $\{\text{object}_1\}$  or  $\{\text{object}_2\}$ . Each of these arguments can be replaced by a specific value, as will be displayed in the following [Table B3](#).

Table B3: Mapping of Arguments to their Potential Values

Argument	Values
$\{\text{object}\}$	abdomen, aortic arch, cardiac silhouette, carina, cavoatrial junction, left apical zone, left breast, left chest wall, left clavicle, left costophrenic angle, left hemidiaphragm, left hilar structures, left lower lung zone, left lung, left mid lung zone, left shoulder, left upper lung zone, mediastinum, neck, right apical zone, right atrium, right breast, right chest wall, right clavicle, right costophrenic angle, right hemidiaphragm, right hilar structures, right lower lung zone, right lung, right mid lung zone, right shoulder, right upper lung zone, spine, svc, trachea, upper mediastinum
$\{\text{attribute}\}$	airspace opacity, alveolar hemorrhage, aspiration, atelectasis, bone lesion, breast/nipple shadows, cabg grafts, calcified nodule, cardiac pacer and wires, chest port, chest tube, clavicle fracture, consolidation, copd/emphysema, costophrenic angle blunting, cyst/bullae, elevated hemidiaphragm, endotracheal tube, enlarged cardiac silhouette, enlarged hilum, enteric tube, fluid overload/heart failure, goiter, granulomatous disease, hernia, hydropneumothorax, hyperaeration, ij line, increased reticular markings/ild pattern, infiltration, interstitial lung disease, intra-aortic balloon pump, linear/patchy atelectasis, lobar/segmental collapse, low lung volumes, lung cancer, lung lesion, lung opacity, mass/nodule (not otherwise specified), mediastinal displacement, mediastinal drain, mediastinal widening, multiple masses/nodules, pericardial effusion, picc, pleural effusion, pleural/parenchymal scarring, pneumomediastinum, pneumonia, pneumothorax, prosthetic valve, pulmonary edema/hazy opacity, rib fracture, rotated, scoliosis, shoulder osteoarthritis, spinal degenerative changes, spinal fracture, sub-diaphragmatic air, subclavian line, subcutaneous air, superior mediastinal mass/enlargement, swan-ganz catheter, tortuous aorta, tracheostomy tube, vascular calcification, vascular congestion, vascular redistribution
$\{\text{category}\}$	anatomicalfinding, device, disease, technicalassessment, tubesandlines
$\{\text{viewpos}\}$	AP, PA
$\{\text{gender}\}$	male, female

☑ **Question template construction - *template component*** We define each question template in our structure with three major components:

- **Filter condition:** This defines the question’s domain or subject area. For instance, in the template “*Is there  $\{\text{attribute}\}$  in the  $\{\text{object}\}$ ?*”, “ $\{\text{object}\}$ ” serves as the filter condition, focusing the question on a particular anatomical location. Filter conditions can include multiple arguments to create more complex queries using unions, intersections, or differences.
- **Target pattern:** This denotes the particular detail within the filter condition’s scope that the question seeks to explore. In the example template, “*Is there  $\{\text{attribute}\}$  in the  $\{\text{object}\}$ ?*”, “ $\{\text{attribute}\}$ ” forms the target pattern. When this is combined with the semantic type, it yields a question with a completed intent.
- **Semantic type:** This labels the question based on the nature of the expected response. There are three primary semantic types: ‘*verify*’ for yes/no questions, ‘*query*’ for answers in the form of a list or set, and ‘*choose*’ for questions that involve selection from provided options.

☑ **Question template construction - content type** Following the construction of our templates, we classify our 48 question templates into seven distinct **content types** (See [Table B4](#)): *anatomy*, *attribute*, *presence*, *abnormality*, *plane*, *gender*, and *size*. Although these categories are often referred to as “question type” in other medical VQA datasets, we choose to refer to them as “content type” to provide a more precise characterization. Each content type is described in detail as follows:

- *anatomy*: We include all question templates related to asking about anatomical locations in the target pattern, but exclude verification questions from this content type.
- *attribute*: We include all question templates related to asking about attributes or categories in the target pattern, but exclude verification questions from this content type.
- *presence*: We include all verify questions that ask about the presence of attributes or categories given the entire image or specific anatomical locations.
- *abnormality*: We include all question templates that are related to abnormality (defining the concept of “*abnormality*” as a superset of four categories) in their questions.
- *plane*: We include the determination of the radiography’s view position, following the VQA-RAD’s QA scope.
- *gender*: We include the identification of gender from the images, following the VQA-RAD’s QA scope.
- *size*: We include two clinically significant measurements: cardiothoracic ratio (*i.e.*, CTR) and mediastinal-thoracic ratio (*i.e.*, MTR). The CTR measures the maximal horizontal cardiac diameter against the maximal horizontal thoracic diameter (inner edge of ribs/edge of pleura). Conversely, the MTR calculates the ratio of the maximum mediastinal width to the maximum thoracic width. We derive these ratios using three measurements: the cardiac silhouette’s width, the upper mediastinum’s width, and the thorax width. The thorax width is defined by the largest x-axis value of the left lung and the smallest x-axis value of the right lung, considering the original reverse orientation of an X-ray. We have established normal measurement thresholds, aligning with the conventional parameters in radiology (CTR: 1/2, MTR: 1/3).

Table B4: Content type of VQA question templates on a chest X-ray image.

Content type	Sample question
anatomy	What are all anatomical locations where both infiltration and interstitial lung diseases can be found?
attribute	List all detected anatomical findings.
presence	Does the cardiac silhouette show any evidence of diseases or devices?
abnormality	Are there signs of abnormalities in both the left lung and the right lung?
plane	Is this X-ray image in the AP or PA view?
gender	Please specify the patient’s gender.
size	Is the cardiac silhouette’s width larger than half of the total thorax width?

☑ **VQA dataset generation - dataset balancing** To build an unbiased VQA dataset, we designed the balancing rules based on the following considerations:

- **Balancing Answers:** To avoid language biases within the VQA dataset, we maximized the answer entropy during the sampling. This approach ensures diverse and well-distributed answers to each question, promoting comprehensive image understanding.
- **Balancing Questions per Image:** We considered the number of questions per image for sampling a variety of images. We limited each question template to one use per CXR image. Therefore, an image can have a minimum of 0 questions and a maximum of 48 (*i.e.*, the total number of our templates). We globally defined an image counter to increase the probability of less frequently sampled images being selected, thereby promoting greater diversity in our image set.
- **Balancing Sampled Questions per Template:** Lastly, we ensured a balanced number of sampled questions per template to maintain uniformity. It ensures that no particular template is over or under-sampled, leading to a fair and diverse question dataset.

❑ **Dataset collection - *paraphrasing*** To generate paraphrases, we leveraged the OpenAI UI, applying [Figure B1](#) to create 30 paraphrases per template using the GPT-4 model (version May 24, 2023) as a base. Following this, human reviewers pruned any paraphrases that strayed from the initial template’s meaning. For enhanced diversity in the training, validation, and test sets, we performed k-means clustering ( $k = 4$ ) on the paraphrases of each template, based on their edit distance. This process grouped alike paraphrases, which we then distributed in a 3-to-1 ratio for the train and validation/test sets respectively. To conclude, we randomly implemented these paraphrases into the datasets, thereby ensuring a broad spectrum of linguistic variations. On an average, we had 16.5 paraphrases representing each template.

```

Prompt Template for Paraphrasing: MIMIC-CXR-VQA

You are an AI paraphraser for the medical domain (radiology).
Write {{num_of_paraphrase}} paraphrases for the given question without changing
its original meaning. The paraphrases must adhere to the following conditions.

Conditions:


- The paraphrased question should be similar to real-world questions asked by a medical doctor when given a chest x-ray image.
- Keep the paraphrased question concise and straightforward.
- The answer to the paraphrased question should be identical to the answer to the original question.
- Maintain the placeholders in the format of ${placeholder} (e.g., ${object}, ${attribute}, ${category}, ${attribute_1}, ${object_1}).
- Ensure that the paraphrased question maintains these placeholders.


{% if content_type in ["anatomy", "attribute", "condition", "abnormality"] %}


- The object-related placeholder will be replaced with the actual anatomical locations found in the image, such as 'left lung' or 'cardiac silhouette'.
- The attribute-related placeholder will be replaced with specific abnormalities that can be found in chest X-ray images, such as 'lung opacity' or 'lung cancer'.
- The category-related placeholder will be replaced with the corresponding category of the attribute, such as 'anatomical finding', 'disease', or 'tubes/lines'.
- Abnormality is a superset of four categories: anatomical finding, disease, device, and tubes/lines.


{% if semantic_type == "verify" %}


- Formulate the paraphrased question so it can be answered with a "yes" or "no" response.


{% elif semantic_type == "query" %}


- Formulate the paraphrased questions to elicit multiple possible answers.


{% elif semantic_type == "choose" %}


- The paraphrased questions should include 'which' (and ',') and be answerable by selecting one of two placeholders.


{% else %}
{% endif %}
{% else %}


- The viewpos-related placeholder will be replaced with the actual view position of the chest x-ray image, such as 'PA' or 'AP'.
- The gender-related placeholder will be replaced with the gender of the patient in the chest x-ray image, such as 'M' or 'F'.
- We define the cardiothoracic ratio (CTR) as the ratio of the width of the heart to the width of the thorax.
- We define the mediastinal thoracic ratio (MTR) as the ratio of the width of the mediastinum to the width of the thorax.


{% endif %}
Question: {{question_template}}
Paraphrased questions:

```

Figure B1: Prompt Template for Paraphrasing Question Templates for MIMIC-CXR-VQA. Elements enclosed within double braces {{ }} are substituted with values specific to each template.

☑ **Dataset statistics of MIMIC-CXR-VQA** Table B5, Table B6, and Table B7 present comprehensive statistics of the MIMIC-CXR-VQA dataset, detailing its overall, content type, and semantic type distributions respectively.

Table B5: Overall statistics of MIMIC-CXR-VQA.

	Training	Validation	Test
Images	133,687	8,610	500
Questions	132,387	31,148	7,565
Answers	6,628	2,508	700
Samples	290,031	73,567	13,793

Table B6: Statistics of MIMIC-CXR-VQA by content type.

Content Type	Training	Validation	Test
presence	109,455 (37.7%)	26,153 (35.5%)	4,566 (33.1%)
anatomy	37,952 (13.1%)	10,210 (13.9%)	1,963 (14.2%)
attribute	49,948 (17.2%)	13,111 (17.8%)	2,578 (18.7%)
abnormality	60,692 (20.9%)	16,109 (21.9%)	3,199 (23.2%)
size	16,000 (5.5%)	4,000 (5.4%)	705 (5.1%)
plane	7,992 (2.8%)	1,992 (2.7%)	386 (2.8%)
gender	7,992 (2.8%)	1,992 (2.7%)	396 (2.9%)

Table B7: Statistics of MIMIC-CXR-VQA by semantic type.

Semantic Type	Training	Validation	Test
verify	162,689 (56.1%)	39,336 (53.5%)	6,945 (50.4%)
choose	28,560 (9.8%)	7,806 (10.6%)	1,523 (11.0%)
query	98,782 (34.1%)	26,425 (35.9%)	5,325 (38.6%)

☑ **Comparison with other medical VQA datasets** Table B8 provides a comparison of MIMIC-CXR-VQA to other medical VQA datasets. Compared to other VQA datasets, MIMIC-CXR-VQA presents broader templates and covers a wider range of question types. While PathVQA, SLAKE, and P-VQA also have diverse question templates, they primarily focus on pathological questions and the utilization of medical knowledge graphs, which differs from our focus. We emphasize questions that can be answered by solely looking at the patient’s X-ray image. When considering the number of templates, other datasets often categorize templates with minor linguistic differences as distinct, even if they express the same content and semantics (e.g., “Is the POS scan normal?” and “Is the POS normal?”). We choose to unify these variations, denoting the count in parentheses in the “# Templates” column of Table B8, thereby recognizing them as identical templates. This approach highlights that our dataset includes a significantly larger number of unique templates.<sup>15</sup> Furthermore, our dataset’s templates are more complex than others, incorporating compositional templates developed through set/logical operations, which is not commonly observed in other datasets.

Table B8: Statistics for MIMIC-CXR-VQA and comparisons with existing datasets.

Dataset	# Images	# QA pairs	Source of images	QA Creation	# Question types	# Templates	Compositional	Publicly accessible
VQA-RAD	315	3,515	MedPix database	natural	11	*		✓
VQA-Med-2019	4,200	15,292	MedPix database	synthetic	4	*		✓
PathVQA	4,998	32,799	Pathology textbook	synthetic	7	*		✓
VQA-Med-2020	5,000	5,000	MedPix database	synthetic	1	18 (8)		✓
SLAKE	642	14,000	Medical Decathlon	natural	10	*		✓
VQA-Med-2021	5,000	5,000	NIH Chest X-ray CHAOS	synthetic	1	6 (4)		✓
RadVisDial	91,060	455,300	MIMIC-CXR	synthetic, natural	1	1 (1)		
OVQA	2,001	19,020	EMRs	synthetic	6	72 (19)		✓
Mimic-VQ	134,400	297,723	MIMIC-CXR	synthetic	6	15 (13)		
P-VQA	2,169	24,800	hospitals	synthetic	13	*		✓
<b>MIMIC-CXR-VQA</b>	<b>142,797</b>	<b>377,391</b>	<b>MIMIC-CXR</b>	<b>synthetic, paraphrased</b>	<b>7</b>	<b>794 (48)</b>	<b>✓</b>	<b>✓</b>

<sup>15</sup>Note that the asterisk (\*) in the “# Templates” column indicates that the templates were either manually created by physicians, derived from natural questions, or undocumented, making it challenging to represent the number of templates accurately.

☑ Full list of VQA question template in MIMIC-CXR-VQA

Table B9: Full list of 48 VQA question templates in MIMIC-CXR-VQA

Index	Content Type	Question Template
1	presence	Are there any \${category} in the \${object}?
2	presence	Is there \${attribute} in the \${object}?
3	abnormality	Is the \${object} abnormal?
4	presence	Are there any \${category_1} or \${category_2} in the \${object}?
5	presence	Are there both \${attribute_1} and \${attribute_2} in the \${object}?
6	presence	Is there either \${attribute_1} or \${attribute_2} in the \${object}?
7	attribute	List all \${category} in the \${object}.
8	abnormality	List all abnormalities in the \${object}.
9	attribute	List all \${category_1} and \${category_2} in the \${object}.
10	attribute	Which \${category} is related to the \${object}, \${attribute_1} or \${attribute_2}?
11	abnormality	Are there any abnormalities in either the \${object_1} or the \${object_2}?
12	abnormality	Are there any abnormalities in both the \${object_1} and the \${object_2}?
13	attribute	List all \${category} in either the \${object_1} or the \${object_2}.
14	attribute	List all common \${category} in both the \${object_1} and the \${object_2}.
15	attribute	List all \${category} only in the \${object_1} but not in the \${object_2}.
16	abnormality	List all abnormalities in either the \${object_1} or the \${object_2}.
17	abnormality	List all common abnormalities in both the \${object_1} and the \${object_2}.
18	abnormality	List all abnormalities only in the \${object_1} but not in the \${object_2}.
19	presence	Are there any \${category}?
20	abnormality	Are there any abnormalities?
21	presence	Are there any \${category_1} or \${category_2}?
22	presence	Is there \${attribute}?
23	presence	Are there both \${attribute_1} and \${attribute_2}?
24	presence	Is there either \${attribute_1} or \${attribute_2}?
25	attribute	List all \${category}.
26	attribute	List all \${category_1} and \${category_2}.
27	abnormality	List all abnormalities.
28	attribute	Which \${category} is related, \${attribute_1} or \${attribute_2}?
29	presence	Are both the \${object_1} and the \${object_2} related to \${attribute}?
30	presence	Is either the \${object_1} or the \${object_2} related to \${attribute}?
31	anatomy	List all anatomical locations related to \${attribute}.
32	anatomy	Which anatomical location is related to \${attribute}, the \${object_1} or the \${object_2}?
33	abnormality	Which anatomical location is abnormal, the \${object_1} or the \${object_2}?
34	anatomy	List all anatomical locations related to either \${attribute_1} or \${attribute_2}.
35	anatomy	List all common anatomical locations related to both \${attribute_1} and \${attribute_2}.
36	anatomy	List all anatomical locations related to \${attribute_1} but not \${attribute_2}.
37	presence	Are there any \${category} related to the \${object_1} and the \${object_2}?
38	presence	Are there any \${category} related to the \${object_1} or the \${object_2}?
39	anatomy	List all anatomical locations related to any \${category}.
40	anatomy	List all anatomical locations related to any \${category_1} or \${category_2}.
41	plane	Is this an \${viewpos} view?
42	plane	Which view is in this image, AP or PA?
43	plane	What is the view of this image?
44	gender	Is this patient \${gender}?
45	gender	What is the gender of this patient, male or female?
46	gender	What is the gender of this patient?
47	size	Is the width of the cardiac silhouette wider than 1/2 of the thorax width?
48	size	Is the width of the upper mediastinum wider than 1/3 of the thorax width?

## C EHRXQA

### C.1 Database construction

#### C.1.1 Database pre-processing

- We create a “*dod*” column to the PATIENTS table and assign it the date of birth calculated as follows:  $dob = anchor\_year - anchor\_age$ . The month and day of dob are randomly sampled.
- We create an “*age*” column in the ADMISSIONS table. To calculate the age at the time of admission for each subject, we subtract their anchor year from their admission year and then add their anchor age. This can be represented as:  $age = (admission\_year - anchor\_year) + anchor\_age$ .
- We includes patients aged between 11 and 89.
- We manually time-shift each patient’s first study time to a random time point between 2100 and 2105, while preserving the same intervals between all records.
- We limit the number of current patients to approximately 10% of the total patient population.
- We sample 800 patients for the silver database and 400 for the gold database.
- If a particular type of value has multiple associated units of measurement, we retain only the value with the most common unit and discard the others from the database.
- All records are converted to lowercase.

#### C.1.2 Overview of EHR database

The entire database schema is illustrated in [Figure C2](#).

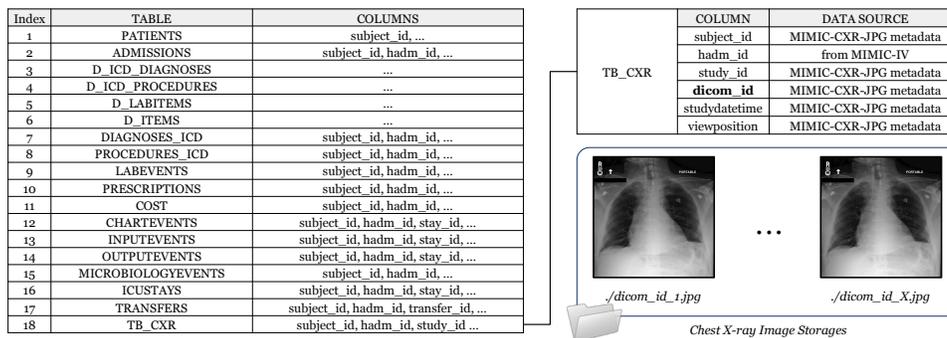


Figure C2: Overview of our EHR database schema, which comprises 18 tables: 17 from MIMIC-IV and one from MIMIC-CXR. The TB\_CXR table includes DICOM image identifiers, enabling the loading of corresponding images directly from CXR image storage.

## C.2 Question template construction

### C.2.1 Detail of template construction strategy

☑ **Image-related question** In the EHRXQA dataset, we present a unique scenario that diverges from the traditional Visual Question Answering (VQA) framework. In this scenario, instead of providing just an image and a question, our question templates also involve retrieving relevant images from a database to answer the question. However, specifying a particular study by directly stating its unique study ID can be complex and inconvenient for users, especially when questions refer to one or two images. To address this issue, we propose using practical, conversational expressions such as “*last study of patient patient\_id in 2023*” or “*compared to the previous study*”. This approach allows users to intuitively identify chest X-ray (CXr) studies using a variety of practical natural language expressions, as demonstrated in [Table C10](#).

Regarding templates for 2-image question templates, our aim is to replicate clinical scenarios where we compare two separate or consecutive patient studies conducted during a hospital stay. In these situations, determining the severity of a particular disease can be subjective across different physicians, which can lead to higher costs for labeling. To address this issue, we have established four comparison labels: “*still present*”, “*still absent*”, “*newly detected*” and “*resolved*”. These labels are automatically assigned based on changes in the presence of an attribute in an object. For example, if an initial study shows no signs of pneumonia in the left lung, but a subsequent study reveals the presence of pneumonia, the comparison label would be assigned as “*newly detected*”.

Table C10: Example expressions for indicating CXr Studies in EHRXQA Dataset

# of images	reference target study	reference to compared study
1-image	study id {study_id}	-
	{time_filter_exact1} study of patient {patient_id} _ {time_filter_global1}	-
	study id {study_id1}	study id {study_id2}
2-image	study id {study_id1}	previous study
	{time_filter_exact1} study of patient {patient_id} {time_filter_global1}	{time_filter_exact2} study of patient {patient_id} {time_filter_global2}
	{time_filter_exact1} study of patient {patient_id} {time_filter_global1}	previous study
	-	-

☑ **Image+Table-related question** In the *Image+Table* modality, our focus is on three primary table events found in structured electronic health records (EHRs) along with CXr events: diagnosis, prescriptions, and procedures. It’s important to note that CXr events are considered at the same admission level as these three medical events, indicating their comparable temporal hierarchy. By incorporating both structured medical events and CXr events, we explore three primary temporal scenarios: co-occurring events, where the events happen simultaneously; CXr events that occur after table events; and table events that follow the CXr events. Furthermore, when constructing our question templates in the *Image+Table* modality, we take into account demographic information such as age and gender.

### C.2.2 Full List of Question Template in EHRXQA

We provide a comprehensive collection of question templates for your reference: 168 image-related templates can be found in [Table C11](#), 174 table-related templates are detailed in [Table C12](#), and a further 75 templates are presented in [Table C13](#).

Table C11: Full list of 168 *Image*-related question templates in EHRXQA

Patient scope	Modality scope	Question Template
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any \${category} in the \${object}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is there \${attribute} in the \${object}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is the \${object} abnormal?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any \${category_1} or \${category_2} in the \${object}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there both \${attribute_1} and \${attribute_2} in the \${object}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is there either \${attribute_1} or \${attribute_2} in the \${object}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all \${category} in the \${object}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all abnormality in the \${object}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all \${category_1} and \${category_2} in the \${object}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], which \${category} is related to the \${object}, \${attribute_1} or \${attribute_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any abnormality in either the \${object_1} or the \${object_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any abnormality in both the \${object_1} and the \${object_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all \${category} in either the \${object_1} or the \${object_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all common \${category} in both the \${object_1} and the \${object_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all \${category} only in the \${object_1} but not in the \${object_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all abnormality in either the \${object_1} or the \${object_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all common abnormality in both the \${object_1} and the \${object_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all abnormality only in the \${object_1} but not in the \${object_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any \${category}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any abnormality?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any \${category_1} or \${category_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is there \${attribute}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there both \${attribute_1} and \${attribute_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is there either \${attribute_1} or \${attribute_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all \${category}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all \${category_1} and \${category_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all abnormality.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], which \${category} is related, \${attribute_1} or \${attribute_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are both the \${object_1} and the \${object_2} related to \${attribute}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is either the \${object_1} or the \${object_2} related to \${attribute}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all anatomical locations related to \${attribute}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], which anatomical location is related to \${attribute}, the \${object_1} or the \${object_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], which anatomical location is abnormal, the \${object_1} or the \${object_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all anatomical locations related to either \${attribute_1} or \${attribute_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all common anatomical locations related to both \${attribute_1} and \${attribute_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all anatomical locations related to \${attribute_1} but not \${attribute_2}.

Continued on next page

Table C11: Full list of 168 *Image*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any \${category} related to the \${object_1} and the \${object_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], are there any \${category} related to the \${object_1} or the \${object_2}?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all anatomical locations related to any \${category}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], list all anatomical locations related to any \${category_1} or \${category_2}.
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is the width of the cardiac silhouette wider than 1/2 of the thorax width?
single	Image 1-image	Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is the width of the upper mediastinum wider than 1/3 of the thorax width?
single	Image 1-image	Given the study {study_id}, are there any \${category} in the \${object}?
single	Image 1-image	Given the study {study_id}, is there \${attribute} in the \${object}?
single	Image 1-image	Given the study {study_id}, is the \${object} abnormal?
single	Image 1-image	Given the study {study_id}, are there any \${category_1} or \${category_2} in the \${object}?
single	Image 1-image	Given the study {study_id}, are there both \${attribute_1} and \${attribute_2} in the \${object}?
single	Image 1-image	Given the study {study_id}, is there either \${attribute_1} or \${attribute_2} in the \${object}?
single	Image 1-image	Given the study {study_id}, list all \${category} in the \${object}.
single	Image 1-image	Given the study {study_id}, list all abnormality in the \${object}.
single	Image 1-image	Given the study {study_id}, list all \${category_1} and \${category_2} in the \${object}.
single	Image 1-image	Given the study {study_id}, which \${category} is related to the \${object}, \${attribute_1} or \${attribute_2}?
single	Image 1-image	Given the study {study_id}, are there any abnormality in either the \${object_1} or the \${object_2}?
single	Image 1-image	Given the study {study_id}, are there any abnormality in both the \${object_1} and the \${object_2}?
single	Image 1-image	Given the study {study_id}, list all \${category} in either the \${object_1} or the \${object_2}.
single	Image 1-image	Given the study {study_id}, list all common \${category} in both the \${object_1} and the \${object_2}.
single	Image 1-image	Given the study {study_id}, list all \${category} only in the \${object_1} but not in the \${object_2}.
single	Image 1-image	Given the study {study_id}, list all abnormality in either the \${object_1} or the \${object_2}.
single	Image 1-image	Given the study {study_id}, list all common abnormality in both the \${object_1} and the \${object_2}.
single	Image 1-image	Given the study {study_id}, list all abnormality only in the \${object_1} but not in the \${object_2}.
single	Image 1-image	Given the study {study_id}, are there any \${category}?
single	Image 1-image	Given the study {study_id}, are there any abnormality?
single	Image 1-image	Given the study {study_id}, are there any \${category_1} or \${category_2}?
single	Image 1-image	Given the study {study_id}, is there \${attribute}?
single	Image 1-image	Given the study {study_id}, are there both \${attribute_1} and \${attribute_2}?
single	Image 1-image	Given the study {study_id}, is there either \${attribute_1} or \${attribute_2}?
single	Image 1-image	Given the study {study_id}, list all \${category}.
single	Image 1-image	Given the study {study_id}, list all \${category_1} and \${category_2}.
single	Image 1-image	Given the study {study_id}, list all abnormality.
single	Image 1-image	Given the study {study_id}, which \${category} is related, \${attribute_1} or \${attribute_2}?
single	Image 1-image	Given the study {study_id}, are both the \${object_1} and the \${object_2} related to \${attribute}?
single	Image 1-image	Given the study {study_id}, is either the \${object_1} or the \${object_2} related to \${attribute}?
single	Image 1-image	Given the study {study_id}, list all anatomical locations related to \${attribute}.
single	Image 1-image	Given the study {study_id}, which anatomical location is related to \${attribute}, the \${object_1} or the \${object_2}?
single	Image 1-image	Given the study {study_id}, which anatomical location is abnormal, the \${object_1} or the \${object_2}?
single	Image 1-image	Given the study {study_id}, list all anatomical locations related to either \${attribute_1} or \${attribute_2}.
single	Image 1-image	Given the study {study_id}, list all common anatomical locations related to both \${attribute_1} and \${attribute_2}.
single	Image 1-image	Given the study {study_id}, list all anatomical locations related to \${attribute_1} but not \${attribute_2}.
single	Image 1-image	Given the study {study_id}, are there any \${category} related to the \${object_1} and the \${object_2}?
single	Image 1-image	Given the study {study_id}, are there any \${category} related to the \${object_1} or the \${object_2}?
single	Image 1-image	Given the study {study_id}, list all anatomical locations related to any \${category}.
single	Image 1-image	Given the study {study_id}, list all anatomical locations related to any \${category_1} or \${category_2}.
single	Image 1-image	Given the study {study_id}, is the width of the cardiac silhouette wider than 1/2 of the thorax width?

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Table C11: Full list of 168 *Image*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
single	Image 2-image	Given the {study_id1} study, list all anatomical locations related to \${attribute} that are \${comparison} compared to the {study_id2} study?
single	Image 2-image	Given the {study_id1} study, list all anatomical locations related to any \${category} that are \${comparison} compared to the {study_id2} study?
single	Image 2-image	Given the {study_id1} study, are there any \${category} that are \${comparison} in the \${object} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, is \${attribute} \${comparison} in the \${object} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, are there any abnormality that are \${comparison} in the \${object} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, are there any \${category} that are \${comparison} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, are there any abnormality that are \${comparison} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, is \${attribute} \${comparison} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, list all \${category} that are \${comparison} in the \${object} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, list all abnormality that are \${comparison} in the \${object} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, list all \${category} that are \${comparison} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, list all abnormality that are \${comparison} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, list all anatomical locations related to \${attribute} that are \${comparison} compared to the previous study?
single	Image 2-image	Given the {study_id1} study, list all anatomical locations related to any \${category} that are \${comparison} compared to the previous study?
single	Image N-image	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} had a chest X-ray study indicating \${attribute} in the \${object} [time_filter_global1]?
single	Image N-image	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} had a chest X-ray study indicating any \${category} in the \${object} [time_filter_global1]?
single	Image N-image	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} had a chest X-ray study indicating any abnormality in the \${object} [time_filter_global1]?
single	Image N-image	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} had a chest X-ray study indicating \${attribute} [time_filter_global1]?
single	Image N-image	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} had a chest X-ray study indicating any \${category} [time_filter_global1]?
single	Image N-image	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} had a chest X-ray study indicating any abnormality [time_filter_global1]?
single	Image N-image	When was the [time_filter_exact1] time that patient {patient_id} had a chest X-ray study indicating \${attribute} in the \${object} [time_filter_global1]?
single	Image N-image	When was the [time_filter_exact1] time that patient {patient_id} had a chest X-ray study indicating any \${category} in the \${object} [time_filter_global1]?
single	Image N-image	When was the [time_filter_exact1] time that patient {patient_id} had a chest X-ray study indicating any abnormality in the \${object} [time_filter_global1]?
single	Image N-image	When was the [time_filter_exact1] time that patient {patient_id} had a chest X-ray study indicating \${attribute} [time_filter_global1]?
single	Image N-image	When was the [time_filter_exact1] time that patient {patient_id} had a chest X-ray study indicating any \${category} [time_filter_global1]?
single	Image N-image	When was the [time_filter_exact1] time that patient {patient_id} had a chest X-ray study indicating any abnormality [time_filter_global1]?
single	Image N-image	Has {patient_id} had any chest X-ray study indicating \${attribute} in the \${object} [time_filter_global1]?
single	Image N-image	Has {patient_id} had any chest X-ray study indicating any \${category} in the \${object} [time_filter_global1]?
single	Image N-image	Has {patient_id} had any chest X-ray study indicating any abnormality in the \${object} [time_filter_global1]?
single	Image N-image	Has {patient_id} had any chest X-ray study indicating \${attribute} [time_filter_global1]?
single	Image N-image	Has {patient_id} had any chest X-ray study indicating any \${category} [time_filter_global1]?
single	Image N-image	Has {patient_id} had any chest X-ray study indicating any abnormality [time_filter_global1]?
single	Image N-image	Count the number of times that patient {patient_id} had chest X-ray studies indicating \${attribute} in the \${object} [time_filter_global1].
single	Image N-image	Count the number of times that patient {patient_id} had chest X-ray studies indicating any \${category} in the \${object} [time_filter_global1].
single	Image N-image	Count the number of times that patient {patient_id} had chest X-ray studies indicating any abnormality in the \${object} [time_filter_global1].
single	Image N-image	Count the number of times that patient {patient_id} had chest X-ray studies indicating \${attribute} [time_filter_global1].
single	Image N-image	Count the number of times that patient {patient_id} had chest X-ray studies indicating any \${category} [time_filter_global1].
single	Image N-image	Count the number of times that patient {patient_id} had chest X-ray studies indicating any abnormality [time_filter_global1].

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Table C11: Full list of 168 *Image*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
group	Image N-image	Count the number of patients who had any chest X-ray study indicating \${attribute} in the \${object} [time_filter_global1].
group	Image N-image	Count the number of patients who had any chest X-ray study indicating any \${category} in the \${object} [time_filter_global1].
group	Image N-image	Count the number of patients who had any chest X-ray study indicating any abnormality in the \${object} [time_filter_global1].
group	Image N-image	Count the number of patients who had any chest X-ray study indicating \${attribute} [time_filter_global1].
group	Image N-image	Count the number of patients who had any chest X-ray study indicating any \${category} [time_filter_global1].
group	Image N-image	Count the number of patients who had any chest X-ray study indicating any abnormality [time_filter_global1].
group	Image N-image	List the IDs of patients who had any chest X-ray study indicating \${attribute} in the \${object} [time_filter_global1].
group	Image N-image	List the IDs of patients who had any chest X-ray study indicating any \${category} in the \${object} [time_filter_global1].
group	Image N-image	List the IDs of patients who had any chest X-ray study indicating any abnormality in the \${object} [time_filter_global1].
group	Image N-image	List the IDs of patients who had any chest X-ray study indicating \${attribute} [time_filter_global1].
group	Image N-image	List the IDs of patients who had any chest X-ray study indicating any \${category} [time_filter_global1].
group	Image N-image	List the IDs of patients who had any chest X-ray study indicating any abnormality [time_filter_global1].

Table C12: Full list of 174 *Table*-related question templates in EHRXQA

Patient scope	Modality scope	Question Template
none	Table	What is the intake method of {drug_name}?
none	Table	What is the cost of a procedure named {procedure_name}?
none	Table	What is the cost of a {lab_name} lab test?
none	Table	What is the cost of a drug named {drug_name}?
none	Table	What is the cost of diagnosing {diagnosis_name}?
none	Table	What does {abbreviation} stand for?
single	Table	What is the gender of patient {patient_id}?
single	Table	What is the date of birth of patient {patient_id}?
single	Table	What was the [time_filter_exact1] length of hospital stay of patient {patient_id}?
single	Table	What is the change in the weight of patient {patient_id} from the [time_filter_exact2] value measured [time_filter_global2] compared to the [time_filter_exact1] value measured [time_filter_global1]?
single	Table	What is the change in the value of {lab_name} of patient {patient_id} from the [time_filter_exact2] value measured [time_filter_global2] compared to the [time_filter_exact1] value measured [time_filter_global1]?
single	Table	What is the change in the {vital_name} of patient {patient_id} from the [time_filter_exact2] value measured [time_filter_global2] compared to the [time_filter_exact1] value measured [time_filter_global1]?
single	Table	Is the value of {lab_name} of patient {patient_id} [time_filter_exact2] measured [time_filter_global2] [comparison] than the [time_filter_exact1] value measured [time_filter_global1]?
single	Table	Is the {vital_name} of patient {patient_id} [time_filter_exact2] measured [time_filter_global2] [comparison] than the [time_filter_exact1] value measured [time_filter_global1]?
single	Table	What is_verb the age of patient {patient_id} [time_filter_global1]?
single	Table	What is_verb the name of insurance of patient {patient_id} [time_filter_global1]?
single	Table	What is_verb the marital status of patient {patient_id} [time_filter_global1]?
single	Table	What percentile is the value of {lab_value} in a {lab_name} lab test among patients of the same age as patient {patient_id} [time_filter_global1]?
single	Table	How many [unit_count] have passed since patient {patient_id} was admitted to the hospital currently?
single	Table	How many [unit_count] have passed since patient {patient_id} was admitted to the ICU currently?
single	Table	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} was transferred to careunit {careunit} on the current hospital visit?
single	Table	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} was diagnosed with {diagnosis_name} on the current hospital visit?
single	Table	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} was prescribed {drug_name} on the current hospital visit?
single	Table	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} received a {lab_name} lab test on the current hospital visit?
single	Table	How many [unit_count] have passed since the [time_filter_exact1] time patient {patient_id} had a {intake_name} intake on the current ICU visit?
single	Table	What was the [time_filter_exact1] hospital admission type of patient {patient_id} [time_filter_global1]?
single	Table	What was the [time_filter_exact1] careunit of patient {patient_id} [time_filter_global1]?

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Table C12: Full list of 174 *Table*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
single	Table	What was the [time_filter_exact1] measured height of patient {patient_id} [time_filter_global1]?
single	Table	What was the [time_filter_exact1] measured weight of patient {patient_id} [time_filter_global1]?
single	Table	What was the name of the diagnosis that patient {patient_id} [time_filter_exact1] received [time_filter_global1]?
single	Table	What was the name of the procedure that patient {patient_id} [time_filter_exact1] received [time_filter_global1]?
single	Table	What was the name of the drug that patient {patient_id} was [time_filter_exact1] prescribed via {drug_route} route [time_filter_global1]?
single	Table	What was the name of the drug that patient {patient_id} was [time_filter_exact1] prescribed [time_filter_global1]?
single	Table	What was the name of the drug that patient {patient_id} was prescribed [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
single	Table	What was the name of the drug that patient {patient_id} was prescribed [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?
single	Table	What was the dose of {drug_name} that patient {patient_id} was [time_filter_exact1] prescribed [time_filter_global1]?
single	Table	What was the total amount of dose of {drug_name} that patient {patient_id} were prescribed [time_filter_global1]?
single	Table	What was the name of the drug that patient {patient_id} were prescribed [n_times] [time_filter_global1]?
single	Table	What is the new prescription of patient {patient_id} [time_filter_global2] compared to the prescription [time_filter_global1]?
single	Table	What was the [time_filter_exact1] measured value of a {lab_name} lab test of patient {patient_id} [time_filter_global1]?
single	Table	What was the name of the lab test that patient {patient_id} [time_filter_exact1] received [time_filter_global1]?
single	Table	What was the [agg_function] {lab_name} value of patient {patient_id} [time_filter_global1]?
single	Table	What was the organism name found in the [time_filter_exact1] {culture_name} microbiology test of patient {patient_id} [time_filter_global1]?
single	Table	What was the organism name found in the [time_filter_exact1] {test_name} test of patient {patient_id} [time_filter_global1]?
single	Table	What was the name of the specimen that patient {patient_id} was [time_filter_exact1] tested [time_filter_global1]?
single	Table	What was the name of the microbiology test that patient {patient_id} [time_filter_exact1] received [time_filter_global1]?
single	Table	What was the name of the intake that patient {patient_id} [time_filter_exact1] had [time_filter_global1]?
single	Table	What was the total volume of {intake_name} intake that patient {patient_id} received [time_filter_global1]?
single	Table	What was the total volume of intake that patient {patient_id} received [time_filter_global1]?
single	Table	What was the name of the output that patient {patient_id} [time_filter_exact1] had [time_filter_global1]?
single	Table	What was the total volume of {output_name} output that patient {patient_id} had [time_filter_global1]?
single	Table	What was the total volume of output that patient {patient_id} had [time_filter_global1]?
single	Table	What is the difference between the total volume of intake and output of patient {patient_id} [time_filter_global1]?
single	Table	What was the [time_filter_exact1] measured {vital_name} of patient {patient_id} [time_filter_global1]?
single	Table	What was the [agg_function] {vital_name} of patient {patient_id} [time_filter_global1]?
single	Table	What is_verb the total hospital cost of patient {patient_id} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] hospital admission time of patient {patient_id} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] hospital admission time that patient {patient_id} was admitted via {admission_route} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] hospital discharge time of patient {patient_id} [time_filter_global1]?
single	Table	What was the [time_filter_exact1] length of ICU stay of patient {patient_id}?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} was diagnosed with {diagnosis_name} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] procedure time of patient {patient_id} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} received a {procedure_name} procedure [time_filter_global1]?
single	Table	When was the [time_filter_exact1] prescription time of patient {patient_id} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} was prescribed {drug_name} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} was prescribed {drug_name1} and {drug_name2} [time_filter_within] [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} was prescribed a medication via {drug_route} route [time_filter_global1]?
single	Table	When was the [time_filter_exact1] lab test of patient {patient_id} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} received a {lab_name} lab test [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} had the [sort] value of {lab_name} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] microbiology test of patient {patient_id} [time_filter_global1]?
single	Table	When was patient {patient_id}'s [time_filter_exact1] {culture_name} microbiology test [time_filter_global1]?
single	Table	When was patient {patient_id}'s [time_filter_exact1] {test_name} test [time_filter_global1]?

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Table C12: Full list of 174 *Table*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
single	Table	When was the [time_filter_exact1] time that patient {patient_id} had a {intake_name} intake [time_filter_global1]?
single	Table	When was the [time_filter_exact1] intake time of patient {patient_id} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} had a {output_name} output [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} had a {vital_name} measured [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that the {vital_name} of patient {patient_id} was [comparison] than {vital_value} [time_filter_global1]?
single	Table	When was the [time_filter_exact1] time that patient {patient_id} had the [sort] {vital_name} [time_filter_global1]?
single	Table	Has_verb patient {patient_id} been admitted to the hospital [time_filter_global1]?
single	Table	Has_verb patient {patient_id} been to an emergency room [time_filter_global1]?
single	Table	Has_verb patient {patient_id} received any procedure [time_filter_global1]?
single	Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_global1]?
single	Table	What was the name of the procedure that patient {patient_id} received [n_times] [time_filter_global1]?
single	Table	Has_verb patient {patient_id} received any diagnosis [time_filter_global1]?
single	Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_global1]?
single	Table	Has_verb patient {patient_id} been prescribed {drug_name1}, {drug_name2}, or {drug_name3} [time_filter_global1]?
single	Table	Has_verb patient {patient_id} been prescribed any medication [time_filter_global1]?
single	Table	Has_verb patient {patient_id} been prescribed {drug_name} [time_filter_global1]?
single	Table	Has_verb patient {patient_id} received any lab test [time_filter_global1]?
single	Table	Has_verb patient {patient_id} received a {lab_name} lab test [time_filter_global1]?
single	Table	Has_verb patient {patient_id} had any microbiology test result [time_filter_global1]?
single	Table	Has_verb patient {patient_id} had any {culture_name} microbiology test result [time_filter_global1]?
single	Table	Has_verb patient {patient_id} had any {test_name} test result [time_filter_global1]?
single	Table	Has_verb there been any organism found in the [time_filter_exact1] {culture_name} microbiology test of patient {patient_id} [time_filter_global1]?
single	Table	Has_verb there been any organism found in the [time_filter_exact1] {test_name} test of patient {patient_id} [time_filter_global1]?
single	Table	Has_verb patient {patient_id} had any {intake_name} intake [time_filter_global1]?
single	Table	Has_verb patient {patient_id} had any {output_name} output [time_filter_global1]?
single	Table	Has_verb the {vital_name} of patient {patient_id} been ever [comparison] than {vital_value} [time_filter_global1]?
single	Table	Has_verb the {vital_name} of patient {patient_id} been normal [time_filter_global1]?
single	Table	List the hospital admission time of patient {patient_id} [time_filter_global1].
single	Table	List the [unit_average] [agg_function] {lab_name} lab value of patient {patient_id} [time_filter_global1].
single	Table	List the [unit_average] [agg_function] weight of patient {patient_id} [time_filter_global1].
single	Table	List the [unit_average] [agg_function] volume of {intake_name} intake that patient {patient_id} received [time_filter_global1].
single	Table	List the [unit_average] [agg_function] volume of {output_name} output that patient {patient_id} had [time_filter_global1].
single	Table	List the [unit_average] [agg_function] {vital_name} of patient {patient_id} [time_filter_global1].
single	Table	Count the number of hospital visits of patient {patient_id} [time_filter_global1].
single	Table	Count the number of ICU visits of patient {patient_id} [time_filter_global1].
single	Table	Count the number of times that patient {patient_id} received a {procedure_name} procedure [time_filter_global1].
single	Table	Count the number of drugs patient {patient_id} were prescribed [time_filter_global1].
single	Table	Count the number of times that patient {patient_id} were prescribed {drug_name} [time_filter_global1].
single	Table	Count the number of times that patient {patient_id} received a {lab_name} lab test [time_filter_global1].
single	Table	Count the number of times that patient {patient_id} had a {intake_name} intake [time_filter_global1].
single	Table	Count the number of times that patient {patient_id} had a {output_name} output [time_filter_global1].
group	Table	Count the number of current patients.
group	Table	Count the number of current patients aged [age_group].
group	Table	What is the [n_survival_period] survival rate of patients diagnosed with {diagnosis_name}?
group	Table	What is the [n_survival_period] survival rate of patients who were prescribed {drug_name} after having been diagnosed with {diagnosis_name}?
group	Table	What are the top [n_rank] diagnoses that have the highest [n_survival_period] mortality rate?
group	Table	What is_verb the [agg_function] total hospital cost that involves a procedure named {procedure_name} [time_filter_global1]?
group	Table	What is_verb the [agg_function] total hospital cost that involves a {lab_name} lab test [time_filter_global1]?
group	Table	What is_verb the [agg_function] total hospital cost that involves a drug named {drug_name} [time_filter_global1]?

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Table C12: Full list of 174 *Table*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
group	Table	What is_verb the [agg_function] total hospital cost that involves a diagnosis named {diagnosis_name} [time_filter_global1]?
group	Table	List the IDs of patients diagnosed with {diagnosis_name} [time_filter_global1].
group	Table	What is the [agg_function] [unit_average] number of patient records diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	Count the number of patients who were dead after having been diagnosed with {diagnosis_name} [time_filter_within] [time_filter_global1].
group	Table	Count the number of patients who did not come back to the hospital [time_filter_within] after diagnosed with {diagnosis_name} [time_filter_global1].
group	Table	Count the number of patients who were admitted to the hospital [time_filter_global1].
group	Table	Count the number of patients who were discharged from the hospital [time_filter_global1].
group	Table	Count the number of patients who stayed in careunit {careunit} [time_filter_global1].
group	Table	Count the number of patients who were diagnosed with {diagnosis_name} [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1].
group	Table	Count the number of patients who were diagnosed with {diagnosis_name2} [time_filter_within] after having been diagnosed with {diagnosis_name1} [time_filter_global1].
group	Table	Count the number of patients who were diagnosed with {diagnosis_name} [time_filter_global1].
group	Table	Count the number of patients who received a {procedure_name} procedure [time_filter_global1].
group	Table	Count the number of patients who received a {procedure_name} procedure [n_times] [time_filter_global1].
group	Table	Count the number of patients who received a {procedure_name2} procedure [time_filter_within] after having received a {procedure_name1} procedure [time_filter_global1].
group	Table	Count the number of patients who received a {procedure_name} procedure [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1].
group	Table	Count the number of {procedure_name} procedure cases [time_filter_global1].
group	Table	Count the number of patients who were prescribed {drug_name} [time_filter_global1].
group	Table	Count the number of {drug_name} prescription cases [time_filter_global1].
group	Table	Count the number of patients who were prescribed {drug_name} [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1].
group	Table	Count the number of patients who were prescribed {drug_name} [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1].
group	Table	Count the number of patients who received a {lab_name} lab test [time_filter_global1].
group	Table	Count the number of patients who received a {culture_name} microbiology test [time_filter_global1].
group	Table	Count the number of patients who received a {test_name} test [time_filter_global1].
group	Table	Count the number of patients who had a {intake_name} intake [time_filter_global1].
group	Table	What are_verb the top [n_rank] frequent diagnoses [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent diagnoses of patients aged [age_group] [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent diagnoses that patients were diagnosed [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent diagnoses that patients were diagnosed [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent procedures [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent procedures of patients aged [age_group] [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent procedures that patients received [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent procedures that patients received [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequently prescribed drugs [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequently prescribed drugs of patients aged [age_group] [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent prescribed drugs for patients who were also prescribed {drug_name} at the same time [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent drugs that patients were prescribed [time_filter_within] after having been prescribed with {drug_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequently prescribed drugs that patients were prescribed [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequently prescribed drugs that patients were prescribed [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequently prescribed drugs that patients aged [age_group] were prescribed [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequently prescribed drugs that {gender} patients aged [age_group] were prescribed [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?

Continued on next page

Table C12: Full list of 174 *Table*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
group	Table	What are_verb the top [n_rank] frequent lab tests [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent lab tests of patients aged [age_group] [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent lab tests that patients had [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent lab tests that patients had [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent specimens tested [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent microbiology tests [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent specimens that patients were tested [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent microbiology tests that patients had [time_filter_within] after having been diagnosed with {diagnosis_name} [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent specimens that patients were tested [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent microbiology tests that patients had [time_filter_within] after having received a {procedure_name} procedure [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent intake events [time_filter_global1]?
group	Table	What are_verb the top [n_rank] frequent output events [time_filter_global1]?

Table C13: Full list of 75 *Image+Table*-related question templates in EHRXQA

Patient scope	Modality scope	Question Template
Single	Image + Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_global1] and also had a chest X-ray study indicating \${attribute} in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_global1] and also had a chest X-ray study indicating any \${category} in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_global1] and also had a chest X-ray study indicating any abnormality in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_global1] and also had a chest X-ray study indicating \${attribute} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_global1] and also had a chest X-ray study indicating any \${category} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_global1] and also had a chest X-ray study indicating any abnormality within the same period?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_global1] and also had a chest X-ray study indicating \${attribute} in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_global1] and also had a chest X-ray study indicating any \${category} in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_global1] and also had a chest X-ray study indicating any abnormality in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_global1] and also had a chest X-ray study indicating \${attribute} within the same period?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_global1] and also had a chest X-ray study indicating any abnormality within the same period?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_global1] and also had a chest X-ray study indicating any abnormality within the same period?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_global1] and also had a chest X-ray study indicating \${attribute} in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_global1] and also had a chest X-ray study indicating any \${category} in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_global1] and also had a chest X-ray study indicating any abnormality in the \${object} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_global1] and also had a chest X-ray study indicating \${attribute} within the same period?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_global1] and also had a chest X-ray study indicating any abnormality within the same period?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_global1] and also had a chest X-ray study indicating any abnormality within the same period?

Continued on next page



Table C13: Full list of 75 *Image+Table*-related question templates in EHRXQA (Continued)

Patient scope	Modality scope	Question Template
Single	Image + Table	Has_verb patient {patient_id} been diagnosed with {diagnosis_name} [time_filter_within] after having had a chest X-ray study indicating any abnormality [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_within] after having had a chest X-ray study indicating any {attribute} in the \${object} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_within] after having had a chest X-ray study indicating any {category} in the \${object} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_within] after having had a chest X-ray study indicating any abnormality in the \${object} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_within] after having had a chest X-ray study indicating any {attribute} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_within] after having had a chest X-ray study indicating any {category} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} received a {procedure_name} procedure [time_filter_within] after having had a chest X-ray study indicating any abnormality [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_within] after having had a chest X-ray study indicating any {attribute} in the \${object} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_within] after having had a chest X-ray study indicating any {category} in the \${object} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_within] after having had a chest X-ray study indicating any abnormality in the \${object} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_within] after having had a chest X-ray study indicating any {attribute} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_within] after having had a chest X-ray study indicating any {category} [time_filter_global] ?
Single	Image + Table	Has_verb patient {patient_id} been prescribed with {drug_name} [time_filter_within] after having had a chest X-ray study indicating any abnormality [time_filter_global] ?
Group	Image + Table	Count the number of patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} in the \${object} [time_filter_global].
Group	Image + Table	Count the number of patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {category} in the \${object} [time_filter_global].
Group	Image + Table	Count the number of patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} [time_filter_global].
Group	Image + Table	List the IDs of patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} in the \${object} [time_filter_global].
Group	Image + Table	List the IDs of patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {category} in the \${object} [time_filter_global].
Group	Image + Table	List the IDs of patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} [time_filter_global].
Group	Image + Table	Count the number of {gender} patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} in the \${object} [time_filter_global].
Group	Image + Table	Count the number of {gender} patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {category} in the \${object} [time_filter_global].
Group	Image + Table	Count the number of {gender} patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} [time_filter_global].
Group	Image + Table	List the IDs of {gender} patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} in the \${object} [time_filter_global].
Group	Image + Table	List the IDs of {gender} patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {category} in the \${object} [time_filter_global].
Group	Image + Table	List the IDs of {gender} patients aged [age_group] who had a chest X-ray study during hospital visit indicating any {attribute} [time_filter_global].

### C.3 QA dataset generation

#### C.3.1 SQL/NeuralSQL annotation and QA pairs sampling

During the construction of our EHRXQA dataset, we sample *table*-related QA pairs by drawing from (Question, SQL) pairs and executing the SQL query to retrieve the answer. However, the process for *image*-related or *image+table*-related QA pairs is more complex, as we cannot sample QA pairs from (Question, SQL) without the label information for images. To overcome this, we create a new temporary table, TB\_CXR\_PLUS, which stores the label information for CXR images. The TB\_CXR\_PLUS table includes all the columns of the TB\_CXR table, as well as additional columns that represent the 563 relationships between objects and attributes, as pre-processed in the MIMIC-CXR-VQA dataset. This table aids in annotating SQL queries to retrieve image information, effectively serving as an ‘answer sheet’ for QA dataset generation process. It is important to note that this temporary table is only used during data construction.

In keeping with our goal of retrieving rich information directly from the images themselves, we employ our new approach, NeuralSQL. As part of this, we use TB\_CXR\_PLUS to annotate SQL queries and TB\_CXR to annotate NeuralSQL queries for all question templates related to *image* and *image+table*. An example of two queries can be seen in [Figure C3](#). To sum up,

- For *table*-related question templates, we annotate the corresponding SQL query. During the dataset sampling process, we use these SQL queries to derive the answers. The final format of this part of the dataset is (Question, SQL, Answer).
- For *image*-related or *image+table*-related question templates, we annotate the corresponding SQL query using TB\_CXR\_PLUS and the NeuralSQL query using TB\_CXR. During the dataset sampling process, we use the TB\_CXR\_PLUS query as an ‘answer sheet’ to derive answers, and the NeuralSQL query to formulate questions directly over the image. The final format of this part of our dataset is (Question, NeuralSQL, Answer).

<b>Question Template:</b> Given the [time_filter_exact1] study of patient {patient_id} [time_filter_global1], is there \${attribute} in the \${object}?
<b>NeuralSQL Template:</b> <pre>SELECT FUNC_VQA("is there \${attribute} in the \${object}?", T1.study_id) FROM (   SELECT tb_cxr.study_id   FROM tb_cxr   WHERE tb_cxr.subject_id = {patient_id}   AND tb_cxr.hadm_id IN (     SELECT admissions.hadm_id     FROM admissions     WHERE admissions.subject_id = {patient_id}     time_filter_global1_event(admissions.admittime, admissions.disctime)   )   time_filter_global1_absolute(tb_cxr.studydatetime)   time_filter_exact1(tb_cxr.studydatetime) ) AS T1</pre>
<b>SQL Template:</b> <pre>SELECT MAX(T1.relation = 1) FROM (   SELECT *   FROM tb_cxr_plus   WHERE tb_cxr_plus.study_id IN (     SELECT DISTINCT tb_cxr_plus.study_id     FROM tb_cxr_plus     WHERE tb_cxr_plus.subject_id = {patient_id}     AND tb_cxr_plus.hadm_id IN (       SELECT admissions.hadm_id       FROM admissions       WHERE admissions.subject_id = {patient_id}       time_filter_global1_event(admissions.admittime, admissions.disctime)     )   )   time_filter_global1_absolute(tb_cxr_plus.studydatetime)   time_filter_exact1(tb_cxr_plus.studydatetime) ) AS T1 WHERE T1.object = "\${object}" AND T1.attribute = "\${attribute}"</pre>

Figure C3: Comparison of NeuralSQL and SQL templates given a *image*-related question template. Components highlighted in green indicate the same semantic meaning across the question, SQL, and NeuralSQL templates.

### C.3.2 NeuralSQL annotation details

- Four individuals, experienced in SQL and familiar with the EHRSQL dataset and its schema, participated in the SQL and NeuralSQL annotations. They were organized into teams to review each other’s work.
- For NeuralSQL, if the sentence to be included in `FUNC_VQA` involved logical or set operations, we assigned the responsibility for these operations to `SQL`.
- In NeuralSQL, we aimed to maintain the natural language style of the original query in the `VQA` sentence to be included in `FUNC_VQA`.

### C.3.3 QA dataset split

We derive our train QA (*i.e.*, from silver database) and testing QA (*i.e.*, from gold database) sets from separate databases, with up to 80 samples for training and 10 for testing per template. The train QA set is divided further into a training QA set and a validation QA set, following a 7:1 ratio. This partitioning results in a validation set of a size comparable to that of the testing set.

### C.3.4 Paraphrasing

To generate paraphrases, we leveraged the OpenAI UI, applying [Figure C4](#) to create 15 paraphrases per template using the GPT-4 model (version May 24, 2023). Following this, human reviewers pruned any paraphrases that strayed from the initial template’s meaning. For the *Image*-related and *Image+Table*-related question templates, we used paraphrases crafted with GPT-4. In contrast, for the *Table*-related templates, we adopted machine paraphrases provided by EHRSQL. On average, each *Table*-related template contained 47.7 paraphrases, while each *Image* or *Image+Table*-related template contained 10.4 paraphrases. We randomly selected from these paraphrase pools and incorporated them into our datasets.

### Prompt Template for Paraphrasing: EHRXQA

You are an AI paraphraser for the medical domain (radiology).  
Write `{{num_of_paraphrase}}` paraphrases for the given question without changing its original meaning. The paraphrases must adhere to the following conditions.

Conditions:

- The paraphrased question should be similar to real-world questions asked by a medical doctor when given the EHR database.
- Keep the paraphrased question concise and straightforward.
- The answer to the paraphrased question should be identical to the answer to the original question.
- Maintain the placeholders in the format of `${placeholder}` (e.g., `${object}`, `${attribute}`, `${category}`, `${attribute_1}`, `${object_1}`).
- Maintain the placeholders in the format of `[placeholder]` (e.g., `[time_filter_exact1]`, `[time_filter_exact2]`, `[time_filter_global1]`, `[time_filter_global2]`).
- Ensure that the paraphrased question maintains these placeholders.
- The unit-related placeholder will be replaced with the corresponding time expression, such as 'days', 'hours'.
- The gender-related placeholder will be replaced with the corresponding gender expression, such as 'male' or 'female'.
- The age-related placeholder will be replaced with the corresponding age expression, such as '30-40'.
- The exact time-related placeholder will be replaced with the corresponding time expression, such as 'first', 'second', or 'last'.
- The global time-related placeholder will be replaced with the corresponding time expression, such as 'on the first hospital visit', 'last year', or 'this month'.
- The procedure-related placeholder will be replaced with the specific procedure name, such as 'temporary tracheostomy' or 'venous cath nec'.
- The diagnosis-related placeholder will be replaced with the specific name of the diagnosis, such as 'PEG Insertion' or 'Invasive Ventilation'.
- The drug-related placeholder will be replaced with the specific medication name, such as 'danazol' or 'aspirin'.
- The comparison-related placeholder will be replaced with the corresponding comparison expression, such as 'still present' or 'newly detected'.
- The object-related placeholder will be replaced with the actual anatomical locations found in the image, such as 'left lung' or 'cardiac silhouette'.
- The attribute-related placeholder will be replaced with specific abnormalities that can be found in chest X-ray images, such as 'lung opacity' or 'lung cancer'.
- The category-related placeholder will be replaced with the corresponding category of the attribute, such as 'anatomical finding', 'disease', or 'tubes/lines'.
- Abnormality is a superset of four categories: anatomical finding, disease, device, and tubes/lines.
- Formulate the paraphrased questions to be answerable with `{{answer_type}}`.

Question: `{{question_template}}`

Paraphrased questions:

Figure C4: Prompt Template for Paraphrasing Question Templates for EHRXQA. Elements enclosed within double braces `{{}}` are substituted with values specific to each template.

#### C.4 Data statistics

Table C14 presents detailed statistics of the EHRXQA dataset, providing a comprehensive breakdown of sample counts across various modality and patient categories in the training, validation, and test sets.

Table C14: Detailed Statistics of EHRXQA

modality-based	patient-based	# of samples			
		train set	valid set	test set	
Image	single	1-image	6,615 (18.3%)	945 (18.3%)	840 (17.5%)
		2-image	3,410 (9.4%)	488 (9.4%)	468 (9.7%)
	N-image	1,890 (5.2%)	279 (5.2%)	240 (5.0%)	
	group	945 (2.6%)	135 (2.6%)	120 (2.5%)	
	none	396 (1.1%)	54 (1.0%)	50 (1.0%)	
Table	single	8,219 (22.7%)	1,151 (22.3%)	1,080 (22.5%)	
	group	4,346 (12.0%)	647 (12.5%)	586 (12.2%)	
Image + Table	single	9,517 (26.3%)	1,362 (26.3%)	1,210 (25.2%)	
	group	836 (2.3%)	118 (2.3%)	214 (4.5%)	

#### D NeuralSQL with visual question answering

To ensure compatibility with the original SQL grammar, we extend the production rules of the SQL query language for our API call `FUNC_VQA`. We achieve this by using the `sqlgot`<sup>16</sup> parser in the NeuralSQL interpreter. The `sqlgot` parser is designed to handle a wide range of SQL inputs and generate syntactically correct SQL in the targeted dialects. In our implementation, we perform batch-wise inference for the external VQA API to handle questions that involve multiple CXR images. This allows us to effectively process queries such as “Count the number of patients who had a chest X-ray study indicating...”.

<sup>16</sup><https://github.com/tobymao/sqlgot>

## E Experiments

### E.1 MIMIC-CXR-VQA

#### E.1.1 MIMIC-CXR-VQA: Experimental settings

☑ **Standardization and Pre-processing of Pre-training Corpus** To ensure fair comparisons, we standardize the pre-training corpus across all VLP models. Our strategy mitigates biases from varied data sources and ensures performance differences are attributed to the models’ architectural characteristics and fine-tuning efforts rather than discrepancies in pre-training data. We adopt MedViLL’s pre-processing strategy for both image and text data from MIMIC-CXR-JPG. For X-ray images, we remove the marginal space, adjust the resolution to fit the model’s input size, and maintain the aspect ratio, discarding outliers not within 0.8 and 1.2. In processing the text data, we extract<sup>17</sup> the ‘findings’ and ‘impressions’ sections from the reports and then concatenate these sections for our models. If the token count, as tokenized by BERT, exceeds 253, we opt for the longer of the two sections. By adhering to the original MIMIC-CXR splits, we compile a corpus comprising 156,260 image-text pairs for the training set and 1,276 pairs for validation. We present results for both the original and controlled models, with the latter—pretrained on a carefully curated MIMIC-CXR corpus—denoted by an asterisk (\*).

#### ☑ Implementation details of VQA baselines

- Prior (Most): This model is a prior model that outputs the most popular answer in the training and validation set, which is “yes”.
- Prior (Question): This model is an advanced prior model that outputs the most popular answer in the training and validation set for each question (template).
- PubMedCLIP: We follow the original implementation code<sup>18</sup>
- MedViLL: We follow the original implementation code<sup>19</sup>
- M<sup>3</sup>AE: We follow the original implementation code<sup>20</sup>

Table E15: Training, model configurations for VQA baselines along with resource information. Some model configurations are not reported if not applicable. For any other configurations that are not reported here, we followed the original paper.

Name	M <sup>3</sup> AE*	M <sup>3</sup> AE	MedViLL*	PubMedCLIP*	PubMedCLIP
<b>Model configurations</b>					
Visual encoder	ViT-B/16	ViT-B/16	RN50	RN50	RN50
Text encoder	RoBERTa <sub>base</sub>	RoBERTa <sub>base</sub>	BERT <sub>base</sub>	Transformer / GRU	Transformer / GRU
<b>Pre-training configurations</b>					
Training epoch	50	50	50	100	100
Batch size	256	256	128	64	64
Learning rate	5e-5	5e-5	1e-5	1e-5	1e-5
<b>Finetuning configurations</b>					
Training epoch	50	50	20	20	20
Batch size	64	64	32	16	16
Learning rate	5e-6	5e-6	3e-5	1e-3	1e-3
<b>Resources (pretraining / finetuning)</b>					
GPU device	A6000 × 4 / 1	A6000 × 4 / 1	A6000 × 4 / 1	A6000 × 1 / 1	A6000 × 1 / 1
Training time	35 / 16 hours	69 / 16 hours	32 / 66 hours	226 / 62 hours	226 / 62 hours

<sup>17</sup><https://github.com/MIT-LCP/mimic-cxr/tree/master/txt>

<sup>18</sup><https://github.com/sarahESL/PubMedCLIP>

<sup>19</sup><https://github.com/SuperSupermoon/MedViLL>

<sup>20</sup><https://github.com/zhjohnchan/M3AE>

## E.1.2 MIMIC-CXR-VQA: Experimental results

Table E16: Comparison of performance of models on **MIMIC-CXR-VQA**.

Model	Valid		Test	
	Acc	F1 (micro)	Acc	F1 (micro)
Prior (Most)	26.8	0.27	25.4	0.25
Prior (Question)	34.3	0.34	32.4	0.32
PubMedCLIP	55.1 ± 1.7	0.56 ± 0.02	54.9 ± 1.3	0.54 ± 0.02
PubMedCLIP*	56.6 ± 1.9	0.58 ± 0.02	56.5 ± 2.1	0.56 ± 0.02
MedViLL*	64.7 ± 0.2	0.69 ± 0.00	63.6 ± 0.1	0.67 ± 0.00
M <sup>3</sup> AE	68.9 ± 0.2	0.73 ± 0.00	68.9 ± 0.3	0.72 ± 0.00
M <sup>3</sup> AE*	70.2 ± 0.1	0.74 ± 0.00	69.2 ± 0.4	0.73 ± 0.00

Table E17: Comparison of performance (Acc) of models across content types on **MIMIC-CXR-VQA**.

Model	Valid						
	Plane	Gender	Size	Abnormality	Anatomy	Attribute	Presence
Prior (Most)	16.7	16.7	50.0	24.8	0.0	0.0	50.1
Prior (Question)	50.0	50.0	50.0	29.5	12.8	15.7	50.1
PubMedCLIP	84.5 ± 1.0	44.3 ± 6.6	75.2 ± 1.2	49.7 ± 2.0	34.6 ± 1.8	40.8 ± 3.0	69.1 ± 0.9
PubMedCLIP*	89.8 ± 4.2	53.5 ± 13.3	74.7 ± 1.9	50.9 ± 1.9	35.7 ± 2.5	43.0 ± 2.5	70.2 ± 0.9
MedViLL*	89.4 ± 5.2	65.0 ± 5.2	77.7 ± 0.2	60.3 ± 0.4	43.8 ± 0.6	55.0 ± 0.3	76.6 ± 0.3
M <sup>3</sup> AE	98.3 ± 1.2	92.9 ± 0.4	81.7 ± 0.3	64.4 ± 0.5	48.1 ± 0.6	59.4 ± 0.2	78.6 ± 0.1
M <sup>3</sup> AE*	97.7 ± 1.6	91.2 ± 1.1	82.5 ± 0.4	65.0 ± 0.5	49.1 ± 0.3	60.4 ± 0.3	81.0 ± 0.1
Model	Test						
	Plane	Gender	Size	Abnormality	Anatomy	Attribute	Presence
Prior (Most)	17.1	16.7	43.3	23.9	0.0	0.0	50.4
Prior (Question)	48.7	50.0	43.3	29.0	11.7	12.4	50.4
PubMedCLIP	80.7 ± 2.0	44.3 ± 8.4	73.1 ± 0.1	49.6 ± 1.6	37.8 ± 1.0	42.3 ± 2.3	69.1 ± 0.8
PubMedCLIP*	87.5 ± 5.4	51.3 ± 11.0	74.1 ± 0.9	50.3 ± 1.8	38.5 ± 2.4	45.2 ± 2.4	70.1 ± 1.2
MedViLL*	90.2 ± 5.2	67.2 ± 5.0	75.1 ± 0.1	59.2 ± 0.6	45.3 ± 2.0	53.1 ± 0.3	76.0 ± 0.5
M <sup>3</sup> AE	98.0 ± 1.0	94.1 ± 0.8	79.1 ± 0.5	64.6 ± 0.5	51.6 ± 0.4	59.7 ± 0.6	78.3 ± 1.3
M <sup>3</sup> AE*	98.6 ± 1.0	90.9 ± 1.0	80.2 ± 1.1	63.9 ± 0.2	51.9 ± 1.7	60.2 ± 0.4	79.5 ± 0.7

### E.1.3 MIMIC-CXR-VQA: Relative metric for VQA grounding

☑ **Overview** To estimate the achievable perception accuracy for single-image verification questions in MIMIC-CXR-VQA, we designed the reference model as a classification model. This model is capable of addressing our basic verification questions, which follow the template: “*Is there  $\{attribute\}$  in the  $\{object\}$ ?*”. The reference model is trained using a decomposed version of the MIMIC-CXR-VQA dataset. The details of the dataset construction and the reference model implementation are provided below.

☑ **Construction of train/valid/test (*verify*)** The dataset is constructed with a focus on the basic verification template (*i.e.*, “*Is there  $\{attribute\}$  in  $\{object\}$ ?*”). Note that all questions within the MIMIC-CXR-VQA dataset can be restructured as combinations of this basic verification template. For instance, a question such as “*Are there both  $\{attribute\_1\}$  and  $\{attribute\_2\}$  in the  $\{object\}$ ?*” can be divided into “*Is there  $\{attribute\_1\}$  in the  $\{object\}$ ?*” and “*Is there  $\{attribute\_2\}$  in the  $\{object\}$ ?*”. Using this approach, we build the *verify* dataset, which consists of train (*verify*), valid (*verify*), and test (*verify*) sets. We decomposed the questions in each MIMIC-CXR-VQA dataset split to construct these subsets. We excluded category-related questions to avoid potential label imbalance.

☑ **Reference model structure** The reference model focuses on local regions within the overall CXR image, guided by the bounding box data from Chest ImaGenome. Instead of considering the entire image as input, the model concentrates on these local regions in combination with attribute-specific headers to facilitate output for a grounding task. These headers identify the presence or absence of each attribute based on the local information provided. Through this strategy, the model can classify the relationship between objects and attributes, offering a distinct contrast to VQA models that rely on natural language questions to infer such relationships. The backbone of the reference model is the Vision Transformer (ViT), which is pre-trained using the Self-Distillation with No Labels (DINO) method. DINO is a self-supervised learning strategy that utilizes a momentum encoder and multi-crop training. This approach empowers the self-supervised ViT features to effectively capture explicit semantic segmentation information from an image. Considering that our VQA task requires attention to the anatomical locations specified in each question (*i.e.*, “*... in the  $\{object\}$ ?*”) and classifying its attribute relationship (*i.e.*, “*Is there  $\{attribute\}$  ...*”), the features derived from the DINO method offer significant advantages. Consequently, our reference model incorporates the DINO pre-trained ViT model as its backbone and adds a 3-layer MLP head for each attribute.

☑ **Experimental details** We train our reference model following the setting of the previous work. We first pre-train the DINO model using our pre-training corpus (Appendix E.1.1). This pre-trained model is then fine-tuned using both the Train (*verify*) and Valid set (*verify*). The backbone of our model is ViT-S/16, and we use a 2D convolution layer with ReLU activation in each MLP head. During the pre-training phase, the model is trained using the AdamW optimizer with a batch size of 512, distributed over 8 GPUs. The learning rate increases linearly for the initial 10 epochs to a base value determined by the following linear scaling rule:  $lr = 0.0005 \times \text{batchsize}/256$ . Following this warm-up period, the learning rate decays according to a cosine schedule. For fine-tuning, we train the model for 100 epochs with a batch size of 1024. Here, we use the Adam optimizer with an initial learning rate of  $1e-3$ .

**Experimental results with relative metric** The performance of our VQA models is evaluated by utilizing AUROC (Area Under the Receiver Operating Characteristic Curve) and relative AUROC metrics. Note that we only used object-attribute pairs with 10 or more instances where the corresponding object-attribute relationship was identified as positive (1) in the test set, to enhance the reliability of the evaluation. Thus, these metrics are computed across 82 specific (object, attribute) pairs within the MIMIC-CXR-VQA Test set (*verify*). These metrics deliver an all-encompassing view on the model’s predictive precision and its ability to accurately identify attributes within objects.

Table E18: Comparison of performance of models across 82 (object, attribute) pairs on **MIMIC-CXR-VQA** Test set (*Verify*).

object	attribute	support	AUROC			AUROC <sub>rel</sub>			
			ref. model	M <sup>3</sup> AE*	MedViLL	PubMedCLIP*	M <sup>3</sup> AE*	MedViLL	PubMedCLIP*
aortic arch	tortuous aorta	69	0.719	0.880	0.852	0.645	1.225	1.185	0.898
aortic arch	vascular calcification	61	0.773	0.862	0.779	0.721	1.115	1.009	0.933
cardiac silhouette	cardiac pacer and wires	55	1.000	0.997	0.992	0.551	0.997	0.992	0.551
cardiac silhouette	enlarged cardiac silhouette	117	0.909	0.910	0.903	0.802	1.001	0.993	0.882
cardiac silhouette	fluid overload/heart failure	58	0.861	0.856	0.874	0.760	0.995	1.016	0.883
carina	endotracheal tube	64	0.671	0.916	0.883	0.754	1.369	1.319	1.126
left costophrenic angle	costophrenic angle blunting	62	0.681	0.873	0.762	0.689	1.286	1.123	1.016
left costophrenic angle	lung opacity	151	0.694	0.864	0.799	0.682	1.246	1.152	0.983
left costophrenic angle	pleural effusion	105	0.803	0.893	0.817	0.664	1.112	1.018	0.828
left hemidiaphragm	hernia	63	0.801	0.888	0.794	0.722	1.110	0.993	0.903
left hilar structures	enlarged hilum	60	0.671	0.778	0.709	0.634	1.161	1.059	0.945
left hilar structures	lung opacity	145	0.744	0.817	0.820	0.694	1.099	1.102	0.933
left hilar structures	pulmonary edema/hazy opacity	102	0.862	0.921	0.904	0.702	1.068	1.049	0.814
left hilar structures	vascular congestion	106	0.833	0.869	0.905	0.793	1.044	1.087	0.953
left lower lung zone	aspiration	63	0.897	0.898	0.820	0.746	1.001	0.914	0.831
left lower lung zone	atelectasis	113	0.833	0.841	0.735	0.646	1.010	0.883	0.776
left lower lung zone	linear/patchy atelectasis	69	0.661	0.766	0.643	0.643	1.159	0.972	0.973
left lower lung zone	low lung volumes	102	0.742	0.805	0.690	0.693	1.088	0.932	0.938
left lower lung zone	lung opacity	151	0.770	0.788	0.741	0.561	1.023	0.962	0.728
left lower lung zone	pneumonia	92	0.813	0.830	0.748	0.719	1.021	0.919	0.885
left lung	aspiration	75	0.901	0.871	0.839	0.707	0.967	0.931	0.785
left lung	atelectasis	123	0.871	0.874	0.779	0.684	1.004	0.895	0.786
left lung	copd/emphysema	52	0.904	0.904	0.866	0.678	1.000	0.958	0.751
left lung	costophrenic angle blunting	70	0.762	0.883	0.760	0.664	1.159	0.998	0.872
left lung	enlarged hilum	60	0.772	0.765	0.695	0.585	0.991	0.901	0.758
left lung	fluid overload/heart failure	60	0.827	0.864	0.893	0.753	1.045	1.080	0.910
left lung	hyperaeration	81	0.924	0.943	0.924	0.741	1.020	1.000	0.802
left lung	linear/patchy atelectasis	67	0.636	0.784	0.681	0.616	1.234	1.072	0.969
left lung	low lung volumes	107	0.904	0.913	0.865	0.714	1.010	0.957	0.790
left lung	lung lesion	85	0.685	0.685	0.654	0.577	1.004	0.958	0.845
left lung	lung opacity	158	0.802	0.785	0.739	0.662	0.979	0.921	0.825
left lung	mass/nodule (not otherwise specified)	87	0.661	0.763	0.588	0.548	1.159	0.893	0.832
left lung	pleural effusion	120	0.865	0.893	0.809	0.674	1.032	0.935	0.779
left lung	pleural/parenchymal scarring	86	0.782	0.824	0.768	0.602	1.056	0.984	0.772
left lung	pneumonia	99	0.820	0.766	0.711	0.668	0.936	0.868	0.815
left lung	pulmonary edema/hazy opacity	109	0.901	0.912	0.890	0.711	1.011	0.988	0.789
left lung	vascular congestion	103	0.869	0.871	0.885	0.786	1.001	1.018	0.904
left mid lung zone	lung opacity	148	0.685	0.821	0.712	0.523	1.200	1.041	0.765
mediastinum	cardiac pacer and wires	54	0.999	0.997	0.992	0.543	0.998	0.993	0.544
mediastinum	enlarged cardiac silhouette	122	0.905	0.899	0.875	0.793	0.994	0.968	0.876
mediastinum	enteric tube	66	0.890	0.998	0.978	0.777	1.122	1.099	0.873
mediastinum	fluid overload/heart failure	57	0.825	0.851	0.865	0.749	1.033	1.049	0.908
mediastinum	hernia	76	0.894	0.915	0.755	0.647	1.024	0.844	0.724
mediastinum	ij line	47	0.951	0.990	0.976	0.784	1.041	1.026	0.824
mediastinum	superior mediastinal mass/enlargement	68	0.752	0.804	0.689	0.625	1.070	0.916	0.831
mediastinum	tortuous aorta	74	0.904	0.867	0.837	0.619	0.959	0.926	0.685
mediastinum	vascular calcification	63	0.866	0.870	0.803	0.724	1.005	0.928	0.837
right costophrenic angle	lung opacity	149	0.828	0.888	0.827	0.699	1.074	1.000	0.845
right costophrenic angle	pleural effusion	102	0.733	0.844	0.804	0.618	1.151	1.096	0.843
right hemidiaphragm	elevated hemidiaphragm	58	0.912	0.968	0.775	0.547	1.062	0.850	0.600
right hilar structures	enlarged hilum	58	0.739	0.838	0.751	0.620	1.134	1.017	0.839
right hilar structures	lung opacity	152	0.790	0.855	0.831	0.689	1.082	1.051	0.872
right hilar structures	pulmonary edema/hazy opacity	96	0.867	0.908	0.896	0.693	1.047	1.034	0.799
right hilar structures	vascular congestion	100	0.860	0.857	0.884	0.798	0.997	1.028	0.929
right lower lung zone	aspiration	63	0.883	0.939	0.856	0.783	1.064	0.969	0.888
right lower lung zone	atelectasis	113	0.790	0.814	0.753	0.642	1.031	0.953	0.813
right lower lung zone	linear/patchy atelectasis	64	0.743	0.800	0.680	0.680	1.077	0.915	0.916
right lower lung zone	low lung volumes	106	0.827	0.833	0.713	0.708	1.010	0.864	0.858
right lower lung zone	lung opacity	154	0.786	0.769	0.741	0.600	0.979	0.943	0.764
right lower lung zone	pneumonia	91	0.835	0.789	0.768	0.612	0.945	0.920	0.733
right lung	airspace opacity	62	0.825	0.839	0.786	0.562	1.018	0.954	0.682
right lung	aspiration	65	0.936	0.953	0.864	0.740	1.019	0.924	0.791
right lung	atelectasis	129	0.809	0.833	0.758	0.685	1.031	0.938	0.848
right lung	copd/emphysema	51	0.912	0.916	0.877	0.702	1.004	0.962	0.770
right lung	enlarged hilum	62	0.768	0.830	0.715	0.586	1.082	0.931	0.763
right lung	fluid overload/heart failure	67	0.859	0.861	0.886	0.763	1.002	1.032	0.888
right lung	hyperaeration	78	0.961	0.941	0.940	0.766	0.979	0.978	0.797
right lung	linear/patchy atelectasis	65	0.804	0.806	0.751	0.728	1.002	0.935	0.905
right lung	low lung volumes	105	0.922	0.915	0.861	0.715	0.993	0.934	0.775
right lung	lung lesion	78	0.767	0.832	0.698	0.557	1.085	0.910	0.726
right lung	lung opacity	153	0.803	0.779	0.722	0.622	0.971	0.899	0.775
right lung	mass/nodule (not otherwise specified)	83	0.823	0.810	0.775	0.639	0.985	0.943	0.777
right lung	pleural effusion	113	0.841	0.851	0.803	0.632	1.012	0.955	0.751
right lung	pleural/parenchymal scarring	98	0.741	0.845	0.706	0.602	1.140	0.953	0.813
right lung	pneumonia	92	0.867	0.816	0.785	0.668	0.941	0.905	0.770
right lung	pulmonary edema/hazy opacity	111	0.928	0.924	0.895	0.727	0.995	0.964	0.783
right lung	vascular congestion	107	0.878	0.849	0.865	0.798	0.967	0.985	0.909
right mid lung zone	lung opacity	145	0.674	0.866	0.730	0.635	1.285	1.082	0.941
trachea	endotracheal tube	61	0.973	0.975	0.947	0.795	1.003	0.974	0.817
upper mediastinum	superior mediastinal mass/enlargement	65	0.774	0.821	0.712	0.644	1.062	0.920	0.832
upper mediastinum	tortuous aorta	67	0.843	0.881	0.845	0.621	1.045	1.003	0.737
upper mediastinum	vascular calcification	63	0.871	0.859	0.777	0.734	0.986	0.892	0.843

## E.2 MIMIC-CXR-VQA: Exploring data redundancy and the impact of paraphrasing

Given the brittleness of templates in prior EHR QA work, where the large sample size of emrQA (medication=220K, relation=900K) led to the redundancy issue, we decided to investigate the MIMIC-CXR-VQA dataset specifically, as it has a larger dataset size (377K).

First, we explore the degree to which additional templates actually improve the model to determine whether our dataset simply contains repetitive templates without any novelty. To this end, we conducted an ablation experiment with the MIMIC-CXR-VQA dataset. We evaluate the test set performance by randomly sampling training data at various template usage proportions (*i.e.*, how many unique templates are used for training), such as 5%, 10%, 20%, 50%, and 100%.

As shown in [Table E19](#), our experiment with MIMIC-CXR-VQA demonstrated that using a higher number of questions (*i.e.*, training size increases) generated from templates questions generated from more diverse templates positively impacts the model’s performance (*i.e.*, test Acc/F1) across all models. This observation suggests that MIMIC-CXR-VQA does not have the redundancy of questions, and question diversity generated from all templates contributes to the performance improvement.

Table E19: Results of the ablation experiment on the MIMIC-CXR-VQA test set. Comparison of performance across different training data proportions based on unique template usage: 5%, 10%, 20%, 50%, and 100%. We ran the experiments with one seed.

template usage (%)	PubMedCLIP*	MedViLL	M <sup>3</sup> AE*
	test (Acc/F1)	test (Acc/F1)	test (Acc/F1)
5%	49.1 / 0.39	44.8 / 0.44	56.9 / 0.56
10%	48.4 / 0.50	54.4 / 0.55	61.3 / 0.64
20%	51.2 / 0.50	60.0 / 0.62	65.0 / 0.67
50%	55.8 / 0.56	62.6 / 0.65	68.9 / 0.72
100%	56.5 / 0.56	63.6 / 0.67	69.2 / 0.73

Next, we explored the relationship between the variety of paraphrases produced using GPT-4 and model performance. To investigate whether increasing the diversity of paraphrases (thus reducing the redundancy of the question) improves the model’s ability, we keep the dataset size constant and vary the number of paraphrases per template for the training dataset. We started with 48 seed templates as the training dataset (denoted as “seed template”) and created two distinct training dataset variants named “low-diversity” and “high-diversity”. These variants contained 20% and 100% paraphrased templates of the original template in the MIMIC-CXR-VQA training set, respectively. Note that each model, trained with three different datasets, was evaluated against the same original MIMIC-CXR-VQA test dataset. We conducted the experiments with three different seeds.

Our findings indicate that using paraphrased templates via GPT-4 improves model performance. This observation is evident when comparing the results of the “seed template” (without paraphrasing) with models trained in the variants “low-diversity” or “high-diversity”. Further, as the diversity of paraphrases increases, the model performance might also improve. The effect of paraphrasing can differ based on the text encoder used. Models that incorporate a BERT-based language architecture, such as MedViLL and M<sup>3</sup>AE, appear to benefit more from increased diversity. This suggests that even templates crafted through automatic paraphrasing can substantially boost performance, especially when there is adequate diversity.

Table E20: Results of the ablation experiment on the MIMIC-CXR-VQA test set. Comparison of performance across different degrees of paraphrasing diversity. We ran the experiments with three different seeds (mean ± std).

Training Dataset	PubMedCLIP*	MedViLL	M <sup>3</sup> AE*
	test (Acc/F1)	test (Acc/F1)	test (Acc/F1)
MIMIC-CXR-VQA (seed template)	39.6 ± 0.4 / 0.36 ± 0.0	46.3 ± 0.3 / 0.48 ± 0.0	65.6 ± 0.5 / 0.68 ± 0.0
MIMIC-CXR-VQA (low-diversity)	56.5 ± 0.3 / 0.57 ± 0.0	62.5 ± 0.3 / 0.65 ± 0.0	69.2 ± 0.4 / 0.72 ± 0.0
MIMIC-CXR-VQA (high-diversity)	56.5 ± 2.1 / 0.56 ± 0.0	63.6 ± 0.1 / 0.67 ± 0.0	69.2 ± 0.4 / 0.73 ± 0.0

## E.3 EHRXQA

### E.3.1 Implementation details of baselines

Our NeuralSQL-based approach integrates a large language model (LLM) as a parser with an external VQA API module. We use ChatGPT [42] (gpt-3.5-turbo-0613)<sup>21</sup> as our parser and utilize the M<sup>3</sup>AE model, pre-trained on the MIMIC-CXR-VQA training set, as the VQA API module (frozen). We conduct in-context learning with few-shot samples, leveraging the capabilities of large language models, specifically in a 10-shot setting.

We have defined two prompting strategies: 1) Fixed: which uses 10-shot (Question, NeuralSQL) pairs; 2) BM25 (train): which retrieves 10 relevant pairs via BM25 from the training set for any given question. The fixed examples are randomly selected from the training set, but we ensured that at least one pair was sampled from each modality to provide the minimum required information (3 for *Table*-related, 4 for *Image*-related, and 3 for *Image+Table*-related). When executing NeuralSQL parsed by LLM, the batch size of the external VQA module is set to 16.

#### Prompt for Fixed strategy.

Generate NeuralSQL (*i.e.*, extended SQL with the following conditions) given the question to answer the question correctly. If the question can only be answered by examining a chest X-ray image and requires a VQA model, use the new syntax FUNC\_VQA() to create a query. When the VQA sentence in FUNC\_VQA() syntax contains logical operations such as union, difference, intersection, disjunction, or conjunction, decomposes the VQA statement into minimal semantic units and uses the SQL syntax to generate NeuralSQL. For example, decompose the original sentence "Are there any technical assessment or tubes/lines?" into "Are there any technical assessment?" and "Are there any tubes/lines?" by separating the logical disjunction (or) and creating two separate questions.

```
Q: {{1st question}}  
NeuralSQL: {{1st query}}
```

...

```
Q: {{10th question}}  
NeuralSQL: {{10th query}}
```

```
Parse the question into NeuralSQL.  
Q: {{target question}}  
NeuralSQL:
```

<sup>21</sup>Since the Codex API is no longer supported, we conducted all our experiments using ChatGPT (gpt-3.5-turbo-0613) instead.

### Prompt for BM25 strategy.

Generate NeuralSQL (*i.e.*, extended SQL with the following conditions) given the question to answer the question correctly. If the question can only be answered by examining a chest X-ray image and requires a VQA model, use the new syntax FUNC\_VQA() to create a query. When the VQA sentence in FUNC\_VQA() syntax contains logical operations such as union, difference, intersection, disjunction, or conjunction, decomposes the VQA statement into minimal semantic units and uses the SQL syntax to generate NeuralSQL. For example, decompose the original sentence "Are there any technical assessment or tubes/lines?" into "Are there any technical assessment?" and "Are there any tubes/lines?" by separating the logical disjunction (or) and creating two separate questions. Q: {{1st question retrieved from training QA set}}  
NeuralSQL: {{1st query}}

...

Q: {{10th question retrieved from training QA set}}  
NeuralSQL: {{10th query}}

Parse the question into NeuralSQL.

Q: {{target question}}  
NeuralSQL:

### E.3.2 EHRXQA: Experimental results

Table E21: Performance of ChatGPT + M<sup>3</sup>AE (BM25 (train)) on the **EHRXQA** dataset, categorized by modality-based and patient-based scope.

Modality-based	Patient-based	$Acc_{LF}$	$Acc_{EX gt}$	$Acc_{EX pred}$	
Image	single	1-image	94.4	57.6	56.3
		2-image	73.3	51.1	50.0
		N-image	90.8	39.6	39.6
	group	85.0	5.0	1.7	
	none	98.0	100.0	98.0	
Table	single	87.1	100.0	95.6	
	group	44.7	100.0	87.5	
Image + Table	single	70.5	78.3	75.2	
	group	83.6	15.0	13.1	

Table E22: Performance of ChatGPT + M<sup>3</sup>AE (Fixed) on the **EHRXQA** dataset, categorized by modality-based and patient-based scope.

Modality-based	Patient-based	$Acc_{LF}$	$Acc_{EX gt}$	$Acc_{EX pred}$	
Image	single	1-image	1.4	57.6	27.7
		2-image	0.2	51.1	10.3
		N-image	0.0	39.6	3.8
	group	5.0	5.0	0.8	
	none	0.0	100.0	6.0	
Table	single	5.9	100.0	33.6	
	group	3.4	100.0	25.4	
Image + Table	single	3.3	78.3	40.8	
	group	13.1	15.0	6.5	

## **F Author statement**

The authors of this paper bear all responsibility in case of violation of rights, etc. associated with the MIMIC-CXR-VQA and EHRXQA dataset.