

Deep learning prediction models based on EHR trajectories: A systematic review

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Background and motivations

Electronic health records (EHRs) are generated at an ever-increasing rate. EHR trajectories, the temporal aspect of health records, facilitate predicting patients' future health-related risks. It enables healthcare systems to increase the quality of care by early identification and primary prevention. Deep learning techniques have shown great capacity for analyzing complex data and have been successful for prediction tasks using complex EHR trajectories.

This systematic review aims to analyze recent studies to identify challenges, knowledge gaps, and ongoing research directions. Table1 shows an example of a patient's EHR sequence data.

| Visit number | Visit 1 | 41 days | Visit 2 | 13 days | Visit 3 | 134 days | Visit 4 | 52 days | Visit 5 | 23 days | Visit 6 | 37 days | Visit 7 |
|--|------------|---|---|---------|--|----------|---|---------|---|---------|---|---------|--|
| Diagnosis | | ABD. PAIN | GASTROPARSIS,HYPERTENSION | | MALIGNANT HYPERTENSION | | GASTROPARSIS | | NAUSEA/VOMITTING, HYPOTENSION | | HYPERTENSIVE URGENCY | | UNCONTROLLED HYPERTENSION- NAUSEA/VOMITTING |
| Patients demographic information: Gender: M, Date_of_M: date: 1978-04-23, Date_of_death: 2018-02-10, Religion: Catholic, Ethnicity:White | Medication | Clonidine TTS 1 Patch | Insulin, Cefazolin, DSW, Metoprolol, Lorazepam, Clonidine TTS 1 Patch, Oxidantone, Heparin, Nitroprusside Sodium | | Clonidine TTS 1 Patch, Heparin, Lorazepam, Metoprolol, Magnesium Sulfate, Hydralazine HCl | | Insulin, Heparin Flush Port, Acetaminophen, Multivitamins, Nifedipine, Nitroglycerin, Oxidantone 2%, Dolasetron Mesylate | | Heparin, Hydralazine HCl, Ondansetron, Metoprolol, Promethazine HCl, Lorazepam | | Heparin, Insulin Heparin, Aspirin, Heparin Flush CVL (100 units/ml), Insulin, Dextrose 50% | | Lisinopril, Sevelamer, Heparin Flush Port, (10units/ml), Calcium Acetate, Pantoprazole, Atorvastatin |
| Procedures | | Venous catheterization, Parent infus nutrit sub | Hemodialysis, Debridement of nail, Venous catheterization | | Arterial catheterization | | Hemodialysis, enous catheterization | | Hemodialysis | | Hemodialysis | | Insert vasc access dev |
| Lab test | | Urea Nitrogen:26_abnormal, AnionGap:2, Basophil:0.8 | White Blood Cells:6.5, Magnesium:1.5_abnormal | | Glucose:285_abnormal, Hematocrit:34_abnormal | | Hematocrit:39_abnormal, Hemoglobin:10_abnormal | | Hematocrit:39_abnormal, Hemoglobin:10_abnormal | | White Blood Cells:6, Chloride:100 | | Glucose:172_abnormal, Creatinine:7.1_abnormal ,Chloride:100 |
| Clinical Text | | Social History: Denies alcohol or tobacco use. Family History: His father recently died of ESRD and diabetes. you should take all your medications as directed, return immediately to the ER for any chest pain | Discharge Instructions: You were admitted to the hospital for abdominal pain and high blood pressure. You were treated with in intravenous pain medication which was converted to pills | | Local anaesthesia was provided by lidocaine spray. No TEE 12P11 further evolution of the anteroseptal, lateral and apical myocardial infarction. Clinical correlation is suggested. TRACING #2 | | Sinus rhythm. Compared to the prior tracing of 11*1187-1-12P11 further evolution of the anteroseptal, lateral and apical myocardial infarction. Clinical correlation is suggested. TRACING #2 | | The central line tip is in the right brachiocephalic vein or proximal most SVC. The cardiac and mediastinal contours are stable. The lungs are clear. The lateral costophrenic angles are sharp without effusion. | | 38 year old man with recurrent episodes of abdominal pain and hypertension | | increase in bilateral perihilar opacities is suggesting progression of pulmonary edema, although there is no stable right or left pleural effusion |
| Admission and marital information | | Marital_status:Single, Admission_type: Emergency, Discharge_Location:Home, Insurance: Private | Marital_status:Single, Admission_type: Emergency, Discharge_Location:Home, Insurance: Private | | Marital_status:Single, Admission_type: Emergency, Discharge_Location:Home, Insurance: Private | | Marital_status:Single, Admission_type: Emergency, Discharge_Location:Home, Insurance: Private | | Marital_status:Single, Admission_type: Emergency, Discharge_Location:Home, Insurance: Private | | Marital_status:Single, Admission_type: Emergency, Discharge_Location:Home, Insurance: Private | | Marital_status:Single, Admission_type: Emergency, Discharge_Location:Home, Insurance: Private |

Table1: An example of a patient's EHR sequence data and its different parts from MIMIC-III dataset.

Results

Publication characteristics

- After 2018, the number of publications has grown about three times from 6 to 17 (fig 2).
- The main reason for this growth could be the rise in EHR data availability rate and progress in deep learning methods and their availability to address data complexity.

Predicted subjects

In order to improve health care service quality, there are many areas where AI can be useful. We reviewed most frequent topics in table 2.

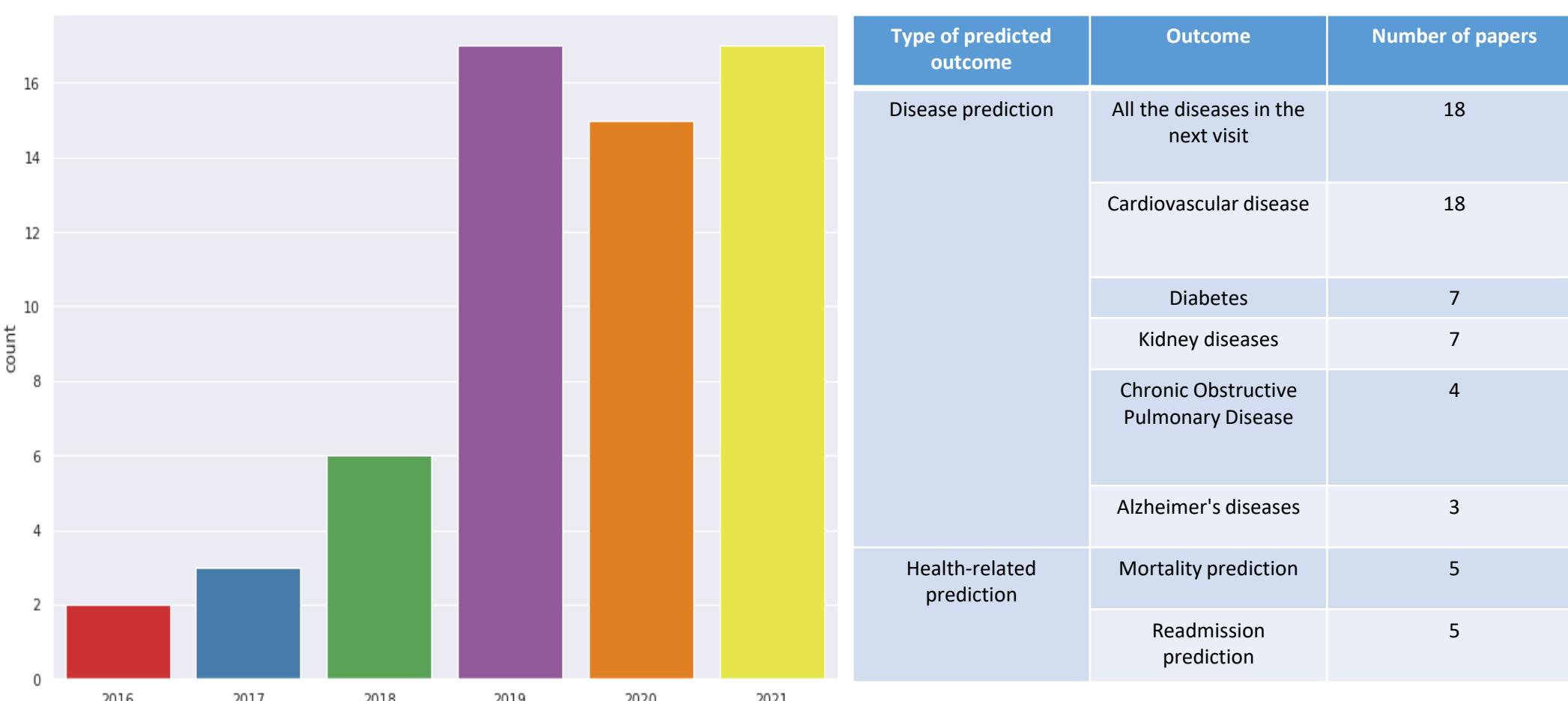


Fig2: Number of publications per year in collected papers.

Table2: The most frequent predicted topics in reviewed papers.

Challenges and solutions

Predicting patients' future health-related risks is a complex task that is full of obstacles and difficulties. We review the most important challenges and suggested solutions as follow:

- Heterogeneous data**
 - EHRs consist of heterogeneous data sources with multiple data modalities
 - Each one intends to record specific aspects of patients' health status and different methods have used to extract information from these modalities. Fig3 Shows an summary of extracting information from different modalities workflow and some of corresponding references.

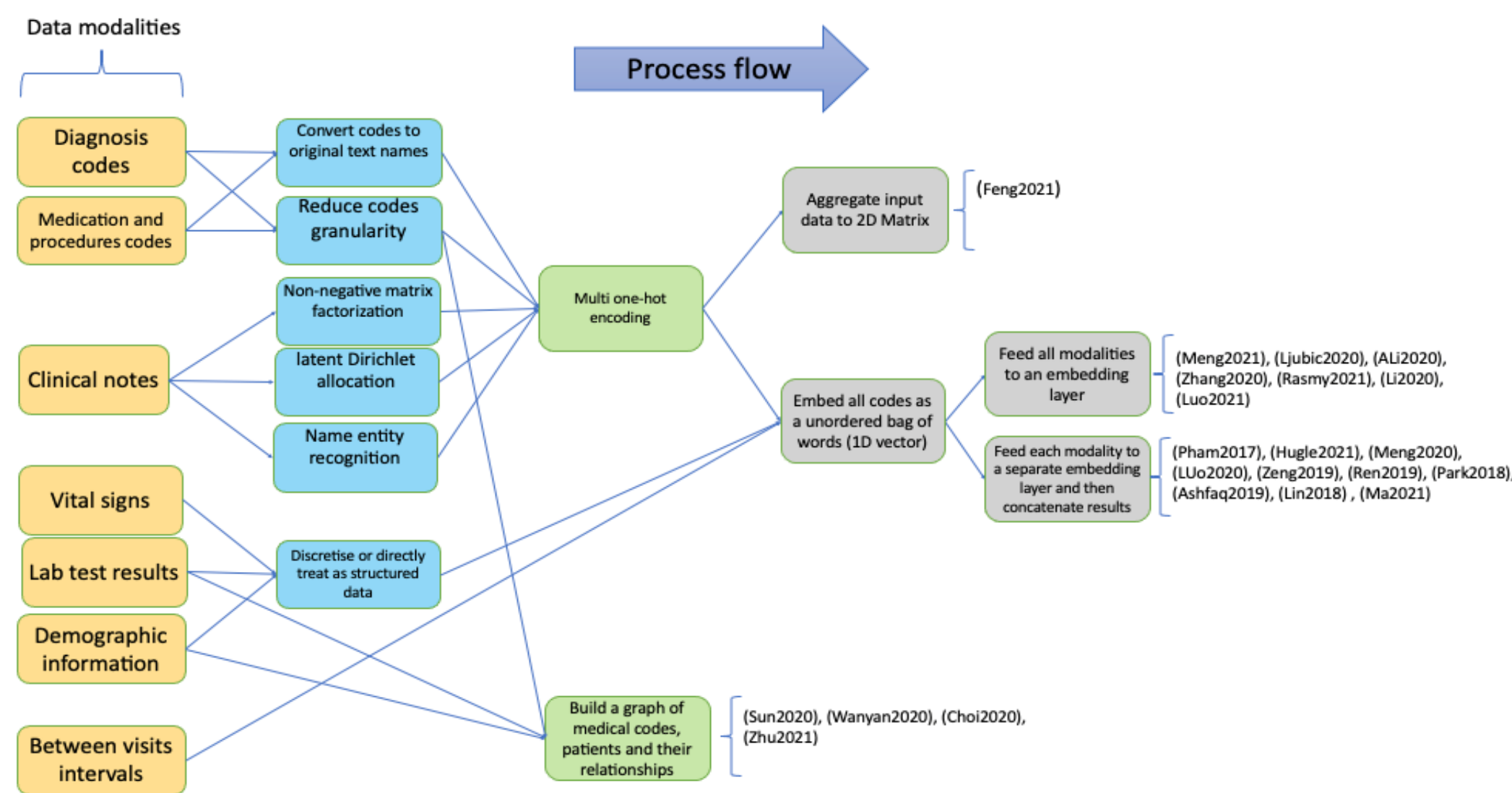


Fig3: Used methods to handle data heterogeneity in revied papers.

- Representation of admission information**
 - EHRs often have high dimensionality, sparsity and contain a large number of inconspicuous relations.
 - In the dynamic approach, networks are trained end-to-end and usually in a supervised manner, while in the static approach, we train a separate network for data representation, e.g. using unsupervised learning
 - Co-occurrence based methods build representation by considering relations within a single visit while sequential occurrence focuses on relations in neighbour visits (Fig 4)

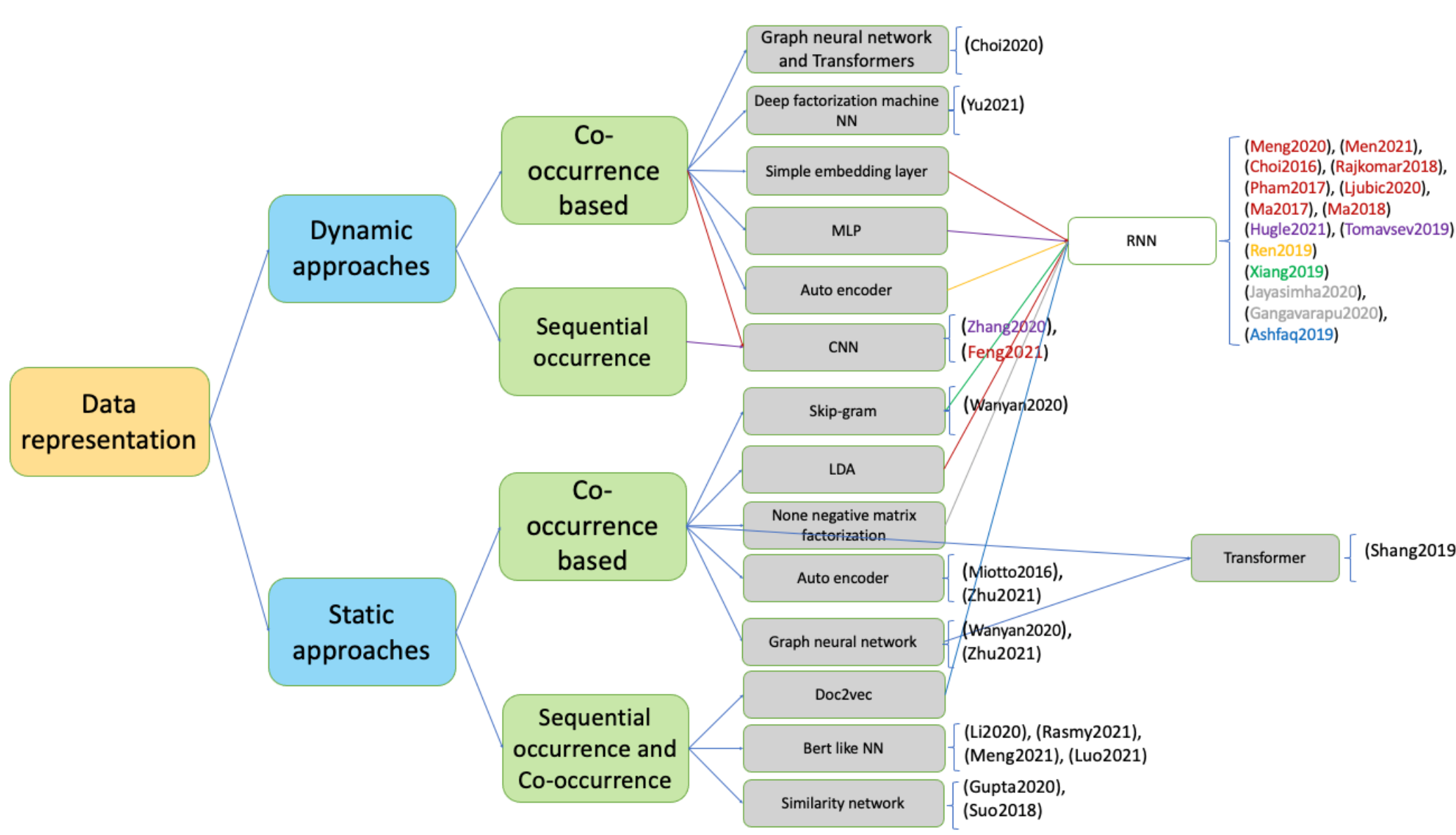


Fig4: Different data representation methods in reviewed papers.

- Long term dependencies and irregularity in time**
 - EHR data are longitudinal by nature where current state of a patient typically depends on data for previous visits.
 - Considering the information of past visits is essential.
 - To this end, using RNN, CNN and attention mechanism were the most common ways (Fig5).

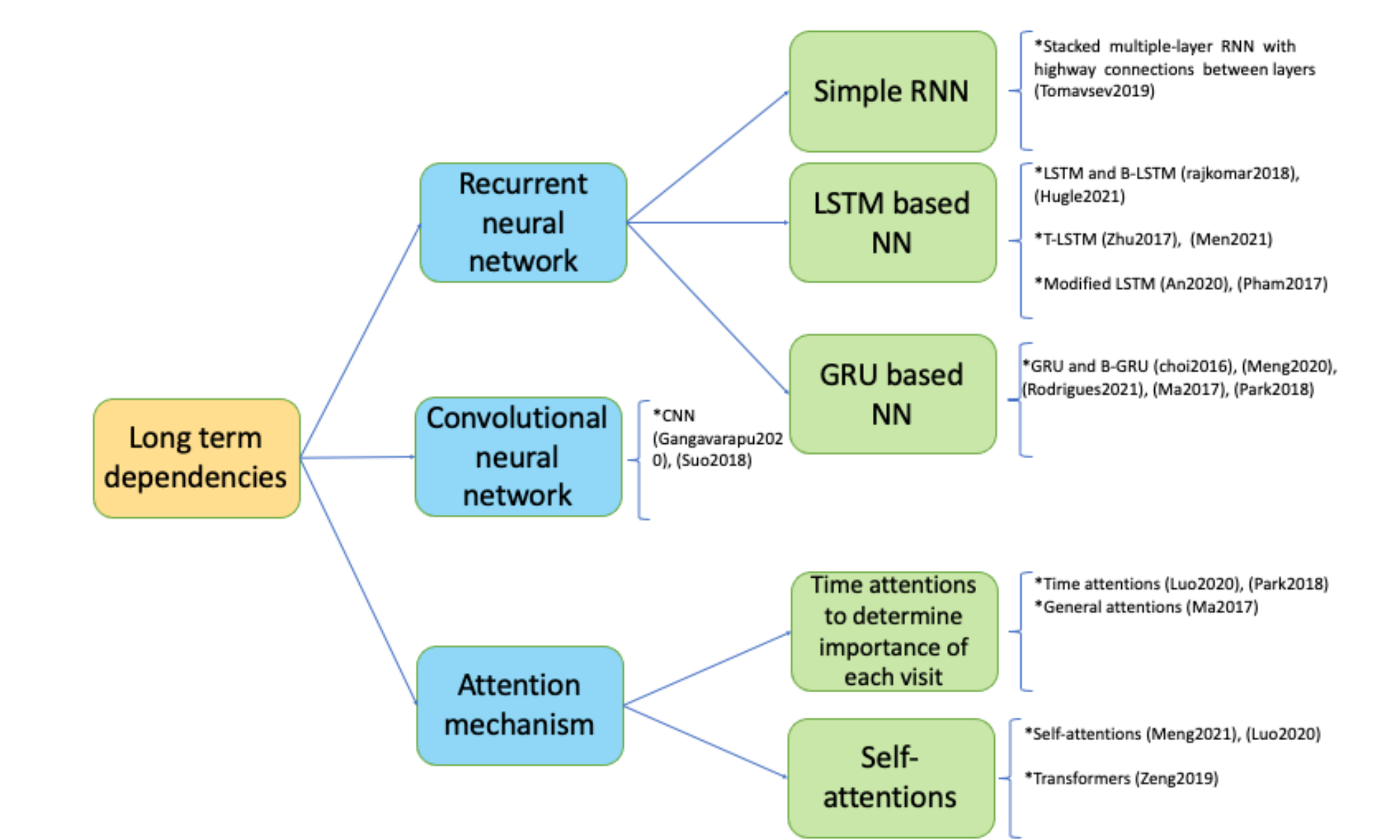


Fig5: Different ways to deal with long term dependencies in reviewed papers.

- Interpretability and explainability**
 - Explainability of models' decisions will be essential for acceptance among intended users.
 - Here we found methods such as gradient based localization, visualizing attention weights and visualizing embedded feature space, in reviewed papers (Fig8).

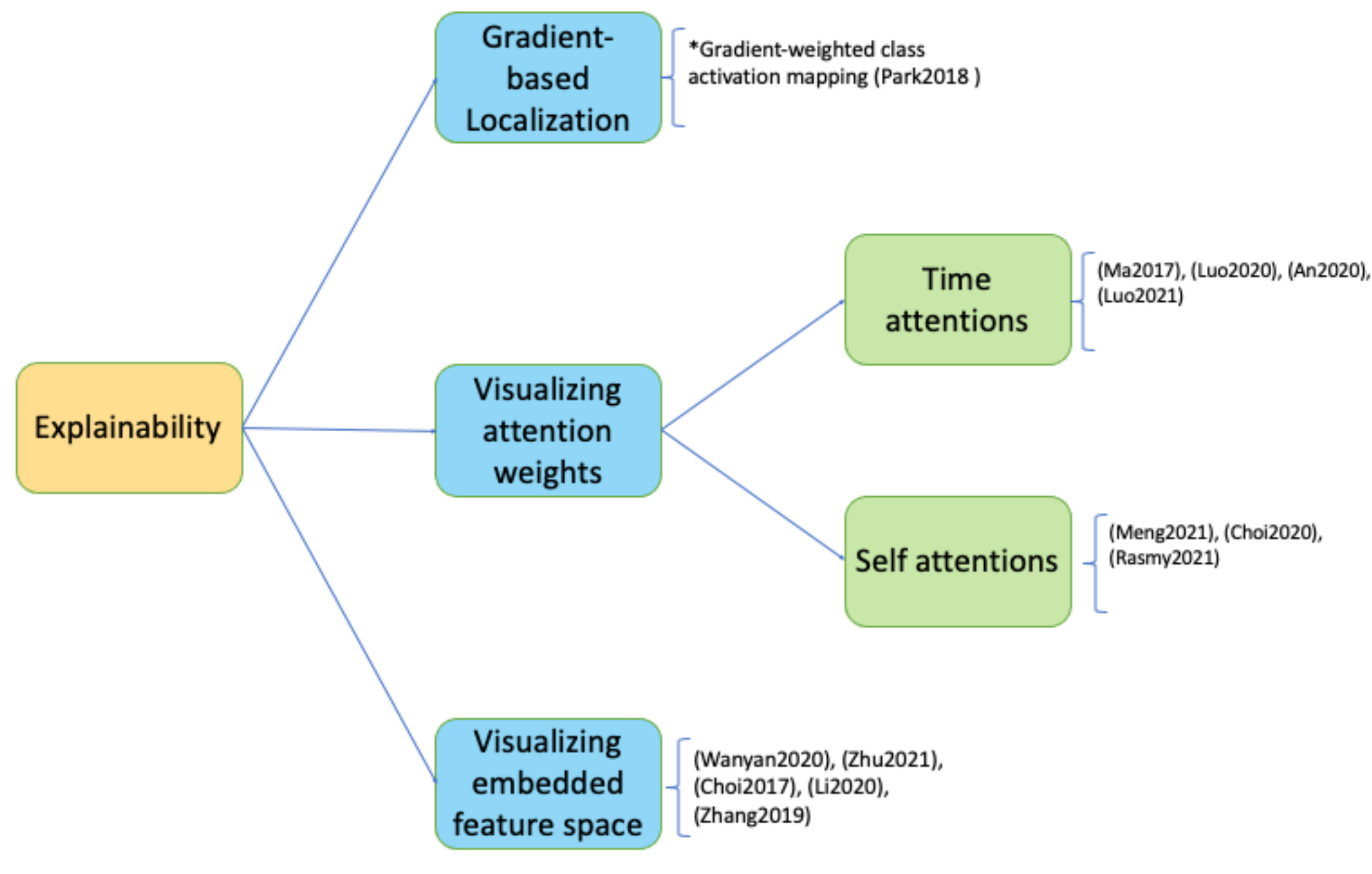


Fig6: Explainability methods that used in reviewed papers.

Conclusion

Identified challenges and directions of future research:

- Fully handling all aspects of EHR data in a single model is still challenging.
- There is a need to further develop models that can use both structured and unstructured data of different sources effectively.
- Representation methods should consider inter and intra dependencies between and within visits to make more accurate models.
- Handling the effect of rare diseases is another obstacle to model EHR data.
- Benchmark datasets to evaluate the accuracy and degree of explainability of NN models in this field is required.
- The privacy and fairness of EHRs predictive models need more investigations.