Research Article

MKA: A Scalable Medical Knowledge-Assisted Mechanism for Generative Models on Medical Conversation Tasks

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Using natural language processing (NLP) technologies to develop medical chatbots makes the diagnosis of the patient more convenient and efficient, which is a typical application in healthcare AI. Because of its importance, lots of researches have come out. Recently, the neural generative models have shown their impressive ability as the core of chatbot, while it cannot scale well when directly applied to medical conversation due to the lack of medical-specific knowledge. To address the limitation, a scalable medical knowledge-assisted mechanism (MKA) is proposed in this paper. The mechanism is aimed at assisting general neural generative models to achieve better performance on the medical conversation task. The medical-specific knowledge graph is designed within the mechanism, which contains 6 types of medical-related information, including department, drug, check, symptom, disease, and food. Besides, the specific token concatenation policy is defined to effectively inject medical information into the input data. Evaluation of our method is carried out on two typical medical datasets, MedDG and MedDialog-CN. The evaluation results demonstrate that models combined with our mechanism outperform original methods in multiple automatic evaluation metrics. Besides, MKA-BERT-GPT achieves state-of-the-art performance.

1. Introduction

Difficulty in seeing a doctor, long queuing time, and inconvenience of making appointments have long been hurdles facing patients when they try to access primary care services. To solve these challenges, many advanced artificial intelligence (AI) technologies [1–3] have been combined with healthcare to boost the availability of medical resources, such as applying pattern recognition methods on medical images [4, 5] and leveraging natural language processing (NLP) technologies to design medical chatbots [6, 7]. The medical chatbot is mainly aimed to offer the medical assistants including disease identification, self-reports based medical suggestions for drugs, foods and checks, and medical front desk service guiding the patient to suitable healthcare service department, etc [8, 9]. It has a significant potential to simplify the diagnostic process and relieve the cost of collecting information from patients. Besides, the preliminary diagnosis results generated by the model may assist doctors to make a diagnosis more efficiently.

As the core of the medical chatbot, different methods have been investigated recently. In general, typical methods can be divided into two types [10], including information retrieval-based methods and neural generative methods. As for the first type, the methods usually match the response from the user-built question and answer (Q&A) pool based on the dialogue context, which means it can only provide the response that occurred in the existing pool. In another word, the poor-quality pool will influence a lot on the response. The second type of methods usually takes the dialogue context history as input and generates the suitable response word by word. Compared to retrieval-based methods, neural generative methods are more intelligent and flexible, which is what we focus on in this paper.
To address the limitations, the objective of the paper is to propose a medical knowledge-assisted mechanism (MKA) to assist common neural generative models to achieve better performance for the medical conversation task. MKA is an effective and lightweight method to integrate the medical knowledge with neural generative models. The mechanism first introduces a medical knowledge generation module to generate the related medical knowledge, which generates the medical knowledge subgraph $\text{MKG}_{\text{sub}}$ generated from the patients’ self-report. The designed knowledge graphs contain related medical knowledge for each patient, including 6 types of entities (i.e., $\epsilon_{\text{department}}$, $\epsilon_{\text{disease}}$, $\epsilon_{\text{symptom}}$, $\epsilon_{\text{food}}$, $\epsilon_{\text{check}}$, and $\epsilon_{\text{drug}}$) and 6 types of relations (i.e., $\gamma_{\text{has-disease}}$, $\gamma_{\text{has-symptom}}$, $\gamma_{\text{need-drug}}$, $\gamma_{\text{need-check}}$, $\gamma_{\text{need-food}}$, and $\gamma_{\text{no-food}}$). Then, the medical knowledge information is fed into the token processor together with the dialogue contexts. Within the token processor, all the tokens will be reorganized based on the specific token concatenation policy. Finally, the processed data will be taken by selected generative models for training. In summary, we make the following contributions:

1. The paper proposes an effective and lightweight mechanism to integrate the medical knowledge into different neural generative models, MKA. Besides, the specific medical knowledge graph is designed to store the medical knowledge. To the best of our knowledge, MKA is the first scalable work that can integrate the medical knowledge into all kinds of neural generative models, especially for large-scale pretrained model, such as BERT-GPT.

2. To verify our method, we implement two models based on our mechanism, MKA-Transformer and MKA-BERT-GPT. The evaluation is carried out on 2 typical medical conversation benchmarks: MedDialog [11] and MedDG [12]. Our experiments
show that the model combined with our method outperforms previous methods in multiple automatic evaluation metrics. Besides, the MKA-BERT-GPT achieves the best performance on the task.

The paper will be separated into 5 parts. Section 2 will present the existing works related to medical dialogue generation tasks. Section 3 will explain the details of the proposed mechanism. Section 4 shows the experiment results and the analysis of the results. Section 5 concludes the advantages and disadvantages of our work and its potential future works.

2. Related Works

Recent research on medical chatbots focuses on natural language understanding which leverages different advanced natural language processing (NLP) techniques. In general, the medical dialogue methods can be divided into information retrieval-based methods and neural generative methods according to the types of the applied NLP techniques. The retrieval-based methods can be further classified into different subtypes, such as the entity inference [12, 13], relation prediction [14, 15], symptom matching and extraction [16, 17], and slot filling [18–20]. However, the retrieval-based methods are not so intelligent and flexible that they required a well-defined user-built question and answer (Q&A) pool, which can offer different potential response to different kinds of answer. In another word, the retrieval-based methods only predict the link between question and answers in the pool, instead of learning how to respond to different questions like the doctors. Therefore, the neural generative methods have drawn more and more attention.

Nowadays, there is merely research on developing neural generative methods on medical domain. As an emerging research direction, most of the existing researches focus on testing different neural generative models on the benchmark domain-specific datasets. To figure out well the generative tasks in NLP, Hochreiter and Schmidhuber first proposed long short-term memory (LSTM) [21], which inspires multiple LSTM-based models [22–24]. Later, with the proposal of Transformer [25], researchers start to leverage Transformer units into novel dialogue generation models [26, 27]. Then, a more accurate and faster mechanism GPT is proposed [28]; different large-scale dialogue generative models are developed based on it [29, 30]. Meanwhile, some of the works also attempt to combine the different units to develop novel methods, where the state-of-the-art model is BERT-GPT model [31, 32]. However, the existing generative models for medical domain only learn the experience knowledge from the training procedure; few works effectively integrate the medical knowledge with the generative models.

3. Methodology

In this section, we discuss the methodology of MKA, which is a scalable, effective, and lightweight mechanism to integrate the medical knowledge into neural generative models, especially for large-scale pretrained model, such as BERT-GPT.

As shown in Figure 1, our MKA consists of 3 parts, including the medical knowledge generation module, token processor, and neural generative model. The medical knowledge generation module is constituted by medical knowledge subgraph generator, topic detector, and medical knowledge extractor. It is aimed at generating related medical knowledge information tuple. The token processor is proposed to concatenate the medical knowledge information tuple with the dialogue context for each conversation turn. Besides, the neural generative model is leveraged for training and prediction. The details of each module will be illustrated in Sections 3.1, 3.2, and 3.3.

3.1. Medical Knowledge Generation Module. The medical knowledge generation module is proposed to generate the related medical knowledge information when the doctor handles a case. Within the module, there exist three parts, including medical knowledge subgraph generator, topic detector, and medical knowledge extractor. The medical knowledge subgraph generator first takes the patient self-report which contains the department and disease/symptom information described in Section 1 as input and generates the medical knowledge subgraph (MKG\textsubscript{base}) based on a global medical knowledge base (MKG\textsubscript{base}). MKG\textsubscript{base} can be treated as a container which contains all the required medical professional books, while MKG\textsubscript{sub} stores the potential useful medical knowledge related to the specific case. Different questions will be asked in different turns for the multi-turn conversation task. To reduce the redundant information, the topic detector inputs the patient question at the \(n\)th turn and infers what question topic it related to. With the question topic and MKG\textsubscript{sub}, the medical knowledge

| Relation type | Description |
| --- | --- |
| ϵ has disease | Relations between \(\epsilon_{\text{department}}\) entity and \(\epsilon_{\text{disease}}\) entity |
| ϵ has symptom | Relations between \(\epsilon_{\text{disease}}\) and \(\epsilon_{\text{symptom}}\) entity |
| ϵ need drug | Relations between \(\epsilon_{\text{disease}}\) and \(\epsilon_{\text{drug}}\) entity |
| ϵ need check | Relations between \(\epsilon_{\text{disease}}\) and \(\epsilon_{\text{check}}\) entity |
| ϵ need food | Relations between \(\epsilon_{\text{disease}}\) and \(\epsilon_{\text{symptom}}\) entity and \(\epsilon_{\text{food}}\) entity |
| ϵ no food | Relations between \(\epsilon_{\text{disease}}\) and \(\epsilon_{\text{symptom}}\) entity and not recommended \(\epsilon_{\text{food}}\) entity |
Algorithm 1: the generation of the medical knowledge subgraph

Input:
Medical knowledge base $\mathcal{MKG}_{\text{base}} = (\mathcal{E}_b, \mathcal{R}_b, \mathcal{S}_b)$.
Patient self-report PSR. (PSR $\rightarrow$ Department represents the blank for the patient’s ideal clinical department, and PSR $\rightarrow$ Disease/Symptom represents the blank for the description of the patient’s disease or symptom.)

Output:
Medical knowledge subgraph $\mathcal{MKG}_{\text{sub}} = (\mathcal{E}_s, \mathcal{R}_s, \mathcal{S}_s)$

Main:
1: if PSR $\rightarrow$ Department exists then
2: Extract the Info$_1$ from PSR $\rightarrow$ Department.
3: $\epsilon^*_i = \arg\min_{\epsilon} \text{dist}(\text{Info}_1, \epsilon)$, where $\epsilon \in \epsilon_{\text{department}}$ and $\epsilon \in \mathcal{E}_b$.
4: $G_i = (\mathcal{E}_i, \mathcal{R}_i, \mathcal{S}_i)$, where $\forall \{\epsilon_{11}, \epsilon_{12}\} \subset \mathcal{E}_b, \forall \{\epsilon_{11}, \epsilon_{12}\} \subset \mathcal{E}_b, \gamma_{11} = \gamma_{\text{has-disease}}, \gamma_{12} = \gamma_{\text{has-symptom}} \exists \epsilon_{11} = (\epsilon^*_{11}, \gamma_{11}, \epsilon_{11}) \in \mathcal{E}_1, g_{12} = (\epsilon^*_{12}, \gamma_{12}, \epsilon_{12}) \in \mathcal{E}_1$.
5: end if
6: if PSR $\rightarrow$ Disease/Symptom exists then
7: Extract the Info$_2$ from PSR $\rightarrow$ Department/Symptom.
8: $\epsilon^*_i = \arg\min_{\epsilon} \text{dist}(\text{Info}_2, \epsilon)$, where $\epsilon \in (\epsilon_{\text{disease}} \cup \epsilon_{\text{symptom}})$ and $\epsilon \in \mathcal{E}_b$.
9: $G_2 = (\mathcal{E}_2, \mathcal{R}_2, \mathcal{S}_2)$, where $\forall \{\epsilon_{21}, \epsilon_{22}, \epsilon_{23}, \epsilon_{24}\} \subset \mathcal{E}_b, \forall \{\epsilon_{21}, \epsilon_{22}, \epsilon_{23}, \epsilon_{24}\} \subset \mathcal{E}_b, \gamma_{21} = \gamma_{\text{has-disease}}, \gamma_{22} = \gamma_{\text{has-symptom}} \exists \epsilon_{21} = (\epsilon^*_{21}, \gamma_{21}, \epsilon_{21}) \in \mathcal{E}_2, g_{22} = (\epsilon^*_{22}, \gamma_{22}, \epsilon_{22}) \in \mathcal{E}_2, g_{23} = (\epsilon^*_{23}, \gamma_{23}, \epsilon_{23}) \in \mathcal{E}_2, g_{24} = (\epsilon^*_{24}, \gamma_{24}, \epsilon_{24}) \in \mathcal{E}_2$.
10: end if
11: $\mathcal{MKG}_{\text{sub}} = (\mathcal{E}_s, \mathcal{R}_s, \mathcal{S}_s) = (\mathcal{E}_s \cup \mathcal{E}_2, \mathcal{R}_s \cup \mathcal{R}_2, \mathcal{S}_s \cup \mathcal{S}_2) = G_1 \cup G_2$

Algorithm 2: the detection of the question topic

Input:
Key phrase set $\mathcal{KPS} = \{\mathcal{KPS}_d, \mathcal{KPS}_s, \mathcal{KPS}_d, \mathcal{KPS}_s\}$. ($\mathcal{KPS}_d$ is the set for disease topic, $\mathcal{KPS}_s$ is the set for symptom topic, $\mathcal{KPS}_d$ is the set for drug topic, $\mathcal{KPS}_s$ is the set for check topic, $\mathcal{KPS}_d$ is the set for the positive food topic, and $\mathcal{KPS}_s$ is the set for the negative food topic.)

The patient question in $i$th conversation turn $\text{PQ}_i$.

Similarity coefficient $\delta$ for checking whether the phrase is inside of the patient question

Output:
Question topic tuple in $i$th conversation turn $\text{QT}_i$

Main:
1: $\text{QT}_i = \{\}$
2: for $\text{kp}$ in $\mathcal{KPS}_{\text{do}}$
3: $\text{for } \text{kp}$ in $\mathcal{KPS}_{\text{do}}$
4: if $|\text{dist}(\text{PQ}_i, \text{kp}) > \delta|$ then
5: if $\text{kp}$ is $\mathcal{KPS}_d$ then
6: Append the “disease” topic in $\text{QT}_i$
7: else if $\text{kp}$ is $\mathcal{KPS}_s$ then
8: Append the “symptom” topic in $\text{QT}_i$
9: else if $\text{kp}$ is $\mathcal{KPS}_s$ then
10: Append the “drug” topic in $\text{QT}_i$
11: else if $\text{kp}$ is $\mathcal{KPS}_d$ then
12: Append the “check” topic in $\text{QT}_i$
13: else if $\text{kp}$ is $\mathcal{KPS}_d$ then
14: Append the “recommended food” topic in $\text{QT}_i$
15: else if $\text{kp}$ is $\mathcal{KPS}_s$ then
16: Append the “not recommended food” topic in $\text{QT}_i$
17: end if
18: end for
19: end for
Algorithm 3: the extraction of medical knowledge information tuple

Input:
Medical knowledge base MKG_sub = (E_s, R_s, G_s).
Question topic tuple in i-th conversation turn QT_i.
Corresponding ϵ_department and ϵ_disease/ϵ_symptom entities in patient self-report ϵ_1, ϵ_2 → Table 3.

Output:
Medical knowledge information tuple in i-th conversation turn MKI_i.

Main:
1: MKI_i = {ϵ_1, ϵ_2}
2: for q in QT_i do
3: if QT_i = “disease” then
4: Append all ϵ_disease entities except ϵ_2 in MKG_sub to MKI_i
5: else if QT_i = “symptom” then
6: Append all ϵ_symptom entities except ϵ_2 in MKG_sub to MKI_i
7: else if QT_i = “drug” then
8: Append all ϵ_drug entities in MKG_sub to MKI_i
9: else if QT_i = “check” then
10: Append all ϵ_check entities in MKG_sub to MKI_i
11: else if QT_i = “recommended food” then
12: Append all ϵ_food entities connected with γ_need−food relation in MKG_sub to MKI_i
13: else if QT_i = “not recommended food” then
14: Append all ϵ_food entities connected with γ_no−food relation in MKG_sub to MKI_i
15: end if
16: end for

Algorithm 3: Pseudocode of the medical knowledge extractor.

Table 3: Comparison of the models on MedDialog-CN, where the best results are in bold.

| Model        | Dialog-GPT | Transformer | BERT-GPT | MKA-Transformer | MKA-BERT-GPT |
|--------------|------------|-------------|----------|-----------------|--------------|
| Perplexity   | 9.71       | 9.52        | 8.23     | 8.81            | 8.04         |
| BLEU-2       | 5.21%      | 4.92%       | 4.88%    | 5.02%           | 5.71%        |
| BLEU-4       | 1.83%      | 0.90%       | 0.97%    | 0.99%           | 1.35%        |
| NIST-2       | 0.36       | 0.42        | 0.40     | 0.43            | 0.44         |
| NIST-4       | 0.32       | 0.40        | 0.39     | 0.40            | 0.43         |
| METEOR       | 12.32%     | 13.11%      | 12.83%   | 13.4%           | 13.94%       |
| Entropy-4    | 13.73      | 13.51       | 13.8     | 13.72           | 14.1         |
| Dist-1       | 0.02%      | 0.03%       | 0.03%    | 0.03%           | 0.04%        |
| Dist-2       | 2.01%      | 2.02%       | 2.14%    | 2.11%           | 2.22%        |

The extractor will extract the related medical knowledge information tuple. The details of each part will be shown as follows.

3.1.1. Medical Knowledge Subgraph Generator. Within the medical knowledge subgraph generator, the medical knowledge subbase can be generated from the medical knowledge base based on the medical-related information extracted from patient self-report. In this paper, the knowledge base is represented the knowledge graph (KG), which is constituted by entities and relations. Besides, it is formally defined as below:

\[
KG = (\mathcal{E}, \mathcal{R}, \mathcal{G} = \mathcal{E} \times \mathcal{R} \times \mathcal{E}),
\]

where \(\mathcal{E}\) represents the set of entities (e.g., persons), \(\mathcal{R}\) represents the considered types of relations between entities (e.g., friendship between persons), and \(\mathcal{G}\) is a set of 3-element fact tuples where each tuple represents a factual relation between two entities.

Therefore, two kinds of the medical knowledge graph (MKG) are proposed, including the medical knowledge base (MKG_base) generated based on [33] by removing the redundant information and medical knowledge subgraph (MKG_sub). Both MKG_base and MKG_sub contain 6 types of entities and 6 types of relations as shown in Tables 1 and 2. The entity and relation types are decided based on the working experiences of the author for the common medical conversation topics.
Table 4: Comparison of the models on MedDG, where the best results are in bold.

| Model               | Dialog-GPT | Transformer | BERT-GPT | MKA-Transformer | MKA-BERT-GPT |
|---------------------|------------|------------|----------|-----------------|--------------|
| Perplexity          | 8.53       | 8.52       | 5.98     | 8.41            | 5.95         |
| BLEU-2              | 6.41%      | 6.30%      | 7.62%    | 6.62%           | 8.09%        |
| BLEU-4              | 2.12%      | 2.08%      | 2.57%    | 2.40%           | 2.87%        |
| NIST-2              | 0.38       | 0.37       | 0.42     | 0.39            | 0.43         |
| NIST-4              | 0.35       | 0.35       | 0.39     | 0.38            | 0.41         |
| METEOR              | 13.78%     | 14.32%     | 16.25%   | 14.88%          | 16.63%       |
| Entropy-4           | 10.56      | 10.17      | 13.38    | 10.28           | 13.37        |
| Dist-1              | 0.01%      | 0.01%      | 0.02%    | 0.01%           | 0.02%        |
| Dist-2              | 1.72%      | 1.67%      | 2.00%    | 1.69%           | 2.00%        |

Table 5: Improvements of the models with MKA compared to the baseline model on MedDialog-CN and MedDG test sets.

| Dataset        | Model               | Perplexity | BLEU-2,4 | NIST-2,4 | METEOR | Entropy-4 | Dist-1,2 |
|----------------|---------------------|------------|----------|----------|--------|-----------|----------|
| MedDialog-CN   | MKA-Transformer     | -0.71      | 0.10%    | 0.09%    | 0.01   | 0.29%     | 0.21     |
|                | MKA-BERT-GPT        | -0.19      | 0.83%    | 0.38%    | 0.04   | 1.11%     | 0.3      |
| MedDG          | MKA-Transformer     | -0.11      | 0.32%    | 0.32%    | 0.02   | 0.56%     | 0.11     |
|                | MKA-BERT-GPT        | -0.03      | 0.47%    | 0.30%    | 0.01   | 0.38%     | -0.01    |

According to the definition of the entity and relation types, MKGbase contains 26910 entities (i.e., 54 $e_{\text{department}}$, 8807 $e_{\text{disease}}$, 5998 $e_{\text{symptom}}$, 4870 $e_{\text{food}}$, 3353 $e_{\text{check}}$, and 3828 $e_{\text{drug}}$) and 158216 fact tuples regarding the different relations (i.e., 8844 $\gamma_{\text{has-disease}}$, 5998 $\gamma_{\text{has-symptom}}$, 59467 $\gamma_{\text{need-drug}}$, 39422 $\gamma_{\text{need-check}}$, 22238 $\gamma_{\text{need-food}}$, and 22247 $\gamma_{\text{no-food}}$).

As for MKGsub, it is specific for each case, which is generated based on Algorithm 1. Within the algorithm, two subgraphs, $G_1$ and $G_2$, are extracted from MKGbase to constitute MKGsub. $G_1$ is the graph with the $e_{\text{department}}$ type entity $\epsilon_1$ as the root. Besides, it only contains $\gamma_{\text{has-disease}}$ and $\gamma_{\text{has-symptom}}$ two types of relations. $G_2$ is the graph with the $e_{\text{symptom}}$ type entity $\epsilon_2$ as the root. Besides, it may contain all kinds of types of relations except $\gamma_{\text{has-disease}}$. For more details, see Algorithm 1.

Meanwhile, it is worth noting that we propose a way to calculate the distance for entity matching as shown in

$$\text{dist}(u, v) = [\alpha, \beta] \times \left[ \frac{\text{dist}_{\text{Levenshtein}}(u, v)}{\text{dist}_{\text{Hamming}}(u, v)} \right],$$

(2)

where $\alpha$ and $\beta$ are two hyperparameters. The distance takes advantage of both the Hamming distance [34] and Levenshtein distance [35]. It can not only care about the meaning of the tokens like the Hamming distance but also the position of the tokens like Levenshtein distance.

3.1.2. Topic Detector. The medical knowledge is related to what medical topic the patient asks. As a preparation for medical knowledge extractor, the question topic should be determined first. The content in the topic set matches with the relation set (i.e., disease, symptom, drug, check, positive food, and negative food). Besides, the six key phrase sets (KPS) are built corresponding to six topics based on the users’ experiences. It consists of some specific phrases related to the question topic. Based on it, the question detector is proposed as shown in Algorithm 2.

3.1.3. Medical Knowledge Extractor. The medical knowledge extractor is aimed at extracting the related medical knowledge information tuples based on question topic and medical knowledge subgraph from the previous two parts. It extracts all entities with the specific entity type and connected with specific relation type in the subgraph. Besides, $\epsilon_1^*, \epsilon_2^*$ extracted from patient self-report will be directly appended into the tuple, since they are also useful medical knowledge extracted from the source. The details are shown in Algorithm 3.

3.2. Token Processor. Compared to general neural generative models just taking dialogue contexts as inputs, our model generates the related medical knowledge information tuple which will be also fed into the models. To achieve this goal, a token processor is proposed to reorganize the tokens based on the policy shown in

$$X = \text{MKI}_i \oplus \text{DR}_{i-1} \oplus \text{PSR}_i \oplus [\text{MKG}_{\text{sub}}, \text{Unseen Features}] \oplus [\text{PSR Seen Features}] \oplus \text{DR}_{i-1} \oplus \text{PQ}_i$$

$$= [\text{All the elements in MKI}_i, \text{except } \epsilon_1^* \text{ and } \epsilon_2^*] \oplus [\epsilon_1^* \oplus \epsilon_2^*] \oplus \text{DR}_{i-1} \oplus \text{PQ}_i,$$

(3)

where $X$ represents the sequence for neural generative models and PSR represents patient self-report. MKI$_i$, DR$_{i-1}$, and PQ,
Table 6: An example of generated responses on the MedDialog-CN test set.

| Patient self-report | 科室 department: 男科 andrology 疾病/症状 disease/symptom: 静脉静脉曲张 varicose veins |
|---------------------|--------------------------------------------------------------------------|
| Patient question 1  | 我很怕是高位结扎手术引起的阴囊炎，希望大夫能给我思量是怎么回事，该怎么处理？ |
| Ground truth        | 中医药调理。 You can recuperate yourself with Chinese medicine. |
| Dialog-GPT          | 手术部位不会引发阴囊炎。 The surgical part does not cause epididymitis. |
| Transformer         | 可能是近期没有充分休息，免疫力下降。建议早点休息。 |
| Doctor response 1   | 你可能没有充足的休息，导致免疫力下降。 It is recommended to sleep early. |
| BERT-GPT            | 不要趴着睡觉，影响伤口恢复。建议多休息。 |
| MKA-Transformer     | 可以吃营养的健康食品，比如西兰花，鸡蛋等，同时注重卫生清洁，每晚可以热敷缓解疼痛。 |
| MKA-BERT-GPT        | 你吃营养的健康食品，比如西兰花，鸡蛋等，同时注重卫生清洁，每晚可以热敷缓解疼痛。 |
| Patient question 2  | 我是这阴囊炎吧？或者什么？恳请大夫给我指点！感谢！ |
| Doctor response 2   | 请问医生这是阴囊炎吗？或者是？恳请大夫您为我指点！感谢！ |
| Ground truth        | 局部气血不畅。 The flow of the blood and qi in the local area is not that smooth. |
| Dialog-GPT          | 放心，只是心理作用。 Relax, it is just a psychological effect. |
| Transformer         | 只是术后伤口疼痛。 |
| BERT-GPT            | 它是术后伤口疼痛。 |
| MKA-Transformer     | 可能是运动过量导致提睾肌过度收缩，导致疼痛。 |
| MKA-BERT-GPT        | 血流不畅。建议过几天复查伤口恢复情况，减轻心理负担。 |

represent the medical knowledge information tuple in the $i$th conversation turn, the doctor response in $i−1$th conversation turn, and the patient question in $i$th conversation turn separately. Besides, $ε^*_1$ and $ε^*_2$ are corresponding $ε_{\text{department}}$ and $ε_{\text{disease}/ε_{\text{symptom}}}$ entities generated in Algorithm 1.

3.3. Neural Generative Model. In this paper, the neural generative model takes a source sequence $X = (x_1, x_2, x_3, \cdots, x_T)$ consisting of $T$ tokens generated from Section 3.2 and generates the response $Y = (y_1, y_2, y_3, \cdots, y_{T'})$ of length $T'$ tokens. In general, the model maximizes the generation probability of $Y$ conditioned on $X : p(y_1, y_2, y_3, \cdots, y_{T'} | x_1, x_2, x_3, \cdots, x_T)$ [8], and the objective function of the sequence-to-sequence generative models is defined as below. Besides, as for the multiturn conversation tasks, the doctor response at $i$th turn will be fed into the model as the existing dialogue context for next turn.

$$p(y_1, \cdots, y_{T'} \mid x_1, \cdots, x_T) = p(y_1 \mid x_1, \cdots, x_T) \prod_{t=2}^{T'} p(y_t \mid x_1, \cdots, x_{T'}, y_1, \cdots, y_{t-1}).$$

4. Experiments

4.1. Experiment Settings. Our approach is implemented in Python 3.7 and PyTorch 1.4.0. We implement two MKA-Diagen models, including MKA-Transformer and MKA-
### Table 7: An example of generated responses on the MedDG test set.

| Patient self-report | Ground truth | Dialog-GPT | Transformer | BERT-GPT | MKA-Transformer | MKA-BERT-GPT |
|---------------------|--------------|-------------|-------------|----------|----------------|--------------|
| 医生你好，最近我大便总是很干燥，而且有好几次大便之后，发现有血，我这个是什么情况? | 你好，可能存在痔疮出血!但还是建议您做个肠镜! | Hello, there may be bleeding from hemorrhoids! But it is still recommended that you have a colonoscopy! | 你好，这种情况容易出现内痔 | 你好，可能存在痔疮，大便干结多久了？ | 你好，可能是痔疮，建议您做个肠镜。 | 你好，可能痔疮出血，此外，建议您做个肠镜。 |
| 医生你好，最近我大便总是很干燥，而且有好几次大便之后，发现有血，我这个是什么情况? | 大便干结是功能性问题，建议您多吃水果蔬菜，养成排便习惯! | The dry stool is a functional problem. It is recommended that you eat more fruits and vegetables to develop a bowel habit! | 你好，可能存在痔疮。 | Hello, there may be hemorrhoids, and how long have the stools been dry and clumpy? | 你好，可能痔疮，建议做个肠镜。 | Hello, it may be hemorrhoids. It is recommended that you have a colonoscopy. |
| 医生你好，最近我大便总是很干燥，而且有好几次大便之后，发现有血，我这个是什么情况? | 你好，可能痔疮出血，此外，建议您做个肠镜。 | Pay attention to your diet and eat more fruits and vegetables. | 你好，可能存在痔疮。 | 你好，可能痔疮。 | 你好，可能痔疮。 | Hello, it may be hemorrhoids. It is recommended that you have a colonoscopy. |
| 医生你好，最近我大便总是很干燥，而且有好几次大便之后，发现有血，我这个是什么情况? | 你好，可能痔疮出血，此外，建议您做个肠镜。 | It is considered as a gastrointestinal disorder. It is recommended that you eat more fruits and vegetables, like apples. | It is recommended that you eat more fruits and vegetables. | It is considered as a gastrointestinal dysfunction. It is recommended that you eat more fruits and vegetables, like apples. | It is considered as a gastrointestinal disorder. It is recommended that you eat more fruits and vegetables, like apples. | It is considered as a gastrointestinal dysfunction. It is recommended that you eat more fruits and vegetables, like apples. |

BERT-GPT. The neural generative models within them are trained with the default parameters in [11, 25]. The hyperparameters $\alpha$ and $\beta$ in Equation (2) are set as 0.1 and -1, and the hyperparameter $\delta$ is set as 0.7. We perform all the experiments on the Matpool server with 11 GB NVIDIA GeForce RTX 2080 Ti. Our experiments were performed on Chinese MedDialog dataset [11] and MedDG [12] with the ratio 0.8:0.1:0.1 of training set: validation set: test set.

The MKA-Transformer and MKA-BERT-GPT were compared with the baseline models (i.e., Transformer and BERT-GPT) and another typical nonsequence to sequence GPT-based model [11]. We followed the automatic evaluation metrics on the datasets to evaluate the performance of our method, including perplexity, NIST-2,4 [36], BLEU-2,4 [37], METEOR [38], Entropy-4 [39], and Dist-1,2 [40]. The perplexity shows the language quality of the generated responses. NIST-n, BLEU-n, and METEOR measure the similarity between the generated responses and ground truth and Entropy-n and Dist-n measure the lexical diversity of generated responses based on n-gram matching. The model with better performance will have the lower value of perplexity, the higher value of the other metrics.

4.2. Experiment Results and Analysis. In this part, the experiment results are shown together with the in-depth analysis of the results. Tables 3 and 4 show the performance on the MedDialog-CN test set and MedDG test set separately. From the tables, we make the following observations.

4.2.1. Ablation Analysis. Focusing on the comparison between MKA-Transformer and Transformer and the performance comparison between MKA-BERT-GPT and BERT-GPT, it is easy to extract Table 5. It is easy to observe that our mechanism improves the performance from all aspects on both datasets. It means that our method is
effective and scalable to be applied to different neural generative models and different datasets.

4.2.2. Performance Comparison Analysis. Compared to the current state-of-the-art models, our MKA-BERT-GPT outperforms all the other methods. It achieves the lowest perplexity. It is because its baseline generative model, BERT-GPT, is pretrained on a large collection of corpora before training on the medical specific datasets. The pertaining procedure helps it to better understand the linguistic structure among words; meanwhile, the medical knowledge-assisted mechanism enables the model more learnable for medical conversation task. Meanwhile, as for the machine translation metrics (i.e., NIST-4, BLEU-2, BLEU-4, and METEOR), the performance of the MKA-BERT-GPT also is the best. It even overturns the performance comparison between BERT-GPT and Transformer. It indicates that our method highly improves the overlap between the generated response and the ground truth. Besides, although the MKA-BERT-GPT improves the value on diversity metrics (i.e., Entropy and Dist), the improvement is still minor. It indicates that our model cannot make a big breakthrough on the capability in generating diverse responses.

4.2.3. Case Study Analysis. Tables 6 and 7 represent the generated response of the models on two examples in the MedDialog-CN and MedDG test set. Since the dataset contains some Chinese medical dialogues, the translation is provided as well as the raw contents. The response generated by MKA-BERT-GPT is clinically informative and accurate. It prescribes “gastrointestinal functional problem.” Meanwhile, it can offer the detailed suggestions with rich medical knowledge information such as what kind of vegetables and fruits is recommended. Besides, the language quality of all the models is great, since all the responses are readable. Besides, there are still some spaces for the further improvement. For example, the responses generated from the models are not that overlap with the ground truth. It is because the ground truth is a Chinese medical response, which contains the concept of “qi,” which is not that easy for a general model to understand and provide the response. However, the responses of MKA-BERT-GPT are still relatively reasonable and also mention the conclusion of “the blood flow is not smooth.”

5. Conclusions
In this paper, we propose a scalable medical knowledge-assisted mechanism (MKA) to assist general neural generative models, especially the large-scale pretrained model, such as BERT-GPT, to achieve better performance on the medical conversation task. The mechanism introduces a medical specific knowledge graph, which contains 6 types of medical-related information, including department, drug, check, symptom, disease, and food. Besides, it also leverages the specific designed token concatenation policy and neural generative models. The promising experiment results have proven our mechanism is effective and scalable to different generative models on different medical conversation data-sets. Besides, it also shows that MKA-BERT-GPT has achieved the state-of-the-art performance based on multiple automatic evaluation metrics compared to other existing models. In the future, we plan to apply the graph neural networks to extract and predict the related medical knowledge based on the medical knowledge base. Besides, it is also worthwhile to carry out the research on leveraging the advantages of both information retrieve methods and the neural generative methods to build a powerful dialogue generation system.

Data Availability
The data used to support the findings of this study are included in the article.

Conflicts of Interest
The authors declare that they have no competing interest.

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