Formalization and computation of diabetes quality indicators with patient data from a Chinese hospital

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Abstract. Clinical quality indicators are tools to measure the quality of healthcare and can be classified into structure-related, process-related and outcome-related indicators. The objective of this study is to investigate whether the electronic medical record (EMR) data from a Chinese diabetes specialty hospital can be used for the automated computation of a set of 38 diabetes quality indicators, especially process-related indicators. The clinical quality indicator formalization (CLIF) tool and SNOMED CT were adopted to formalize diabetes indicators into executable queries. The formalized indicators were run on the patient data to test the feasibility of their automated computation. In this study, we successfully formalized and computed 32 of 38 quality indicators based on the EMR data. The results indicate that the data from our Chinese EMR can be used for the formalization and computation of most diabetes indicators, but that it can be improved to support the computation of more indicators.

Keywords: diabetes mellitus, clinical quality, quality indicators, electronic medical record, formalization, secondary use of patient data

1 Introduction

Clinical quality indicators are tools to evaluate the quality of healthcare services and the performance of hospitals. The most widely adopted classification system for quality indicators has been proposed by Donabedian [1]. In his classification, indicators are distinguished into structure-related, process-related and outcome-related indicators. Structure denotes the attributes of the settings in which care occurs, process denotes what is actually done in giving and receiving care and outcome denotes the effects of care on the health status of patients and populations.

In the background of China's health reform, healthcare quality is affected by the implementation of different health policies, such as the reconstruction of healthcare organizations and workflow improvements, the adjustment of the reimbursement strategy and the innovation of diagnosis and treatment techniques. Therefore, the assessment of healthcare quality is drawing much attention. In China, clinical indicators released by the government are widely adopted among hospitals. These indicators usually aim at the overall quality of a hospital and are mainly structure-related and outcome-related indicators, which are used for the rating of hospitals and performance assessment.

In 2011, Dentler [2] proposed a method to formalize clinical quality indicators. The method consists of 9 steps to formalize any clinical indicator into a computer-interpretable query. Based on this method, Dentler [3,4] also developed the clinical quality indicator formalization tool (CLIF) which was adopted to formalize 159 quality indicators to be computed on Dutch patient data. Our aim for this study is to assess the feasibility of the formalization and computation of diabetes quality indicators based on Chinese patient data.

2 Materials and Methods

2.1 Quality Indicators

As Chinese clinical indicators are mostly structure-related and outcome-related with a lack of process-related indicators, we use the same diabetes indicator set as used in Dentler's research [2], which has been released by the Dutch Healthcare Inspectorate in 2011. The indicator set contains 38 indicators in total, of which 23 are process-related, 10 are outcome-related and the other 5 are demographic indicators. A list of the indicators can be seen in Table 1.

Table 1: Set of diabetes indicators

ID	Definition	Type
I1	known diabetes patients in the practice population at the end of the reporting period	n.a.
I2	type 1 diabetes patients of all known diabetes patients in the practice population at the end of the reporting period	n.a.
I3	type 2 diabetes patients of all known in the practice population at the end of the reporting period	n.a.
I4	diabetes patients who are treated in primary care in the practice population at the end of the reporting period	n.a.
I5	diabetes patients who are treated in primary care and are enrolled for 12 months or longer at the end of the reporting period	n.a.
I6	diabetes patients whose HbA1c has been determined in the last 12 months	process

I8	diabetes patients with HbA1c below 53 mmol/mol (< 53)	outcome
I10	diabetes patients with HbA1c above 69 mmol/mol (> 69)	outcome
I11	diabetes patients whose blood pressure has been determined in the past 12 months	process
I13	diabetes patients with systolic blood pressure of 140 mmHg or lower (≤ 140)	outcome
I16	diabetes patients whose lipid profile (total cholesterol and triglycerides and HDL and LDL) has been determined	process
I17	diabetes patients with total cholesterol value of less than 4.5 mmol/L (< 4.5)	outcome
I18	diabetes patients with LDL-cholesterol value of less than 2.5 mmol/L (< 2.5)	outcome
I19	diabetes patients using a lipid-lowering drug (e.g. statins)	process
I20	diabetes patients whose eGFR was calculated or determined in the past 12 months	process
I23	diabetes patients with eGFR between 60 ml/min (< 60) and 30 (≥ 30)	outcome
I24	diabetes patients with eGFR less than 30 ml/min (< 30)	outcome
I25	diabetes patients with urinalysis (portions) of albumin or albumin / creatinine ratio in the past 12 months	process
I27	diabetes patients whose smoking status was known	process
I28	patients who smoke in the group of patients whose smoking status was known	process
I30	patients who received over the past 12 months advice to quit smoking in the group of patients who smoke	process
I31	diabetes patients whose body mass index has been calculated (known) in the last 12 months	process
I33	diabetes patients whose body mass index less than 25 (< 25)	outcome
I36	diabetes patients whose diet has been discussed in the past 12 months	process
I37	diabetes patients whose alcohol consumption has been registered in the last five years	process

I38	diabetes patients whose physical activity levels has been recorded in the past 12 months	process
I39	diabetes patients with foot examination in the past 12 months	process
I40	diabetes patients with a record of Simm's classification of foot examination	process
I41	patients with diabetic foot abnormalities (abnormal findings at last check)	outcome
I42	diabetes patients with fundus check in the past 24 months	process
I43	diabetes patients with diabetic retinopathy	outcome
I44	patients with only non-medication treatment (lifestyle and/or diet)	process
I45	patients medically treated only with oral antidiabetics	process
I46	patients treated medically with oral antidiabetics and insulin	process
I47	patients medically treated only with insulin	process
I48	patients diagnosed with DM-2 and BMI ≥ 25 who are prescribed metformin (denominator: patients with DM-2 and BMI ≥ 25)	process
I49	patients vaccinated against influenza in the previous 12 months	process
I50	patients with the combination of data on the aforementioned process indicators (HbA1c, blood pressure, lipid profile, kidney function, smoking status, BMI, foot examinations and eye examinations)	process

2.2 Patient Data

We use patient data from an EMR system of a diabetes specialty hospital in China. The EMR adopted in the hospital is consistent with the Chinese EMR data standard, which is adopted by many hospitals in China. For our study, we selected only diabetes patients (major diagnosis or secondary diagnosis). The data set ranges from the year 2010 to the year 2014 and contains 9,094 patients in total. For our computation, we used only patient data of 2013 and 2014, as it was more complete and of higher quality. The original data set is divided into 5 different tables: the diagnosis table, the patient table which mainly contains the admission records, the laboratory test table, the physical examination/imaging table and the treatment table. We applied the following processing: (1) Deleted irrelevant data fields from the tables. (2) Inserted the fields of SNOMED CT codes in every table except the "patient" table. For the diagnosis table, the SNOMED CT mappings were used to automatically map the ICD-10 diagnosis codes to SNOMED CT codes. For the other three tables, the mappings were conducted manually. The database schema can be seen in Figure 1 (omitting some date fields). (3) In the "patient" table, the personal history is stored in the form of text which contains the smoking history, drinking history and injury history. We used a small natural language processing program to extract the information about smoking history and inserted a structured data field to represent the smoking history. The NLP program has previously been validated with sample data from this study and demonstrated a precision of 97% and recall rate of 65%.

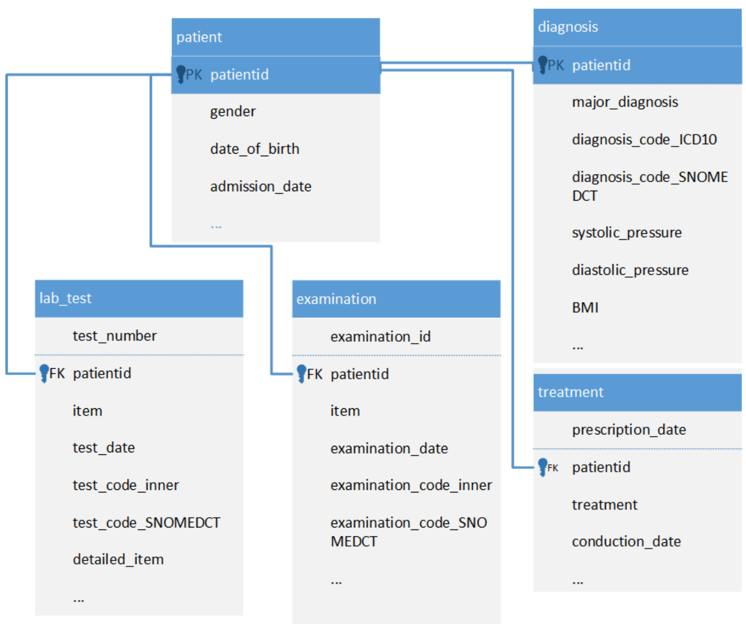

Fig. 1. The database schema of the patients database

2.3 CLIF tool

The CLIF tool was developed by Dentler et al. and is publicly available. The main idea behind the CLIF tool is to divide the formalization of clinical quality indicators into 9 steps [2]. The 9 steps enable a way to represent the knowledge in clinical quality indicators. All steps together with an example based on indicator I6 (HbA1c measured) are detailed in Table 2.

Table 2. The 9 steps of CLIF

Nr.	Step	Definition	An example based on indicator 6
1.	Concepts	Extract relevant concepts based on a terminology	Two SNOMED CT concepts were extracted for the example indicator: diabetes (73211009) and HbA1c measurement (43396009)
2.	Information model	Bind the concepts to the specific data fields of the patient data	The concept of diabetes was mapped to the table of diagnosis as diagnosis.diagnosis_code_SNOMEDCT = 73211009, and the concept of HbA1c measurement was mapped to the table of laboratory test as lab_test.test_code_SNOMEDCT = 43396009
3.	Temporal constraints	Extract temporal constraints from the indicator	The temporal constraints contain the reporting year, HbA1c measurement date and patients birthday (age <80)
4.-6.	Numeric, Boolean and textual constraints	Extract numeric, Boolean and textual constraints from the indicator	No constraint in the example indicator
7.	Grouping of constraints	Group and combine the constraints with Boolean connectors	All constraints were connected by "AND"
8.	Exclusion criteria	Identify the exclusion criteria from the constrains defined in previous steps	No constraint was an exclusion criterion
9.	Numerator	Identify the constraints which only aim at the numerator	Laboratory test code and HbA1c measurement date

The CLIF tool is programmed in PHP and can be connected to a local database to formalize indicators and compute their results. Some modifications were made to the original CLIF tool to suit this study: (1) adjusting the code to fit the requirements of processing Chinese characters; (2) adjusting the database connection to fit the data structure of the patient database. Both the modified CLIF tool and its source code are publicly available[1].

2.4 Evaluation

We adopted three different methods to evaluate our results. Firstly, the computed results were analyzed based on widely adopted Chinese clinical guidelines to see if there were obviously erroneous results. Subsequently, the formalization and computation results were compared with Dentler's original results based on Dutch patient data to see if they were correlated. Finally, an endocrinologist expert review was conducted to assess the accuracy of the computed results. The endocrinologist was informed of the patient data source and the definitions of each indicator. He was then provided with the computed results and was asked to judge by his clinical experience whether the results are accurate or not. For inaccurate results, possible factors which may lead to bias were discussed among the expert and the authors.

3 Results

3.1 Formalization of the indicators

All indicators can be formalized based on an arbitrary patient database structure. However, based on the real patient data structure, 6 of our 38 indicators can not be formalized, namely I5, I30, I36 to I38 and I40. Of these indicators, I5 involves the enrollment of patients, while the EMR did not have a corresponding data field to store this information. I30 is about the patients who received advice to quit smoking, this kind of information can not be classified as laboratory test or examination and there is no specific data field in the patient table to store this information in the EMR. Therefore, the formalization stopped at step 2 (definition of the information model). Similar problems occurred for indicator I36 (diet discussion of the patients), I37 (alcohol consumption registration), I38 (physical activity levels recording) and I40 (recording of Simm's classification of foot examination).

SNOMED CT concepts used In Dentler's study, different coding systems were adopted to represent the concepts, such as the International Classification of Primary Care (ICPT) for diagnosis-related concepts, Anatomical Therapeutic Chemical (ATC) for medication-related concepts and a Dutch national coding

[1] `http://cliftool.org/`
`https://github.com/LiuHaitong/CLIF2`

system for laboratory concepts. In this study, only SNOMED CT codes were used to represent all the concepts of diagnosis, laboratory test, examination and treatment. The diagnosis concepts in the patient data were automatically mapped from ICD-10 codes and other concepts were mapped manually from internal codes of the hospital or from text. A summary of the concepts used in this study is shown in Table 3. An advantage of SNOMED CT is that it can be used to "bridge" concepts that occur in the patient data and typically higher-level concepts that occur in indicators via its subclass hierarchy.

Table 3. Number of SNOMED CT concepts used in this study

Category	In patient data	In formalized indicators
diagnosis-related	110	3
laboratory test-related	48	4
examination-related	17	3
treatment-related	187	6
other	0	2

3.2 Computed results of the indicators

All formalized indicators were run in the CLIF tool to compute their results. Based on the patient data of 2013 and 2014, some indicators return no patient, which may be due to absent data or because there is indeed no patient satisfying the indicator. A comparison of the results between 2013 and 2014 can be seen in Figure 2. The results represent the percentage of patients who satisfy the respective indicator. Most of the results between 2013 and 2014 were similar.

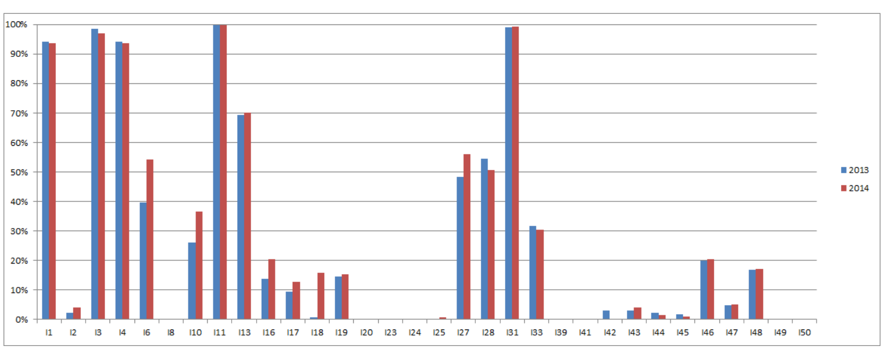

Fig. 2. A comparison of the computation results of 2013 and 2014

3.3 Analysis and evaluation of the results

An analysis based on guidelines
Even though Chinese hospitals implement different clinical guidelines for the management of diabetes patients, there are still some widely adopted guidelines in Chinese hospitals. Based on these, we can interpret the computed results and the clinical quality.

(1) HbA1c measurement.
In Chinese hospitals it is recommended to measure the HbA1c of all admitted patients as it reflects the seriousness of the patients' condition during admission. However, the main treatment plan is developed based on the value of blood glucose, not the HbA1c. The computed results of I6 (patients with measured HbA1c) indicated that about 54 patients had HbA1c measured, which means that the quality is not satisfying. For all the patients with HbA1c measured, no patient had a value of < 53 mmol/L while more than half had a value of > 69mmol/L, which means that most patients were in a serious condition during their admission.

(2) Lipids profile measurement.
Chinese guidelines recommend to measure the lipids profile for all patients and the core goal of lipids control is to lower the LDL cholesterol level to less than 2.6 mmol/L. The computed results indicated that most patients' blood cholesterol is well controlled, for example, in 2014, 100 of 154 patients had a total cholesterol < 4.5 mmol/L and 120 of 122 had a LDL cholesterol < 2.5 mmol/L. This may also be the reason why few patients were prescribed anti-lipids drugs (I19).

(3) Other laboratory tests.
The three indicators about the calculation of estimated glomerular filtration rate (eGFR) (I20, I23, I24) return no patient, as the calculation of eGFR is usually not recorded in EMRs. The urinalysis indicator (I25) returns a few patients, indicating that few patients got urinalysis, which is also not a required measurement based on Chinese guidelines.

(4) Examinations indicators.
The computation results indicated that no patient received foot examination or fundus check and only a small percentage of patients have been recorded with foot or eye complications, which may not reflect the reality. As the authors know, the examinations of foot and eye are common for diabetes patients in Chinese hospitals but these examinations are usually not recorded in the EMRs, as the EMRs are mostly used to store imaging information, not physical examinations information.

(5) Treatment indicators.
The treatment indicators classified the treatment into non-medication treatment, insulin treatment and oral anti-diabetic drugs. 467 patients of 2013 and 346

patients of 2014 were recorded with treatment. A small percentage of the patients was treated with only non-medication treatment, only insulin and only oral anti-diabetic drugs. In Chinese guidelines, insulin is recommended to be adopted when non-medication treatments are not adequate to achieve the blood glucose control goal. Also, insulin is recommended to be used in combination with oral anti-diabetic drugs to improve the therapeutic effects and avoid adverse effects of insulin-only treatment, such as hypoglycemia and body weight gain. The computed results indicated that most of the patients with recorded treatment data were prescribed insulin plus oral anti-diabetic drugs, which is in accordance with the guidelines.

Comparison with Dentler's results
The computed results of this study were compared with Dentler's results to test their correlation. The results were not correlated. In Dentler's study, data was collected from primary context, whereas this study used data from a hospital, which usually receives patients in more serious conditions. Besides, Chinese hospitals and Dutch hospitals may adopt different clinical guidelines, which also may contribute to the differences between the results.

Expert review
The expert detected some computed results which were obviously lower than expected, including for foot examination (I39), fundus examination (I42) and eGFR calculation (I20, I23, I24). According to the expert's experience, these examinations are very common among diabetes patients during their admission to hospitals, but the procedures are usually not recorded in the EMR, which may be the reason why these indicators appeared lower.

The expert also considered that patients treated with anti-diabetic drugs seemed lower than expected (I45, I46, I47). After a detailed analysis of the treatment data, we found that quite a lot of patients were treated with Chinese traditional medicine, which can not be classified as oral anti-diabetic drugs, insulin or lifestyle adjustment in SNOMED CT, which lowered this result. The other computation results were basically accurate based on the expert's review.

4 Discussion

Our results indicated that the automated computation of diabetes indicators in Chinese hospitals is feasible to some degree, especially for the outcome-related indicators. This study also indicated that the Chinese EMR data structure can still be improved to better support the formalization of process-related indicators. This study detected some factors about the EMR data impeding the automated computation of indicators.

5 Conclusions

Firstly, The EMR patient data is acute disease-oriented. The EMR is suitable for the collection and storage of acute disease data, not the information about chronic care. For example, the examination of the patients stored in the table of examination are mostly about imaging. So when we want to find the patients with diabetic foot examinations and fundus checks, the query does not return any patient. Also, the treatment data mainly recorded the medication and surgeries of the patients and does not contain details about lifestyle therapy and exercise.

Besides, we found a lack in data standards. In most Chinese hospitals, diagnoses are coded with ICD-10, and surgery procedures are coded with ICD-9, while other data fields such as lab test and physical examination are usually coded by internal hospital codes or not coded at all. The internal codes are usually rough and cannot represent the relations between different codes, which impede greatly the computation of some indicators, especially process-related indicators.

The EMR data quality also influenced the accuracy of the computed results, especially missing and erroneous data. For example, the foot examination and eye examination data are both not recorded in the EMR, which leads to the fact that the computation of corresponding indicators does not return any patient.

To better support the computation of clinical indicators based on EMRs, some measures must be implemented to improve the EMR structure and data quality. An effective way is to adopt more terminology codes or data standards. The adoption of formal terminology codes such as SNOMED CT or data coding standards are both ways to improve the computability of clinical quality indicators. It will reduce the cost of manual transformation and increase the accuracy of the computation results. Medical ontologies are better than data standards as they contain the relationships of different concepts and are suitable for the computation of process-related indicators.

Another way is to increase the structure degree of the EMR. Chinese EMR data contains some unstructured or semi-structured data fields, such as free text. The unstructured data brought some inconvenience for the computation of clinical indicators. For example, in this study, NLP methods were used to extract information concerning smoking history from the field of personal history, which includes smoking history as well as drinking history and injury history and is stored in the form of free text. Transferring these unstructured and semi-structured data fields to structured data fields is an effective way to improve the feasibility of computing clinical quality indicators.

6 Related Work

Ontologies are important tools in the field of knowledge representation (KR). The adoption of ontologies for the representation of clinical indicators is highly related to the representation of clinical guidelines [5]. Clinical guidelines and clinical quality indicators have much in common, for example they all involve the measurement of physiological data and time-sensitive data. Therefore, early research about the formalization of indicators focused on the mining of common features of different indicators and the construction of indicator ontologies. Beyan [6] constructed an indicator ontology to model clinical indicators, based on which he developed an indicator search system. Surjan [7] developed a public health clinical indicator ontology based on the 19 public health indicators released by WHO, which improved the comparability of different indicators to some degree. The studies above all constructed indicator ontologies, which focused on the modeling of different dimensions of quality indicators and were used to enable convenient retrieval from indicator databases. In contrast, Dentler's [2] study focused on the formalization of the indicators' content, such as the extraction of concepts and relations, which were used for the computation of indicators.

The research of automated computation of clinical indicators is strongly related to the development of healthcare informatics. Early research about the automated computation of clinical indicators mainly focused on the automated collection of patient data and the specific algorithm, which emphasized the construction of information systems (such as EMRs) and the database technology. For example, Newland [8] adopted the database management system of Stockert to achieve the automated computation of clinical quality indicators of cardiopulmonary by-pass surgery. Shabot [9] implemented a clinical information system in Cedars-Sinai medical center to collect the ICU patient data and compute 6 ICU core indicators published by the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) of the US.

In recent years, more researchers began to pay attention to the handling of unstructured data, especially in the format of text. Baldwin [10,11] developed a natural language processing (NLP) tool to extract concepts from clinical narratives. Mehrotra [12] tried to extract usable information from colonoscopy reports by NLP methods to enable the computation of clinical indicators. Garvin [13] adopted NLP methods to construct regular expressions to extract ejection fraction from unstructured data to support the computation of clinical indicators related to heart failure. Brown [14,15] developed the system of eQuality, which is based on SNOMED CT, to extract concepts from text to support the computation of indicators. The system is validated to achieve the precision of 96% and recall of 86%.

7 Future Work

The indicators used in this study were translated from Dutch, because there are no widely adopted diabetes quality indicators in the Chinese context, especially when it comes to process-related indicators. Future studies may investigate the formulation of clinical quality indicators from Chinese evidence-based materials, such as clinical guidelines, and test the feasibility of computing these Chinese indicators.

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