Deriving a sophisticated clinical pathway based on patient conditions from electronic health record data

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Abstract. Clinical pathway (CP), a standardized treatment process based on a clinical guideline, is widely used to reduce costs while maintaining or improving patient care quality. However, there is a gap between the actual clinical process and the guideline, that causes CP application to be disturbed. A study on developing a data-driven automated clinical pathway to obtain insight into real clinical processes has been conducted. Still, patient characteristics and conditions, which could cause a variation, have not been fully considered. In this study, we aimed to develop a framework to derive a sophisticated clinical pathway from electronic health records (EHRs) data by exploring process variations according to the patient characteristics and conditions. To validate the applicability of the proposed framework, We conducted a case study using the Total Laparoscopic Hysterectomy (TLH) CP data, which was retrieved from an EHR system of a tertiary general hospital in South Korea between January 2012 and April 2016. We found that diabetic TLH patients show different medical performances with other TLH patients. We developed a tailored CP that adds eleven orders over the standard TLH CP, and experts evaluated it as meaningful.

Keywords: Clinical pathways · electronic health records(EHR) · statistical analysis · evidence-based approach · clinical features · Business process analysis

1 Introduction

A clinical pathway (CP) is a standardized care process in a specific setting such as a particular surgery [7, 4]. The use of CPs is gaining interest to help decrease hospital costs and improve the quality of medical services by reducing undesired practice variability [13, 12]. Additionally, CPs shorten the length of hospital stays, lower costs, reduce complications and lower mortality [13, 8]. As such, more than 80% of hospitals in the United States adopted CPs in the late 1990s [14], and currently, the implementation of CPs is widely contemplated by hospitals all over the world [21].

The traditional approach for developing a CP relied solely on the knowledge of clinical experts and clinical guidelines. Although the approach was a valuable method derived from solid theoretical backgrounds, it was limited by the time and effort required and the lack of generalization [19, 17]. Due to the highly dynamic, highly complex and ad hoc features of the medical treatment process, there is also a gap between the actual clinical process and the CP. As such, an automated approach from data is needed, and researchers have tried to resolve these challenges using process mining and data mining.

Mans et al. [10] applied heuristic miner, and a further work [11] used fuzzy miner and trace clustering to obtain insights from CPs. Huang et al. [4] proposed a new approach for mining CP patterns with time information from chronicle mining. Rebuge et al. [16] suggested a framework to compare the discovered CP and its variants using sequence clustering. Xu et al. [18] developed a more straightforward CP using the Latent Dirichlet Allocation technique. Additionally, researchers have employed further data mining techniques to develop CPs, such as frequent itemset mining [15], sequential pattern mining [15], and a rule induction algorithm [5].

These studies have contributed to developing the automated and accurate CPs based on data, deriving a standardized CP for the majority of patients. Despite these efforts using the data-driven approaches, it is still challenging to apply and complete CP with little effort in practice. In general, most hospitals only implement a single universal CP for a specific surgery or procedure. But, given the various clinical features of diabetes, cardiovascular, age, and medical history, a single CP cannot cover all different patients even with the same surgery; thus, a CP needs to be subdivided according to the clinical features. Therefore, with the aim of the increase of practical use, it is required to implement an approach for CP segregation with clinical features.

This study aims to identify the distinctive clinical characteristics that affect to distinguish a new clinical pathway. To this end, this paper suggests a framework consisting of four phases: data preparation, feature engineering, statistical analysis, and CP development. We first define the outcome measures and explanatory variables from the data. The matching rate, which represents a similarity between clinical trace and reference CP, is adopted as one of the medical performances for process-oriented assessment. Then, statistical testing is conducted to identify the key features highly related to clinical performance measures. Based on decisive factors from the statistical results, we distinguish a new CP (i.e., CP development) after post-hoc analysis with trace alignment. To validate the proposed framework, we performed a case study with real data from a tertiary hospital in South Korea.

The remainder of this paper is organized as follows. Section 2 explains the proposed framework. Section 3 shows a case study, and Section 4 discusses the results. Finally, Section 5 concludes the paper with future work.

2 Proposed Framework

In this section, we propose a framework for CP segmentation by patient characteristics. As shown in Fig. 1, the framework consists of four phases: data preparation, feature engineering, statistical analysis, and post hoc analysis & CP development. Data preparation, the first phase, aims to identify the data that can be utilized for data analysis by wrangling the collected data. Then, dependent (i.e., outcomes) and explanatory variables (i.e., patient characteristics) are defined in the feature engineering step. The statistical analysis phase conducts experiment to identify the relationship between outcome and independent variables. Lastly, in the post hoc analysis and CP development phase, we distinguish the new CP based on the result of comparing the clinical orders by statistical analysis and trace alignment.

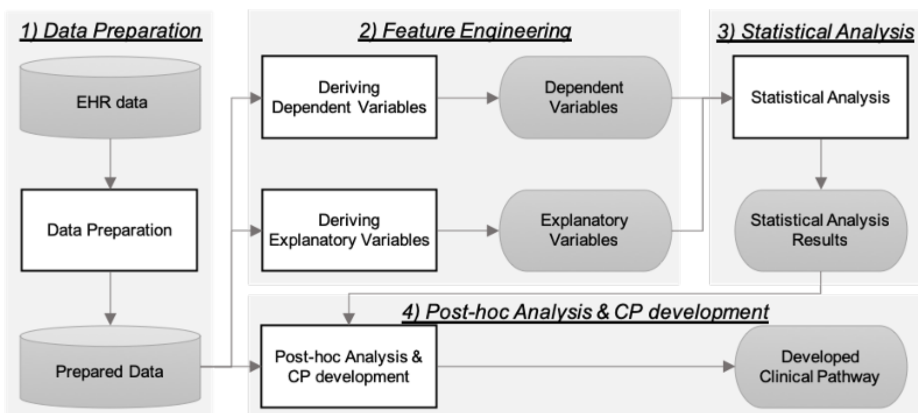

Fig. 1. The proposed framework in this paper.

2.1 Step 1: Data preparation

The first phase of the framework aims to prepare data with a suitable format for statistical analysis by collecting and pre-processing records. Clinical data generally are complex and heterogeneous [3]. There are four kinds of quality issues: missing data, incorrect data, imprecise data, and irrelevant data [1]. Missing data indicates that data is missing from logs, while incorrect data signifies that information recorded is not correct. Imprecise data represents that the level of data is too coarse, whereas irrelevant data means that information is not related at all with the log. These four types of quality issues are explicitly connected with the healthcare environment, and it needs to be processed thoroughly. To resolve these issues, users can choose proper data repair and noise removal methods based on the data quality. In our case, the most of issues was relevant with missing data, and we tried to remove all problematic data. Details will be given in the Result section.

2.2 Step 2: Feature engineering

One of the main parts in our framework is to identify the patient characteristics that are highly relevant to the outcomes. To this end, we perform feature engineering to build a research model before the data analysis. As such, the second phase aims to derive dependent and explanatory variables implied for statistical modelling. In more detail, dependent variables represent the outcomes, such as the length of stays or matching rate, i.e., an indicator that signifies the difference between the clinical pathway and relevant clinical log [20], while independent variables signify the patient characteristics. They are derived by selecting or refining records from the prepared data.

Dependent variables (Outcome measures) Dependent variables represent the materials to evaluate the outcomes, such as length of stays, hospital costs, the amount of antibiotics used, and matching rates with respect to efficiency and complication rates, re-hospitalization rates, and mortality with respect to quality of the clinical services. Among these variables, in this study, we only employed the length of stays and matching rates, i.e., the efficiency-focused, because of the insufficiency of data related to the quality perspective. More in detail, we were not able to collect the patients' records who re-visited the hospital with the same diagnosis within the 30 days (i.e., re-hospitalization) or were turned out to be dead (i.e., mortality).

The length of stays is one of the critical indicators in most hospitals because it lowers the risk of infection and medical costs for patients. In this study, we derived the length of stays by calculating the difference between the admission date and discharge date.

The matching rates signify how patient records collected from the logs coincide with the orders in the CPs. Thus, the rates can be used to evaluate the practical application of the CP in the quantitative approach. The matching rate is formalized as follows [20].

$$CP\ order\ matching\ rate = \frac{1}{2}(1 - \frac{M_{cp}}{N_{cp}}) + \frac{1}{2}(1 - \frac{R_{log}}{N_{log}}) \tag{1}$$

M_{CP} is the number of orders included in the CP but not shown in the log, N_{CP} is the number of orders included in the CP, R_{log} is the number of orders included in the log but not shown in the CP and N_{log} is the number of orders included in the log.

Explanatory variables (Patient characteristics) As introduced earlier, explanatory variables represent the materials that classify patients with their characteristics. Thus, regarding these characteristics, patients can be divided into groups. For example, patients are divided into age groups, such as infants, children, young adults, middle-aged adults, and older adults. Additionally, they may be classified by whether they have a specific history or not.

EHR system contains numerous patient characteristics, including age, sex, family history, past history, and they can be categorized into three types: background information, clinical events, and non-clinical events. The background patient information signifies historical records of patients before hospitalization. This group includes age, sex, allergy, operation history, medication history, family disease history, and chronic diseases (diabetes, hypertension, hyperlipidaemia, and cardiovascular and cerebrovascular diseases). The second group is the data derived from the clinical events during hospitalization, such as transfer of wards, transfer of departments, diagnosis from another department (not from obstetrics and gynaecology), and operation from another department. The last category is related to the administrative information during hospitalization, including severity, admission type, Diagnosis Related Group (DRG).

2.3 Step 3: Statistical analysis

This step performs a statistical analysis to identify the distinctive patient characteristics considered for CP development. To this end, hypothesis testing is performed based on dependent and independent variables derived in Step 2. Regarding hypothesis testing, different types of methods are utilized considering the number of groups and shape of distributions. In this study, we applied two types of statistical analysis methods: Mann-Whitney U test and Jonckheere-Terpstra test.

Mann-Whitney U test The Mann-Whitney U test identifies whether two populations are equal or not [9]. As such, the test was applied when the patients were divided into two groups by a patient characteristic, such as sex and severity. Its null(H_0) and alternative(H_1) hypotheses are as follows.; H_0: Two populations are equal, H_1: Two populations are not equal.

Jonckheere-Terpstra test As a substitute for the Mann-Whitney U test, the Jonckheere-Terpstra test is applied when the number of groups is more than two (i.e., three or more) and they tend to increase or decrease [6]. For example, the changes of outcome variables can be identified by the increase in the number of operations. Letting di be the median for the population i, the null and alternative hypotheses are defined as follows; $H_0 : d_1 = d_2 = d_3 = \cdots = d_k, H_1 : d_1 \leq d_2 \leq d_3 \leq \cdots \leq d_k$ (where, k is the number of groups).

2.4 Step 4: Post hoc analysis & CP development

The last step compares the selected patients' clinical orders based on their characteristics and derives a new CP. Here, the critical patient characteristics are employed from the statistically significant factors in Step 3. In this phase, patients are grouped by a specific feature, and the application rates of clinical orders are measured for each group. Then, the difference in the application rates of the orders between groups is identified. For example, if the order applies only to 90% of the severely ill group and 10% of non-severe patients, the order should be included in the CP of the severely ill group. Then, if a group of features differentiates multiple clinical orders, some traces from each group are sampled to visualize the differences and discuss with clinical experts. CP segmentation is performed when the clinical expert concludes that the functional group needs a new CP.

3 Case study

3.1 Introduction

A general tertiary hospital in South Korea has developed and applied numerous electronic CPs based on clinical experience to provide appropriate medical services to patients. In this case study, we primarily analyzed the Total Laparoscopic Hysterectomy (TLH) CP, which has been in use since August 2009. From the hospital's EHR system, log data of patients determined as candidates to be applied to the TLH CP were extracted from January 2012 to April 2016, resulting in data collected from 1100 inpatients. EHR data of patients' demographics, hospitalization, applied CP, surgery, diagnosis, transfers, referrals, physician orders including medications and labs, and CP history was extracted.

3.2 Data Preparation

Based on the collected data from 1100 inpatients, we performed data preprocessing. Among the four types of data quality issues, e.g., missing data, incorrect data, imprecise data, and irrelevant data, our data included the first type as we lacked the medical history of patients, such as operations and medication history. Additionally, the second-hand data collected from surveys, such as drinking and smoking, had many blank spaces. As such, those characteristics were removed from the data to be analysed. Furthermore, part of the clinical orders had incorrect data, such as an unexpected hold (3.4%) and immediate removal by systems (2.5%). These were also excluded, and finally, the data was prepared.

3.3 Feature engineering

Dependent variables (Outcomes) As introduced earlier, we applied the length of stays and matching rates as dependent variables (i.e., outcomes). Regarding the length of stays, the average value was 4.57 days (median: 4 days and standard deviation (SD): 1.8 days). Regarding the matching rate, the average was 0.716 (median: 0.724 and SD: 0.053).

Explanatory variables (Patient characteristics) After preparing the data, we selected 11 explanatory variables based on a thorough discussion with clinical experts: diabetes, hypertension, hyperlipidaemia, cardiovascular, cerebrovascular, severity, operations, transfers of departments, transfers of wards, diagnosis from other departments (not from obstetrics and gynaecology), and referrals to other departments.

Only a small number of patients had chronic diseases, including diabetes, hypertension, hyperlipidaemia, cardiovascular, and cerebrovascular at 3.5%, 4.7%, 1.5%, 0.1%, and 0.6%, respectively. The number of patients with severity, however, was relatively high at 33.1%. Regarding the number of operations, most patients received only one operation while 0.9% of patients received two operations. Regarding transfers of departments, only four patients (0.4%) changed departments. Lastly, regarding the other characteristics (e.g., transfers of wards, diagnosis from other departments, and referrals to other departments), for each feature, more than 50% of the patients were not associated with the feature at all, but the remaining patients had more than one frequency.

3.4 Statistical analysis

Among the 11 independent variables (i.e., patient characteristics), only six, e.g., diabetes, hypertension, severity, transfers of wards, diagnosis from other departments (not from obstetrics and gynaecology), and referrals to other departments, were considered for statistical testing because the sample size for testing should be sufficient (i.e., more than 30) [9], and the sample sizes for the other features are not sufficient.

We applied two different statistical testing methods: the Mann-Whitney U test and Jonckheere test. The Mann-Whitney U test was applied to diabetes, hypertension, and severity while the Jonckheere test was employed for the remaining variables. Table 1 presents the statistical testing results of the length of stays and matching rates on patient characteristics.

Table 1. Statistical testing results on patient characteristics.

Patient characteristics	p-value		Test type
	LOS	Matching rates	
Diabetes	< 0.01	< 0.01	Mann-Whitney U test
Hypertension	0.014	0.045	Mann-Whitney U test
Severity	< 0.01	< 0.01	Mann-Whitney U test
Transfers of wards	< 0.01	0.035	Jonckheere test
Diagnosis from the other departments (not from obstetrics and gynaecology)	< 0.01	0.149	Jonckheere test
Referrals to other departments	< 0.01	< 0.01	Jonckheere test

As a result of the statistical tests, diabetes, severity, transfers of wards, diagnosis from other departments and referrals to other departments significantly affected the length of stays while the matching rates were significantly affected by diabetes, severity, and referrals to other departments. Therefore, we concluded that only three features, e.g., severity, diabetes, and referrals to other departments, are key characteristics for CP segmentation.

Based on these results, we had a thorough discussion with clinical experts. First, regarding severity, we determined that the result was caused by incorrect application of the CP in cancer patients, not the CP target patients. In the hospital, clinicians sometimes applied the CP to cancer patients because there was no significant difference in clinical operation processes between the two. The cancer patients, however, required a longer stay and different routines from the CP patients. Thus, we determined that it was misleading that there was an impact on clinical outcomes. Additionally, regarding the referrals to other departments, the domain experts concluded that the feature needs to be managed by monitoring rather than CP development. For these reasons, we performed further post hoc analysis and CP development based on diabetes.

3.5 Post hoc analysis & CP development

Considering diabetes, we analyzed the differences in clinical orders between diabetic and non-diabetic patients. The total number of diabetic and non-diabetic patients was 38 and 1062, respectively. We performed trace alignment to visualize how the order records of each group differ. For simplicity, in each group, 20 patients, who stay in the hospital for four days, are sampled, and the result of trace alignment is in Fig.2.

Additionally, we employed the CP development methodology [2], which derives an optimal set of clinical orders that maximize the matching rates. Based on the exploited method, we received clinical orders for diabetic and non-diabetic patients. After, the developed CP for diabetes was compared with that for non-diabetes. We identified that 11 clinical orders, e.g., Pot chloride, Humalog, Palonosetron, Ephedrine, Electrolyte panel, Glucose, DM diet (for diabetes), BST, Infusion pump, Interceed, and Simple hysterectomy, were applied for most of the diabetic application rates. In contrast, two clinical orders (i.e., Granisetron and Other dermatological) were utilized only for non-diabetic patients.

Table 2 provides the clinical order application rates of diabetic and non-diabetic patients. Overall, we were able to identify a clear difference in each code's application rates by the group. Therefore, we concluded that the new CP for diabetes should be distinguished from the general one.

4 Discussion

The results of the analysis showed that diabetes affects medical outcomes, such as the length of stays and matching rates. To this end, we identified that glucose control is the reason for the extended hospital stays and the lower matching rates. Patients with diabetes require a specific amount of time to control their

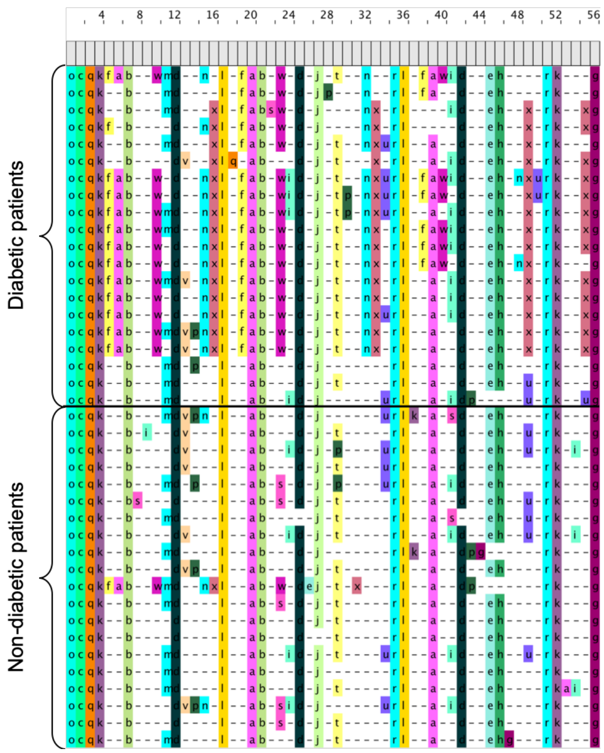

Fig. 2. Trace alignment result of diabetic patients and non-diabetic patients.

blood sugar before surgery, which can lead to longer hospital stays. Additionally, the diabetic patients received surgery later than general patients.

Regarding the lower matching rate for diabetic patients, we found that controlling the patient's blood sugar affected the results through the post hoc analysis. We identified that diabetic patients received insulin (e.g., humalog) with Alberti regimen and dextrose fluid (e.g., pot chloride) containing potassium chloride to ensure adequate water, electrolyte, and feeding before operations. Additionally, diabetic patients received tests to check blood sugar and electrolytes for glucose control. Moreover, some materials (e.g., infusion pump) were also utilized for diabetic patients to inject the proper medicines. Therefore, we determined that these orders are required entirely for diabetic patients with both data and clinical perspectives.

This research has important contributions for both practice and research standpoints. As far as practical use is concerned, this research helps to develop the clinical decision support system by resolving the large demands from hospitals to continuously improve and manage CPs. Despite the facts that hospitals generally cannot develop and enhance CPs due to an insufficient workforce, time, and costs, however, it is required to implement a tool that gives accurate clinical

Table 2. Clinical order application rates of diabetic and non-diabetic patients.

Order Information		Application rates (%)	
Type	Name	Diabetic	Non-diabetic
Medications	Pot Chloride	84.2	2.7
	Humalog	84.2	2.0
	Palonosetron	57.9	47.1
	Ephedrine	50	36.3
	Granisetron	42.1	56.2
	Other Dermatologicals	44.7	49.3
Lab Test	Electrolyte panel	79.0	9.5
	Glucose	79.0	3.2
Diet	DM diet (for diabetes)	71.1	1.6
Treatment	BST	89.5	2.2
Procedures	Infusion Pump	81.6	7.1
	Interceed	57.9	47.6
	Simple Hysterectomy	50	39.9

pathways to clinicians, driving to provide high-qualified patient-centric services. In this standpoint, this paper is of value as it automatically recommends distinctive patient characteristics and develops a new CP with a data-driven approach.

Also, as far as the research standpoint is concerned, this paper is different from existing works that merely discover a one-off CP and provides a direction that enables the continuous development of improved CPs with a statistical approach. Furthermore, the patient characteristics and clinical outcome measures derived in this research are applicable to multiple clinical research disciplines, such as real-time monitoring and prescriptive analytics in hospitals.

Despite these contributions, this paper has some challenges. First, there has been a problem that the number of patients to be analyzed is reduced because latest data of short-term period data must be used to reflect the latest order information. Nonetheless, it is significant that we were able to segment the CP according to the patient condition of diabetes. The framework presented in this study considerably contributes in terms of managing the clinical pathway and practical use of the clinical pathway and will continue to demonstrate its usefulness through further data acquisition.

Also, this research did not address the inter-relationship between patient characteristics and thus only aimed at developing new CPs for each patient feature. However, it is possible to construct CPs that consider multiple patient characteristics at once (e.g., diabetic-female-TLH CP). Furthermore, we limited clinical outcome measures to length of stays and matching rates. Future studies should be expanded to more scalable methodologies, including patient costs and the use of antibiotics. Lastly, the analysis result presented in this paper was only based on a single hospital. As there are differences in CPs and data between hospitals, the study may lack generalizability. Thus, we need to perform more case studies using data from multiple hospitals. We believe that we can build a more robust framework for CP segmentation by resolving these issues.

5 Conclusion

In this paper, we proposed a framework for CP segmentation based on patient characteristics. In this process, we performed feature engineering to define the clinical outcome measures related to CPs (i.e., dependent variables) and patient characteristics (i.e., independent variables). We also conducted statistical testing using the Mann-Whitney U test and Jonckheere test, and finally a new CP was distinguished from the general CP.

This paper proposes guidelines to increase the applicability of CPs and suggests how to develop CP variants using patient characteristics and clinical outcomes. Additionally, the proposed framework has a distinctiveness that enables the continuous development of improved CPs different from existing works that merely discover a single CP. Therefore, we believe that our methodology is helpful for practical use.

In future studies, we will consider the inter-relationship between patient characteristics for CP segmentation. Additionally, other clinical outcomes, such as patient costs and the use of antibiotics, may be included. Furthermore, more case studies should be performed to validate our approach and make various use cases.

Acknowledgement

This work was approved (IRB No. B-1609/361-105) by the Institutional Review Board of the SNUBH, which waived patients' informed consent. This work was funded by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2020-2018-0-01441) supervised by the IITP (Institute for Information & Communications Technology Promotion).

References

1. Bose, R.J.C., Mans, R.S., van der Aalst, W.M.: Wanna improve process mining results? In: 2013 IEEE symposium on computational intelligence and data mining (CIDM). pp. 127–134. IEEE (2013)
2. Cho, M., Kim, K., Lim, J., Baek, H., Kim, S., Hwang, H., Song, M., Yoo, S.: Developing data-driven clinical pathways using electronic health records: The cases of total laparoscopic hysterectomy and rotator cuff tears. International journal of medical informatics **133**, 104015 (2020)
3. Cios, K.J., Moore, G.W.: Uniqueness of medical data mining. Artificial intelligence in medicine **26**(1-2), 1–24 (2002)
4. Huang, Z., Lu, X., Duan, H.: On mining clinical pathway patterns from medical behaviors. Artificial intelligence in medicine **56**(1), 35–50 (2012)
5. Iwata, H., Hirano, S., Tsumoto, S.: Construction of clinical pathway based on similarity-based mining in hospital information system. Procedia Computer Science **31**, 1107–1115 (2014)

6. Jonckheere, A.R.: A distribution-free k-sample test against ordered alternatives. Biometrika **41**(1/2), 133–145 (1954)
7. Lenz, R., Blaser, R., Beyer, M., Heger, O., Biber, C., Bäumlein, M., Schnabel, M.: It support for clinical pathways—lessons learned. international journal of medical informatics **76**, S397–S402 (2007)
8. Macario, A., Horne, M., Goodman, S., Vitez, T., Dexter, F., Heinen, R., Brown, B.: The effect of a perioperative clinical pathway for knee replacement surgery on hospital costs. Anesthesia & Analgesia **86**(5), 978–984 (1998)
9. Mann, H.B., Whitney, D.R.: On a test of whether one of two random variables is stochastically larger than the other. The annals of mathematical statistics pp. 50–60 (1947)
10. Mans, R., Schonenberg, H., Leonardi, G., Panzarasa, S., Cavallini, A., Quaglini, S., Van Der Aalst, W.: Process mining techniques: an application to stroke care. In: MIE. vol. 136, pp. 573–578 (2008)
11. Mans, R.S., Schonenberg, M., Song, M., van der Aalst, W.M., Bakker, P.J.: Application of process mining in healthcare–a case study in a dutch hospital. In: International joint conference on biomedical engineering systems and technologies. pp. 425–438. Springer (2008)
12. Newman, B.: Enhancing patient care: case management and critical pathways. The Australian journal of advanced nursing: a quarterly publication of the Royal Australian Nursing Federation **13**(1), 16 (1995)
13. Panella, M., Marchisio, S., Di Stanislao, F.: Reducing clinical variations with clinical pathways: do pathways work? International Journal for Quality in Health Care **15**(6), 509–521 (2003)
14. Pearson, S.D., Goulart-Fisher, D., Lee, T.H.: Critical pathways as a strategy for improving care: problems and potential. Annals of internal medicine **123**(12), 941–948 (1995)
15. Perer, A., Wang, F., Hu, J.: Mining and exploring care pathways from electronic medical records with visual analytics. Journal of biomedical informatics **56**, 369–378 (2015)
16. Rebuge, Á., Ferreira, D.R.: Business process analysis in healthcare environments: A methodology based on process mining. Information systems **37**(2), 99–116 (2012)
17. Weiland, D.E.: Why use clinical pathways rather than practice guidelines? The American journal of surgery **174**(6), 592–595 (1997)
18. Xu, X., Jin, T., Wei, Z., Wang, J.: Incorporating topic assignment constraint and topic correlation limitation into clinical goal discovering for clinical pathway mining. Journal of Healthcare Engineering **2017** (2017)
19. Yang, W., Su, Q.: Process mining for clinical pathway: Literature review and future directions. In: 2014 11th International Conference on Service Systems and Service Management (ICSSSM). pp. 1–5. IEEE (2014)
20. Yoo, S., Cho, M., Kim, S., Kim, E., Park, S.M., Kim, K., Hwang, H., Song, M.: Conformance analysis of clinical pathway using electronic health record data. Healthcare informatics research **21**(3), 161–166 (2015)
21. Zhang, Y., Padman, R., Patel, N.: Paving the cowpath: Learning and visualizing clinical pathways from electronic health record data. Journal of biomedical informatics **58**, 186–197 (2015)