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The development of dentist practice profiles and management

Chinho Lin PhD,[1] Chun-Mei Lin MPH PhD[2] and Chienwen Hong PhD[3]

[1]Professor, Department of Industrial Management Science and Institute of Information Management, National Cheng Kung University, Tainan, Taiwan

[2]Researcher, Department of Industrial Management Science and Institute of Information Management, National Cheng Kung University, Tainan, Taiwan and Manager, Bureau of National Health Insurance, Southern Region Branch, Taiwan

[3]PhD student, Department of Industrial Management Science and Institute of Information Management, National Cheng Kung University, Tainan, Taiwan and Senior Lecturer, Department of Information Management, Chia-Nan University of Pharmacy and Science, Tainan, Taiwan

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Correspondence
Chinho Lin
Department of Industrial Management Science and Institute of Information Management
National Cheng Kung University
Tainan 704
Taiwan
E-mail: linn@mail.ncku.edu.tw

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Abstract

Rationale and objectives With the current large computerized payment systems and increase in the number of claims, unusual dental practice patterns to cover up fraud are becoming widespread and sophisticated. Clustering the characteristic of dental practice patterns is an essential task for improving the quality of care and cost containment. This study aims at providing an easy, efficient and practical alternative approach to developing patterns of dental practice profiles. This will help the third-party payer to recognize and describe novel or unusual patterns of dental practice and thus adopt various strategies in order to prevent fraudulent claims and overcharges.

Methodology Knowledge discovery (or data mining) was used to cluster the dentists' profiles by carrying out clustering techniques based on the features of service rates. It is a hybrid of the knowledge discovery, statistical and artificial neural network methodologies that extracts knowledge from the dental claim database.

Results The results of clustering highlight characteristics related to dentists' practice patterns, and the detailed managerial guidance is illustrated to support the third-party payer in the management of various patterns of dentist practice.

Conclusion This study integrates the development of dentists' practice patterns with the knowledge discovery process. These findings will help the third-party payer to discriminate the patterns of practice, and also shed more light on the suspicious claims and practice patterns among dentists.

Introduction

There are many variations in dentist practice patterns with regard to diagnosis of caries and recommendations for treatment [1]. Development of dental practice profiles can help the third-party payer to monitor the dental costs and quality [2,3]. With the current large computerized payment systems and increase in the number of claims, unusual dental practice patterns to cover up fraud are becoming widespread and sophisticated [4]. The US department of Health and Human Services [5] has estimated that approximately 7–14% of all reimbursements are improper payments. Inappropriate practice deals with issues such as providing services that are unreasonable, unnecessary or duplicate. The third-party payer must explore more proactive and advanced analytics to avoid potentially avoidable costs. However, these claims databases of analysis rely on human experts, who are both expensive and scarce. With the use of computerized dental claim profiles and new statistical algorithms, detecting improper claims often involves doing extensive data mining or knowledge discovery initiatives from a database.

Knowledge discovery or data mining, which starts by gathering, characterizing, visualizing and clustering unfamiliar data sets, attempts to find patterns, associations, or dissimilarities between groups of data in order to uncover improper and abusive behaviour to prevent inappropriate practices [6–8].

Knowledge discovery differs from statistical techniques in that there is no prior hypothesis or null hypothesis, and power calculations are not performed. It combines soft computing methods and self-organization map networks (SOM), in which clustering plays a vital role in knowledge acquisition to detect fraud in health insurance [9]. For example, the Health Insurance Commission of Australia uses an automated multilayer perceptron neural network to classify the practice profiles of Medicare practitioners [10]. It helps to identify those dentists who are over-treating patients by performing more services than are necessary for their oral conditions, or who see their patients more often than is warranted. The clustering of dental practice profiles gives a quick survey to analyse dentists and suspicious activities, and then the third-party insurance payer enhances the investigative efficiency and saves personnel cost. Knowledge discovery thus helps the third-party insurance payer to recognize and describe suspicious or unusual dentists' practice patterns to prevent fraud and abuse from slipping through undetected [11].

However, very few studies have attempted a comprehensive exploration of dentists' practice pattern profiles and management. This paper seeks to bridge this gap. Our study aims at providing an easy, efficient and practical alternative approach in dentists' practice pattern segmentation. It is a hybrid of the knowledge discovery, statistical and artificial neural network (ANN) methodologies that extracts the knowledge from the low level database in the dentists' claims. Second, while the features and characteristics of dental practice patterns were segmented from anterior procedures, an in-depth interview was also conducted. The detailed managerial guidance on the diversity of dentist practice patterns is illustrated to provide the third-party payer with information to determine the appropriate audit trail and prevent fraudulent practices.

Theoretical background

This section introduces some necessary background, including on the reimbursement of dental care in Taiwan and dentist practice profiles as well as the application of knowledge discovery and SOM neural networks to discover knowledge from dentist practice patterns. Detailed discussions of these topics are in the following subsections.

Reimbursement of dental care in Taiwan and dentist practice profiles

Since the National Health Insurance (NHI) of Taiwan was inaugurated in March 1995, the Bureau of National Health Insurance (BNHI) has had the role of both payer and purchaser [12]. By December 2006, BNHI had contracted with 96% of the 5906 private dentists in Taiwan. Dentists are reimbursed on a retrospective fee-for-service payment system by the BNHI [13], which authorizes each health insurance region to form a peer review organization under the supervision of the National Dentist Association (NDA) to process and audit claims and undertake other peer review functions. By 2006, the dental fee schedule contained 133 items of dental care services, including consultation fees, X-ray diagnoses, treatments and operations. Cosmetic services, such as dentures and orthodontics, are not included in the dental fee schedule [13]. The major dental treatments can be generalized into four categories, such as (i) amalgam or composite resin fillings on various surfaces; (ii) endodontic treatment; (iii) teeth scaling or cleaning in any area of the mouth; and (iv) teeth extractions. The order of profit in the four categories is: restoration, scaling, endodontic treatment and extraction. Both the restoration and endodontic treatment made up about 70% of the total expenditure for outpatient dental care in 2005 [14]. Therefore, the two dental treatments are used as performance assessments of dentists and form the dentist practice profiles [15]. A fee-for-service payment system encourages doctors to provide more care than patients' need. Therefore, the BNHI must control the health care costs by focusing on how to prevent fraudulent claims, overcharges, and duplication of services and tests. Therefore, establishing an effective auditing system is a key action in alleviating any unnecessary and fraudulent health expenditures.

The dentist practice profiles include detailed information regarding the dental costs, utilization of resources and quality outcome (e.g. the amount of claim fees, average fees per patient visit, the percentage of restorations per visit and the percentage of restorative replacements within 2 years). These indicators, in the form of ratios, are compared with other doctors. Practice profiling of providers has been suggested as one source of variation in service rates [1,16]. Other sources of variation include practice characteristics such as type and location of practice, visit factors such as insurance status, and patient factors such as age [17]. Dentist practice profiling involving multiple ratios can more effectively identify over- and under-utilization of services. Profiling also uncovers dentist practice problems, such as abusive behaviour and poor quality of care [11,18].

Dentist practice profiles also are designed to generate auditing indicators for dentists who differ from the average by a certain amount. These rules are derived from the dentists profiles by using ratio-based indicators to evaluate the quantity content of the dentists' cohort [19], which results in discriminate indicators of claim billing and quality score, called 'auditing flags'. This identifying of 'outliers' is sometimes referred to as 'the search for bad apples'. The ratio-based indicators used in dentist profiles attempt to highlight dentist performances that are exceptionally high or low. For example, a large number of dental restorative replacements within 2 years by the same dentist's array of patients would stand out as an indication of possible dental restorative overuse. A score of claim indicators that fits the risk profile for BNHI will increase the likelihood of auditing prior to payment.

Knowledge discovery

Advances in information technology have helped the health care industry to accumulate a large amount of data and to build knowledge directly from clinical practice data decision-support and evidence-based practice [20,21]. Knowledge discovery or data mining by automatic or semi-automatic exploration and analysis of large amounts of data has become widely applied to analyse medical information in the few decades [6,22]. Knowledge discovery has brought improvements in management of limited health care fraud detection and investigative resources over traditional investigation and statistical analysis method. Knowledge discovery successfully applies visualization to very large data sets to dig deeper into the data by recognizing and quantifying the underlying indicators of fraudulent claims, fraudulent providers and fraudulent beneficiaries [23]. Reviews of knowledge discovery in the bio-medical area from different perspectives can be found in various studies, for example, Bath [24]; Cios and Moore [25]; Lavraè [26]; Wilson, Thabane and Holbrook [27].

Knowledge discovery is one appropriate methodology to analyse and understand such huge amounts of data. As an interdisciplinary area between artificial intelligence, databases, statistics and machine learning, the idea of knowledge discovery came into being in the late 1980s. The most prominent definition of knowledge discovery was proposed by Fayyad and Stolorz [6]. In that paper, knowledge discovery is defined as 'the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data'. This definition may also be applied to 'data mining'. Indeed, in the recent literature on data mining and knowledge discovery, the terms are often used interchangeably or without distinction. However, according to classical knowledge discovery methodologies, data mining is the knowledge extraction step in the knowledge discovery process, which also involves the selection and pre-processing of appropriate data from various sources, and proper interpretation of the mining results. In addition, the advent of electronic medical records and data warehouses has contributed greatly to the availability of medical data and offers voluminous data resources for knowledge discovery activities.

Knowledge discovery is a hybrid discipline that integrates the technologies of databases, statistics, machine learning, high performance computing and a deductive database. By uncovering abnormal relationships between claim fees and provider data, and comparing data with known fraud incidents to uncover potential risk indicators for future claims, it has already demonstrated usefulness in health care fraud investigation and in examining health care utilization conflicts, such as home care with inpatient care utilization at the same time [4]. In 2000, the Health Care Financing Administration in the USA used data mining via visualization techniques, clustering and link analysis to recognize and present data anomalies, making it much easier to identify and quantify fraud in the database of 800 million health care claim records [23]. Data mining processes large amounts of data to recognize and models the most complex fraud schemes. In addition, data mining facilitates the finding of hidden patterns that are fraud indicators, as well as offering the ability to reduce the number of 'false positives' and allowing investigators to concentrate on claims that offer a higher probability of a positive outcome [19].

Knowledge discovery can thus discover potentially significant patterns and rules in the underlying database, and can be a solution to a wide variety of problems that rely on extracting information that is hidden in a database [28]. Neural networks form the backbone of most data mining products and integrate the knowledge discovery process in terms of knowledge discovery methodology [6,26,29]. They provide a systematic approach to help the third-party payer extract implicit, previously unknown, and potentially useful information from raw data, allowing knowledge discovery to solve and manage information overload.

The knowledge discovery process can be divided into six sequential, iterative steps, often defined as a six-stage iterative process: (i) develop an understanding of the proposed application; (ii) create a target data set; (iii) remove or correct corrupted data; (iv) apply data-reduction algorithms; (v) apply a data-mining algorithm; and (vi) interpret the mined patterns [6,30].

Self-organizing map neural network

Artificial neural networks are well-established tools in computational intelligence, which have proven to be reliable and flexible in many practical applications. ANN methods have been applied to health care and health insurance in order to improve dental care decision-making [10,26,31]. One type of unsupervised neural network, an SOM, was proposed by Kohonen [32]. An SOM neural network is considered to be an unsupervised algorithm because the user does not train the network to reach a specified goal. The SOM neural network makes a topological map from the high-dimensional input space to the low-dimensional output space. Hence, the dentists' expenditure profile structures are made more transparent and simpler when they are clustered in a one, two or three dimensional features space [33]. The clustering task lets the user gain an insight into the data from efficient visualization and summaries, thus isolating new and unusual patterns of activity [34].

Therefore, the SOM neural network's clustering technology attempts to organize unlabelled input features into clusters or 'natural groups', so that objects within a cluster have a high similarity in comparison to one another, but are very dissimilar to objects in other clusters [35]. The SOM neural network's clustering algorithms (see Kohonen [32]), automatically detect strong features in a huge database, maximizing similarities within and differences between clusters. It can also effectively reduce the complexity of the reconstruction task and noise [36]. By comparing with K-means statistical modelling in a clustering task, SOM networks perform better when the data are skewed [37] and violating the normality assumption will lead to a bias and incorrect results [9,38]. Thus, neural networks provide general and efficient non-linear mapping. The versatile properties of the SOM neural network make it a valuable tool in knowledge discovery and in clustering and visualization techniques [36]. In particular, it has visualization capabilities in providing informative pictures of the data space and in exploring whole data sets. SOM is widely used in knowledge discovery tasks, providing an unsupervised partitioning of data [8]. Clustering techniques are effective in grasping the overall view of a hybrid data set, leading to an understanding of the global context as well as highlighting exceptions, for example 'special patients' and 'efficient dentists' in the health insurance data warehouse [39]. As a result, the SOM neural network's clustering technology is used as the main methodology for partitioning various dentists practice patterns in this study.

Method of knowledge discovery

In this section, we present the conceptual framework used in the knowledge discovery of dentists' practice patterns. The explanatory model and the associated steps will be discussed in detail in this section.

Conceptual framework

Knowledge discovery procedures were used to examine the dentists' practice patterns in health expenditures, and to leverage expert knowledge to execute management strategy based on the SOM neural network unsupervised clustering approach. The conceptual framework of the study consists of eight steps:
Steps 1–3: acquiring claim data set and data transformation;
Step 4: determining the optimal number of clusters;

Step 5: using a two-level SOM neural network for accomplishing clustering features of practice patterns from dentists' profiles;
Step 6: analysing the fraudulent claim records during the last 5 years on each cluster;
Step 7: depicting the features of each cluster;
Step 8: presenting managerial guidance on the clusters for various dentists' practice patterns using in-depth interviews with senior dentists of NDA and senior managers of the BNHI who play a critical role in managerial strategy.

The associated steps of knowledge discovery on dentist's practice patterns are shown in Fig. 1.

Data pre-processing

Data availability is the first consideration before any knowledge discovery task could be undertaken. Based on fee-for-service and retrospective payment mechanisms, reimbursement is calculated and paid after the service is delivered. The payment made for each service provided, and thus the patient volume, per-patient cost and outcome or quality are all of concern to the third-party payer [40,41]. Wang *et al.* [42] argue that the service rate is very significant as a clustering variable. Thus, the related service rate and ratio-based indicators were used for clustering. The dentist profiles data set includes five indicators, which are taken from existing information in the dental claim database of the NHI (see Table 1), such as average total amount of cost, average cost per case, percentage of endodontic treatment in total treatment costs, percentage of restoration in total treatment costs, percentage of restoration replacement by the same dentist within 2 years (PRRSD).

To accelerate the analysis by using an SOM neural network, the raw data should be normalized. The Min-Max method was adopted to yield data values ranging from 0 to 1. The dental claims database contains data for a rolling 1-year period. The data for this study was collected for the calendar year 2006 in the southern region of the BNHI (i.e. containing two cities and three counties, covering 3.2 million residents). The total number of dentists' profiles was 672. Two purification rules were proposed to choose the final data set, which were (i) profiles with continuous general practice service throughout the period of January–December 2006; and (ii) that the dentist practice was located in a clinic.

SOM neural networks for clustering

The optimal number of clusters for an SOM neural networks can be determined by the maximum value of the silhouette coefficient [43], which is the clustering validity index for all input data. The experimental results of the silhouette coefficient cohesion and variance of dentists' practice patterns for different numbers of clusters are shown in Fig. 2.

It can be seen that the silhouette coefficient increases along with the number of clusters. The maximum variant silhouette coefficients are found to be located at cluster 6, and the highest value reached was around 0.43. Therefore, 6 is set as the number of clusters in the clustering phase of the SOM neural network.

The SOM neural network consisted of a first layer of 10×10 neurons arranged in a 2-D square and a second layer of 5×1 neurons in a 1-D grid, but different configurations were considered. For each case, the Euclidean distance between the case and each neuron was calculated based on the five input attributes. The learning rates and distance threshold values were the default values for the SOM neural network toolbox. The SOM neural network was computed using the SOM toolbox in MATLAB (The MathWorks Inc., Natick, MA, USA).

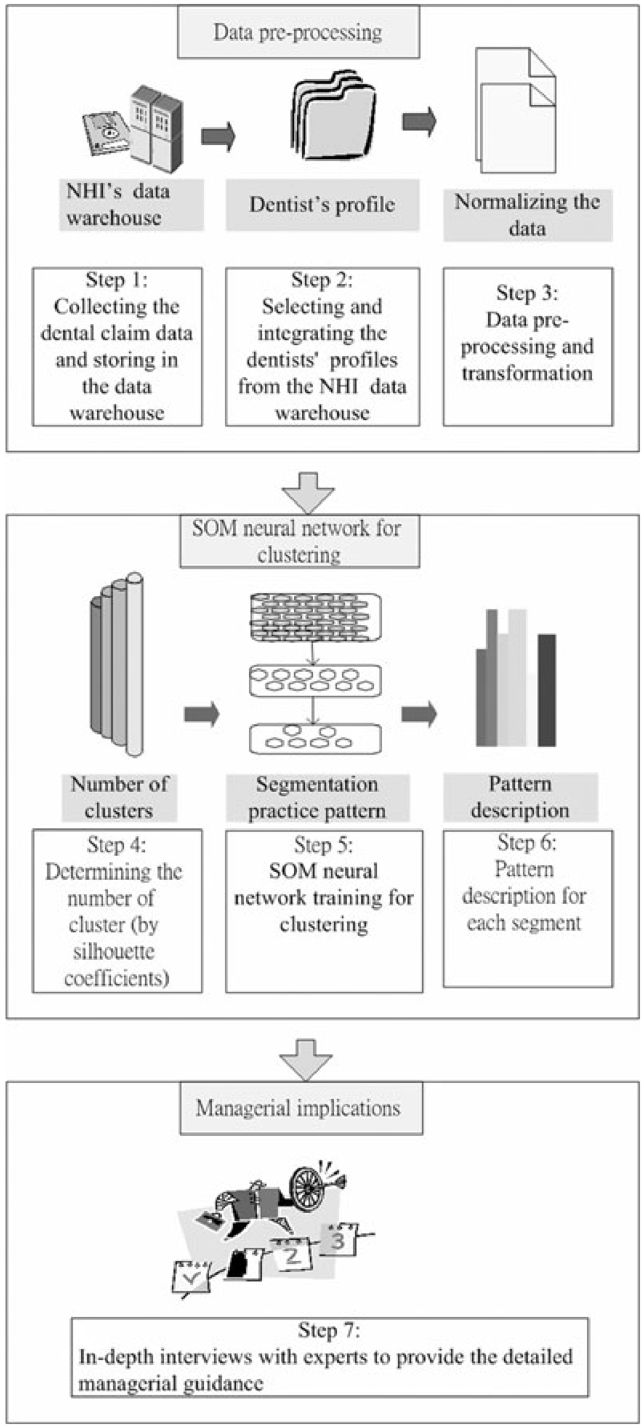

Figure 1 Process of knowledge discovery on dentist's practice patterns.

Table 1 The description of indicators

Indicators	Abbreviations	Description
Average total annual of cost	ATAC	The total annual cost divided by 12 months
Average cost per case	ACPC	The total claim cost divided by total cases per month
Percentage of endodontic in total treatment costs	PETTC	The total treatment cost divided by endodontic cost per month
Percentage of restoration in total treatment costs	PRTTC	The total treatment cost divided by restoration cost per month
Percentage of restoration replacement by the same dentist within 2 years	PRRSD	The number of restoration replacements divided by the number of restorations within 2 years per dentist

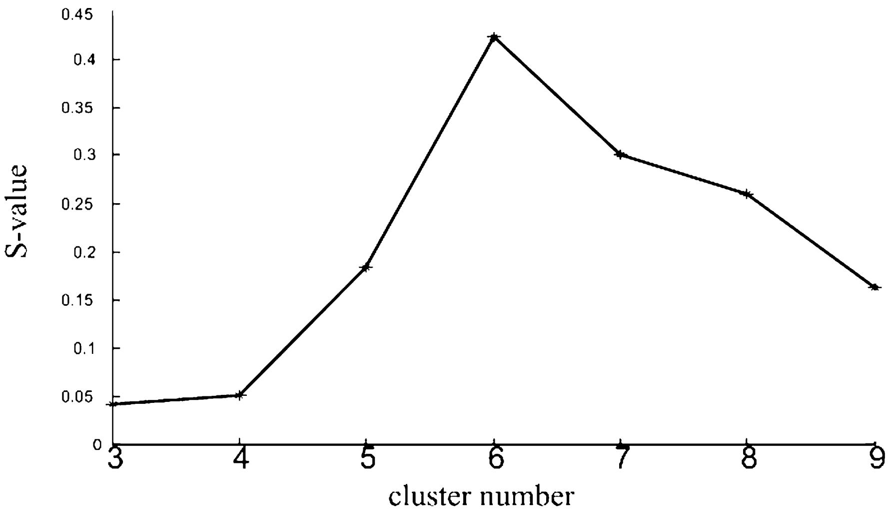

Figure 2 The silhouette coefficients and clustering validation.

Table 2 The descriptive statistics of the five indicators ($n = 672$)

Indicators	Mean	Max	Min	Standard deviation
TAC	467 719	2 982 965	21 620	317 442
ACPC	1 747	4 083	687	469
PETTC	20%	61%	0%	10%
PRTTC	51%	90%	0%	13%
PRRSD	2.2%	19%	0%	2.3%

The fee is in New Taiwan dollar. US dollar \$1 = New Taiwan dollar \$32.3 (1 March 2007). See Table 1 for abbreviations.

Results

The descriptive statistics of the five attributes

Five attributes were used to cluster the dentists' practice profiles, and the descriptive statistics of the five attributes, such as mean, maximum, minimum and standard deviation, are listed in Table 2.

The characteristics of the clusters through SOM neural network training

The five attributes project 5×1 neurons in a 1-D grid through SOM neural network training, as presented in Fig. 3. On the figure's horizontal axis, the 1–5 neurons represent the indicators of dental service rates.

The raw data distribution of the clusters' centroids through the SOM neural network clustering among the five attributes of the dentist claim data is depicted in Table 3. With regard to the size of these six clusters, cluster 5 is the largest, with 179 samples (27%), and cluster 6 is the smallest, with 77 samples (11%). The maximum values of the cluster centroid for each indicator are located in five clusters; for example, cluster 1 has the highest PRRSD at 3.9%. The number of dentists' distribution among the six clusters is shown in Table 4. Cluster 6 has the most number of dentist practices in a clinic. We found that there is a significant difference ($P < 0.001$) between the clusters conducting the ANOVA test of the mean difference of clusters for each attribute (see Table 5).

The fraudulent claim records during 5 years

Table 6 illustrates the dental fraudulent claim records during 5 years in the six clusters. Cluster 4 has the highest percentage of fraudulent claim records, which is significantly different from other clusters ($P < 0.001$), the second highest is cluster 6.

The aggregate features of the six clusters and naming

Each cluster represents feature aggregation. The characteristics of the six clusters of practice by service rate were obtained. Table 7 presents the feature descriptions of these. The naming of each cluster reflecting the expert evaluation of features and interpretation of the data mining results, are as follows:

Table 3 The distribution of clusters' centroids in the five indicators through the SOM neural network training

Indicator number	Indicators	Cluster 1 $n = 127$	Cluster 2 $n = 84$	Cluster 3 $n = 92$	Cluster 4 $n = 113$	Cluster 5 $n = 179$	Cluster 6 $n = 77$
1	TAC	304 691	353 734	455 509	594 456	443 002	747 016^{H}
2	ACPC	1 307	1 857	1 607	2 381^{H}	1 521	2 113
3	PETTC	11%	10%	20%	16%^{H}	32%^{H}	26%
4	PRTTC	53%	65%^{H}	51%	61%^{H}	38%	48%
5	PRRSD	3.9%^{H}	3.6%	3.2%	2.5%	3.1%	2.8%

The superscript letter 'H' denotes the maximum value of attributes in terms of the clusters. The fee is in New Taiwan dollar. See Table 1 for abbreviations.

Table 4 The distribution of dentists in the six clusters ($n = 672$)

The number of dentists	Cluster 1 $n = 127$	Cluster 2 $n = 84$	Cluster 3 $n = 92$	Cluster 4 $n = 113$	Cluster 5 $n = 179$	Cluster 6 $n = 77$
Mean	1.1	1.1	1.2	1.6	1.2	1.8
Max.	2	2	4	6	5	8
Min.	1	1	1	1	1	1
Standard deviation	0.32	0.34	0.52	1.06	0.54	1.41

Table 5 ANOVA test of the six clusters

Attributes	*F*	*P*-value
Number of dentists	14.7	<0.0001
TAC	29.9	<0.0001
ACPC	221.6	<0.0001
PETTC	275.8	<0.0001
PRTTC	171.3	<0.0001
PRRSD	4.8	<0.0001

d.f. = 5; $n = 672$. See Table 1 for abbreviations.

Table 6 The dental fraudulent claim record within 5 years in the six clusters

	On record $n = 96$		Non-record $n = 576$			
	n	%	*n*	%	χ^2	*P*-value
Cluster 1	9	7.09	118	92.9	38.45	<0.0001
Cluster 2	6	7.14	78	92.9		
Cluster 3	10	10.87	82	89.1		
Cluster 4	36	31.86	77	68.1		
Cluster 5	19	10.61	160	89.4		
Cluster 6	16	20.78	61	79.2		

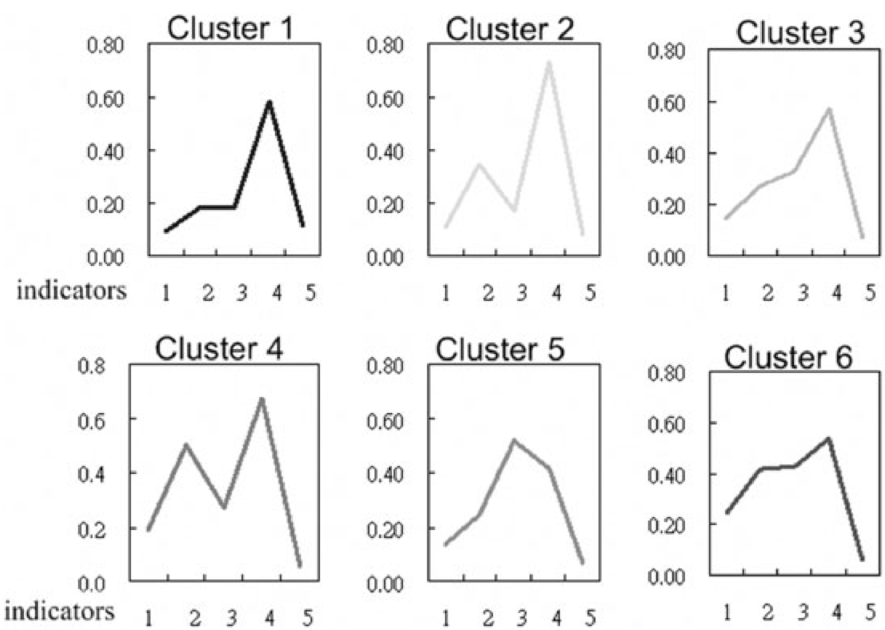

Figure 3 The five indicators of the SOM neural network projected into a 1-D grid in each cluster.

Table 7 The features description of the six clusters

Cluster 1 Conservative practice patterns • 127 dentists • The highest percentage of restoration replacement within 2 years by the same dentist (3.9%) • The lowest total fees (NT$ 304 691)	Cluster 2 Actively exploitative practice patterns • 84 dentists • The highest percentage of restoration rate per visit (65%) • The lowest of endodontic treatment (10.3%)
Cluster 3 Typical practice patterns • 92 dentists	Cluster 4 Higher frauds practice patterns • 113 dentists • The highest rate of fraudulent claims (32%) • The highest average fee per visit (NT$ 2381)
Cluster 5 Academic practice patterns • 179 dentists • The highest percentage of endodontic treatment (32%)	Cluster 6 More efficient practice patterns • 77 dentists • The higher rate of fraudulent frauds (21%) • The highest total claim fees (NT$ 747 016) • Group practices

The fee is in New Taiwan dollar. US dollar $1 = New Taiwan dollar $32.3 (1 March 2007).

Cluster 1: the lowest total fee and the highest restoration replacement within 2 years by the same doctor is named the conservative practice pattern;
Cluster 2: the highest restoration rate per visit is named the actively exploitative practice pattern;
Cluster 3: the lowest endodontic treatment is named the typical practice pattern;
Cluster 4: the highest rate of fraudulent claims and the highest average fee per visit is named the higher fraud practice pattern;
Cluster 5: the highest endodontic treatment is named the academic practice patterns;
Cluster 6: the highest total claim fees and the second highest rate of fraudulent claims is named the more efficient practice pattern.

Discussion

This study applies knowledge discovery technology to segment 672 dentists' profiles into six clusters as the fundamental information on which subsequent decisions are made. These results characterize a complete picture relating to the character of dentist practice profiles by reducing the attribute space to a smaller number of dimensions that yield useful information regarding variation in dental practice patterns.

In general, the patterns of practice which have been suggested as one source of variation in service-mix [1,17], such as dental caries, have been the chief oral health problems, and the overall patterns of dental care reflect the dominance of these conditions. Dentists determine when, how long, how intensively and at what cost to treat a patient. Furthermore, the dental practice represents a natural organized setting for observing variation in financial incentives and the impact of those incentives [44]. Hence, the third-party payer needs to focus on patterns that the specific practice costs value the most. Accordingly, the segmentation of practice patterns makes sense of features in each cluster. It facilitates the tackling of suspicious claims or abuse by recognizing and quantifying the underlying features of such patterns.

For early detection of fraudulent claims in health cost management it is necessary for the third-party payers to understand the complex practice patterns of health care providers who present abusive or suspicious practice patterns which may or may not relate to direct medical treatment. The segmentation of dentists' practice patterns with intelligible and accountable tools aimed at analysing and modelling the formal relationships between practice patterns and suspicious claims helps to spot inappropriate practice behaviour [4,9]. Therefore, the patterns of practice occupy a unique position on the spectrum of health cost control guidance. In addition, the domain experts also play an essential role in the paradigm because they decide whether a pattern or rule is relevant and useful [45]. Thus, in order to understand suspicious or abusive behaviour, in-depth interviews were conducted with three senior managers of BNHI and six senior dentists. Based on the interviews, the general types of suspicion or fraud are outlined as follows.

1 claiming for dental treatment not given;
2 submitting claims for unnecessary or redundant services to obtain more reimbursement;
3 falsifying a patient's diagnosis to justify treatments, surgery, or other procedures that are not necessary;
4 provision of additional non-covered services, such as cosmetic treatment;
5 upcoding – claiming for a more costly treatment or more complex caries than the one actually performed to obtain higher reimbursement;
6 unbundling – claiming each stage of a procedure as if it were a separate procedure;
7 waiving patient co-pays or deductibles and over-billing the insurance carrier or benefit plan;
8 use of a formatted dental record for many patients;
9 duplicate claiming of the same treatment on the same patient.
10 dental service provided by unlicensed dentist or dental assistant;
11 inadequate quality on restoration resulting in a re-restoration within 1 year;
12 providing treatment on a dead or non-existent tooth position.
13 offering a 'free' inlay to obtain the patient's insurance identification card for use in fraudulent billings.
14 unreasonable the geographic distribution the dentist treats many patients who live far from the clinic and may actually be claiming treatment without providing any.

Based on the general suspicious or fraudulent symptoms and behaviour of the practice patterns, the managerial guidance obtained from the interview with the experts and senior dentists in each cluster of dentists is given in Table 8.

The experts agree that peer review of dental records is one of the most promising approaches in reducing dental costs and fraud. The BNHI thus needs to strengthen the review of dental records and audit the accuracy of treatments in claims before billing.

Table 8 The summary of managerial guidance for the different clusters in dental claims

Clusters	Characteristics	Potential problems in quality and cost	Managerial guidance
Cluster 1	The highest percentage of restoration replacement within 2 years by the same dentist	Poor restoration quality	Routinely assessing and adopting quality improvement programmes
Cluster 2	The highest percentage of restoration rate per visit	Over-treatment on teeth restoration	Enhancing the peer review to verify the necessity of restoration
Cluster 4	The highest average fee per visit	Falsifying treatments or procedures	Enhancing the peer review on the claim billing and beneficiaries' telephone interview to verify the treatment was actually performed
Cluster 5	The highest percentage of endodontic treatment	Inadequate endodontic treatment or unnecessary endodontic treatment	Enhancing the peer review to evaluate the quality of root canal fillings and evaluation of success rate of endodontic treatment performed
Cluster 6	The highest total claim fees	Falsifying treatments or procedures and treatments performed by illegal provider	Enhancing the peer review on the claim billing and visiting dental clinics to verify the legality of the dentist

Moreover, the dental records can be evaluated to identify whether the treatment is the result of a valid variation or is consistent with potentially fraudulent behaviour. For example, cluster 4, the highest rate of fraudulent records and the highest average fee per visit, has some potential problems in dental costs. It has the suspicions of redundant claims for the same dentist consultation fee on the same day, billing for services not actually performed and waiving patient's insurance identification card for duplicating a claim or encouraging the patient to visit many times. Further peer-review (i.e. by a senior dentist) examines case details such as dental records with documents (i.e. photographs and X-rays for proving the treatment existence and necessity) to verify the reasonableness of such treatments. In addition, developing a check of the amount of working hours can support whether the service was actually performed. With regard to negative quality of care, a higher percentage of re-restoration wastes resources (e.g. cluster 1). However, re-restoration treatment considers the complex interaction of influences such as economic inducements, styles of practice and dentist characteristics, along with the concern for the patient's well-being and demand [1]. The third-party payer thus needs to routinely assess the appropriateness of re-restoration and adopt ongoing quality improvement programmes to encourage more appropriate treatment.

The proposed approach can provide the third-party payer with an easy way to decide managerial guidance and implement stratified sampling in claim auditing procedures according to the results of clustering to prevent health fraud and examining treatment quality. For example, the sampling rate of cluster 4 is 50%, cluster 6 is 30% and the other clusters' sampling rate are 20%. Therefore, the segmentation of dentists' practice patterns coupled with managerial guidance acts as a reference for auditing trails, and the third-party payer can thus gradually reduce the inspection and personnel costs and alleviate another burden on dental care finances.

However, the strengthening of dental record review is the major anti-fraud action recommended. Nevertheless, dental claim auditing or record review is time-consuming, especially for large government-sponsored national insurance programmes such as in France, Australia and Taiwan [46]. The effective segmentation of dentists' practice patterns by recognizing and quantifying the features of claims fosters better direction in detecting claim fraud and investigating the providers with aberrant patterns or practices [4,23]. The third-party payer can thus gradually reduce the inspection and personnel costs in the reimbursement process.

Conclusions and further research suggestions

The study provided a segmentation of dentist patterns into various clusters reflecting the nature and style of their practice. The major contribution of this study is to successfully integrate the segmentation of dentists' practice patterns with the knowledge discovery process. These findings will help the third-party payer to discriminate the patterns of practice, and also shed more light on the fraudulent claims and practice patterns of relationships among dentists. The recognition of these variations on practice patterns has led to considerable process in countering fraudulent claim and cost reduction policies.

Different managerial guidance is provided for the clusters, and this provides a practical way of clustering the anomalies in dentists' practice patterns. The artificial intelligence solution is appropriate as the core of an automatic system by extracting practice relationship rules and applying them repeatedly against new claim submissions for detecting dental care fraud and abuse. In order to identify the providers (and recipients) who are most likely to commit fraud against the dental care programme of health insurance.

Furthermore, our method has been evaluated objectively using a real-world data set gathered from the NHI programme in Taiwan. The empirical experiments show that the model is efficient and capable of identifying suspicious and abusive behaviour. It provides the third-party payer with a new solution to manage health expenditures.

While this study is valuable for health insurance institutions, more detailed and in-depth explorations need to be conducted, for example: (i) developing a data-driven initiative to analyse and model the formal relations between dentists' practice patterns and fraudulent claims, such as a report for abnormal patterns that have been identified and which suggest improper practices; preventing improper or potentially fraudulent practices; (ii) building an intelligent diagnosis system to detect and measure the magnitude of the fraudulent claims with practice patterns; identifying new patterns of abnormalities beyond claims, such as detecting outliers surrounding a dentist profile in relation to enrollee data and services rendered; and (iii) developing a set of recommendations for software developers and users of pattern discrimination to maximize antifraud practices and prevention measures.

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