Artificial Intelligence in Medicine 75 (2017) 40–50

Contents lists available at ScienceDirect

Artificial Intelligence in Medicine

journal homepage: www.elsevier.com/locate/aiim

The evaluation of trustworthiness to identify health insurance fraud in dentistry

Shu-Li Wang[a,c], Hao-Ting Pai[b,*], Mei-Fang Wu[c], Fan Wu[d], Chen-Lin Li[d]

[a] Department of Dental Technology and Materials Science, Central Taiwan University of Science and Technology, 666 Buzih Rd., Taichung 40601, Taiwan
[b] Department of Industrial Engineering and Management, Da-Yeh University, No.168, University Rd., Dacun, Changhua 51591, Taiwan
[c] Department of Industrial Engineering and Systems Management, Feng Chia University, No. 100, Wenhwa Rd., Seatwen, Taichung 40724, Taiwan
[d] Department of Information Management, National Chung Cheng University, 168 University Rd., Minhsiung 62102, Taiwan

ARTICLE INFO

Article history:
Received 11 February 2016
Accepted 10 December 2016

Keywords:
Fraud identification
Social network
Trustworthiness evaluation
Dentistry

ABSTRACT

Objective: According to the investigations of the U.S. Government Accountability Office (GAO), health insurance fraud has caused an enormous pecuniary loss in the U.S. In Taiwan, in dentistry the problem is getting worse if dentists (authorized entities) file fraudulent claims. Several methods have been developed to solve health insurance fraud; however, these methods are like a rule-based mechanism. Without exploring the behavior patterns, these methods are time-consuming and ineffective; in addition, they are inadequate for managing the fraudulent dentists.
Methods: Based on social network theory, we develop an evaluation approach to solve the problem of cross-dentist fraud. The trustworthiness score of a dentist is calculated based upon the amount and type of dental operations performed on the same patient and the same tooth by that dentist and other dentists.
Results: The simulation provides the following evidence. (1) This specific type of fraud can be identified effectively using our evaluation approach. (2) A retrospective study for the claims is also performed. (3) The proposed method is effective in identifying the fraudulent dentists.
Conclusions: We provide a new direction for investigating the genuineness of claims data. If the insurer can detect fraudulent dentists using the traditional method and the proposed method simultaneously, the detection will be more transparent and ultimately reduce the losses caused by fraudulent claims.

1. Introduction

Medical expenditures have increased sharply in recent years due to the aging of the population. To properly allocate medical resources, many health insurance policies have developed programs such as fee for capita and fee for quality, cost containment methods like diagnosis-related groups (DRG), and prospective payment systems like global budget, etc., to help people access adequate health care service with affordable costs. In most countries, such as Taiwan, Germany and Canada, national insurance allows the patients to pay a small amount of money, called a *co-payment*, when they consult a physician. The physician, in turn, files a claim for medical expenses after the medical treatment. The health insurance authority then reimburses the expenses according to the claim. This reimbursement procedure has an advantage in that the patient does not need to pay a significant amount of money when visiting the doctor. The major fiscal load is lifted from the public; the health provider has the responsibility of obtaining reimbursement for the treatment fee instead. However, this type of reimbursement procedure creates a moral hazard in that the physicians may generate bogus claims, especially when the patients do not fully understand what medical services they received. For instance, a dentist may request a reimbursement for providing a dental filling treatment to a patient who does not need or even does not actually receive the treatment. Fraudulent claims for these types of filling treatments in dentistry often occur because the patient is normally not aware or does not confirm how many and upon which teeth the filling treatments are performed.

The ratio of fraudulent claims varies across different departments. In some departments, patients have knowledge regarding the common diseases (e.g., colds and fever) as well as regarding their treatment. If physicians in these departments file fraudulent claims, the insurer can easily audit or verify them. However, in other departments, such as the dental department, it is hard for patients to know what medical services they receive because most of them

* Corresponding author.
E-mail addresses: slwang@ctust.edu.tw (S.-L. Wang), htpai@mail.dyu.edu.tw (H.-T. Pai), mfwu@fcu.edu.tw (M.-F. Wu), kfwu@mis.ccu.edu.tw (F. Wu), porkcircle@gmail.com (C.-L. Li).

http://dx.doi.org/10.1016/j.artmed.2016.12.002
0933-3657/

lay down on the chair, open their mouths and have no precise idea about what type of treatment they are receiving; in addition, dental treatment is normally conducted only by the dentist in a dental clinic; no other nurse or staff witnesses the treatment. Thus, dental clinics have a higher ratio of fraudulent claims, especially for dental filling operations, which are the hardest claims to verify [1].

The Federal Bureau of Investigation (FBI) defined fraudulent claim for medical service [2], such as upcoding of services, duplicate claims, unbundling, etc; simply, it is an intentional deception or misrepresentation made by a physician or a subscriber who can gain some inappropriate benefit from the fraudulent claim. The United States General Accounting Office [3] reported that health care fraud costs are at least 10% of total health care costs annually. Over the past decade, the Economist [4] specifies that: "*fraud added as much as* $98 *billion, or roughly 10%, to annual Medicare and Medicaid spending—and up to* $272 *billion across the entire health system in 2012*". Similar fraud and abuse have been reported for the health insurance programs in other countries. Studies [5,6] also noted that over 10% of the total expenditure on health care was wasted by fraudulent claims. In Taiwan, the amount of money wasted by fraudulent claims is estimated NT$181.4 billion dollars (approximately USD 3.5 billion), accounting for 10% of the total health care expenditure from 2006 to 2009 [7]. If the fraudulent claims cannot be effectively prevented or detected, this type of loss will pose a serious threat to the health insurance system.

To detect fraudulent claims, insurers used to hire specialists to manually review each reimbursement application submitted by the physician. If there is any suspicion, the insurer would investigate to verify whether the application was fraudulent or not. This manual method is very time-consuming, especially given the large volume of government-sponsored insurance programs. Recently, computer-assisted review methods [8–11] have been introduced to facilitate the detection of fraud. These methods investigate fraudulent patterns based on rules and heuristics provided by experienced specialists. For example, the statistical analysis method can identify physician fraudulence if claims fall too often in the outlier area with respect to the service amount, treatment distribution, costs of medicine or procedures without the support of evidence. However, some fraud still cannot be detected because some physicians file sophisticated claims that are not outliers and satisfy all of the practical guidelines. The analysis methods are silent in such cases.

Many researchers [12–19] propose using data mining techniques [20] to discriminate between normal and suspicious claims (see the survey [21] in more detail). These techniques extract characteristics of fraudulent claims by mining past fraudulent claims and then scanning the new claims for characteristics that match the fraudulent ones. This technique is time-consuming. For example, a predictive data mining method is time-efficient after the supervised model has been constructed; however, it probably takes much time in the supervising phase. In real-world applications, data mining is adopted to decision support and specialists (users) manually revise their judgments by tuning the parameters. The extant research detects fraudulent claims using statistical techniques, data mining, neural networks, fuzzy and classification algorithms, and so on, all of which analyze the characteristics of the overall or individual claims data. However, there are some sophisticated frauds that are qualified in the overall viewpoint (i.e., are not outliers) and considered to be normal from the individual viewpoint (i.e., conforming to all claims rules).

In this paper, we evaluate the trustworthiness of each dentist rather than determining whether these claims are fraudulent. For the dentists with a low degree of trustworthiness (i.e., a high degree of suspicion), the authority can investigate the related patients and patient records to clarify the suspicion. The computation for the trustworthiness of each dentist is based on the analysis of the treatments, especially for cross-dentist filling operations. For cross-dentist filling operations, we employ a social network to represent the precedence relationship of the dentists and then adopt the page-ranking concept (discussed later) [22,23] used in search engines to compute the trustworthiness degree for each dentist in the social network.

Our method considers not only the social network among dentists formed by cross-dentist treatments but also the medical behavior and factors affecting dentist trustworthiness (such as the time gap between visits). By using reliable trustworthiness scores for dentists, claims reviewers can understand the trustworthiness of each dentist and easily process a large number of claims because they only need to examine the claims filed by dentists with low trustworthiness scores. Our method can help to ease their workload, improve their review efficiency, and ultimately reduce the loss caused by fraudulent claims.

2. Preliminaries

2.1. Scenarios: health insurance fraud in dentistry

Previously, research on fraud detection primarily analyzed the characteristics of claims data from a micro viewpoint, like whether a patient is qualified to receive a health services, or from a macro viewpoint, like whether the claim of a patient falls in the outlier. However, neither of these viewpoints globally consider that fraud may exist in cross-physician treatments. For instance, fraud may exist if more than one physician filled the same tooth of the same patient, but the fraudulent claim is qualified in the micro viewpoint for a patient and in the macro viewpoints for a physician. We employ a social network to globally represent the precedence relationship of the dentists. Then we adopt the page-ranking concept [22,23] used in search engines to compute the trustworthiness degree for each dentist in the social network. The page-ranking criterion uses two mechanisms, namely, the hub and authority, to rank the pages in the Web space. A type of web pages, called authority pages, are important if they have links pointing to many important web sites; while another type of web pages, called hub pages, are also important if many important web sites having a link pointing to them.

In dentistry, a cross-dentist filling operation relates to two dentists, called *first-hand* and *second-hand* dentists. A fraud suspicion exists between these two dentists. Similar to the page-ranking concept, the first-hand dentist has a higher suspicion degree if many of his/her patients who had received a filling operation by the dentist receive the same filling operation for the same tooth again by other subsequent dentists; while the second-hand dentist has a higher suspicion degree if the second-hand dentist always provides a filling operation to the patients who had received a filling operation for the same tooth by other dentists beforehand.

Below are two examples to illustrate the situation: the first example is of fraud committed by the second-hand physician; while the second is committed by the first-hand physician.

Example 1. Assume that patient A has a toothache in one of his/her teeth and that he consults dentist α for treatment (step 1 in Fig. 1). Dentist α provides a dental filling to the tooth of patient A (step 2 in Fig. 1). After the treatment, dentist α applies for reimbursement for the dental filling of patient A from the insurer (step 3 in Fig. 1). The insurer offers payment to dentist α (step 4 in Fig. 1). Later, patient A consults dentist β for some other treatment (step 5 in Fig. 1). Dentist β does not provide a dental filling for the same tooth treated by dentist α to patient A, but he still applies for reimbursement for the dental filling for the same tooth from the insurer (step 7 in Fig. 1). The insurer also offers payment to dentist β (step 8 in Fig. 1).

Example 2. Patient A visits dentist α for some dental disease (step 1 in Fig. 2). Dentist α does not provide a dental filling to patient A for

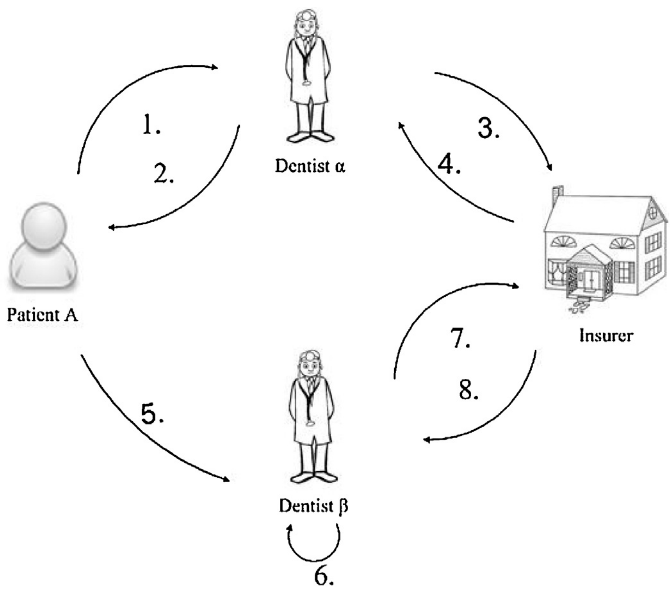


Fig. 1. Steps in the fraud committed by the second-hand physician.

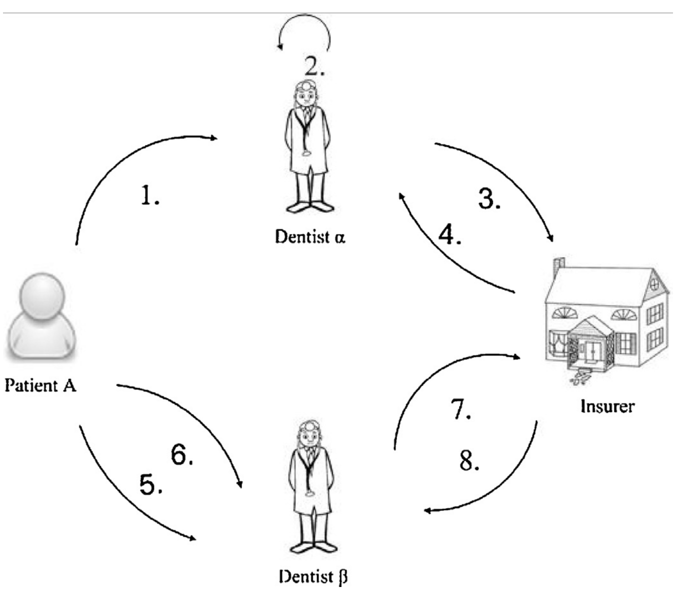


Fig. 2. Steps in the fraud committed by the first-hand physician.

some tooth but still applies for reimbursement for the dental filling for that tooth from the insurer (step 3 in Fig. 2). The insurer offers payment to dentist α (step 4 in Fig. 2). Assume patient *A* consults dentist *β* for treatment for that tooth in some day (step 5 in Fig. 2). Dentist *β* provides a dental filling to patient *A* (step 6 in Fig. 2) and then applies for reimbursement from the insurer (step 7 in Fig. 2). The insurer offers payment to dentist *β* (step 8 in Fig. 2).

As discussed before, dental treatment is normally conducted only by the dentist in a dental clinic; no other nurse or staff witnesses the treatment. During the treatment, the patients lay down on the chair, open their mouths and have no precise idea about how many teeth and what type of treatment they are receiving. The above two examples of fraudulent claims demonstrate the difficulty in identifying which physician applies a fraudulent claim for the dental filling treatment to Patient *A*. In this situation, some effective methods for identifying the dentists who tend to apply fraudulent claims should be developed.

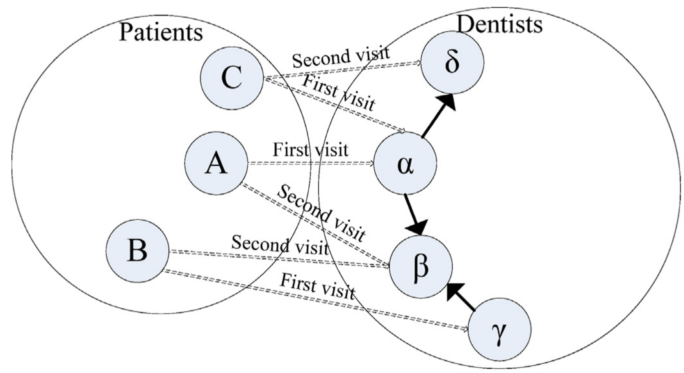


Fig. 3. A social network of dentists since of cross-dentist filling operations.

2.2. Relation modeling based on social networks

To derive the relationship between dentists, we employ the concept of (directed) social networks to represent the precedence relationship of dentists. In detail, the social network consists of nodes and links, where the nodes represent the dentists and the link between two nodes represents two corresponding dentists filling the same tooth for a specific patient. Note that the link between two dentists is directed according to the order in which they were visited.

Example 3. Assume that patient *A* consults dentist α then dentist *β* and that the claims from dentists α and *β* show the dentists both filling the same tooth for patient *A*. Then, there is a directed link starting from dentist α pointing to dentist *β* that denotes the precedence relationship of the visits, as can be seen the social network of dentists in Fig. 3. Assume that patient *B* consults dentist γ then dentist *β*, and patient *C* consults dentist α then dentist δ as the case of patient *A*. Then, there are two directed links starting from dentistγpointing to dentist *β* and from dentist α pointing to dentist *δ* in Fig. 3 that respectively denote the precedence relationship of the two visits. A social network, circled in the right of Fig. 3, among dentists α, *β*, γ, and δ is formed since of the cross-dentist filling operations for patients *A*, *B*, and *C*.

There are two special phenomena in the social network of dentists. The first is that most of the links for some dentists, like dentist α in Fig. 3, point to other dentists, and the second is that many links for some dentists, like dentist *β* in Fig. 3, point from other dentists. The first phenomenon may emerge because the (first-hand) dentists did not cure or provide treatment to their patients, and the patients then consulted the second-hand dentists. The second phenomenon may appear because the (second-hand) dentists apply for reimbursement for their patients since they find the first-hand dentists have performed a well filling operation on the tooth (but they did not treat the tooth). Obviously, most of the dentists in the constructed social network have the suspicion (or *doubt*) of fraud claim.

2.3. The concept of suspicious accumulation

To detect fraudulent dentists, we propose the concept of suspicion accumulation to evaluate the trustworthiness of each dentist. In other words, the dentists' claims data carry doubts to other dentists and the doubts for a dentist can be accumulated if a suspicious claim related to one more dentists. For instance, if suspicious claim data establishes a link between two dentists, both the dentists involved in the links have a doubt because one of them may be committing fraud. The more links a dentist has, the higher suspicion of fraud claims the dentist has. In other words, if a large number of patients are found to have received their initial treatment from

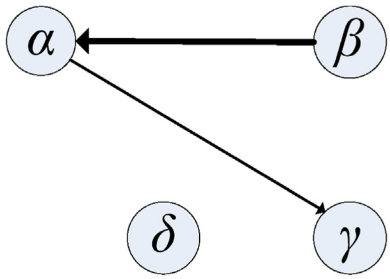


Fig. 4. The social network of the four dentists.

dentist α and then other subsequent dentists for the same tooth, dentist α has a high level of doubtfulness. Doubt is ascribed in this situation because most of these patients need a second-hand treatment after visiting dentist α. It is very possible that dentist α failed to provide adequate treatment to the patient. On the contrary, if a large number of patients receive second-hand treatment from dentist β for the same tooth treated by other dentists in advance, dentist β also has a high level of doubtfulness. It is very likely that dentist β applies for payment without actually rendering treatment to his/her patients.

We will next explore some factors that may affect trustworthiness (such as the time gap between visits) in the next section. These factors will be weighted and will be a basis for developing a measure of the dentists' trustworthiness.

3. Design for evaluating dentists' trustworthiness

Dentistry treatments are varied. Some treatments are easily committed, but others are not. For example, treatments such as split treatments and periodontal flap operations, which are complicated and time-consuming, are easily committed because dentists are required to provide sufficient evidence (such as X-ray films and proof of treatment) during the application for reimbursement for these treatments. Some treatments, such as dental fillings and dental scaling, which are trivial and easily performed, are difficult to commit because the patients cannot confirm what treatment they received. Fraudulent claims often occur in the treatments that are difficult to commit. Then, the trustworthiness of the dentists will be based on genuine treatments that are difficult to commit.

3.1. *The social network of dentists*

Each node in the social network of dentists represents a dentist; each link denotes the relationship between two dentists if they both provide the same treatment to the same patient on the same tooth, and the direction of the link denotes the order of the treatment provided by the two dentists connected by the link, as can be shown in example 3 and Fig. 3. According to the domain knowledge of dentistry, a good operation should guarantee a curing effect for a period (called *year warranty*). For instance, a dental filling treatment should guarantee that the filled tooth will not be filled again within two years after receiving the filling treatment. Thus, we construct the link between two nodes only when the time gap for the two treatments performed by the two dentists on the same tooth for the same patient is within the warranty of the treatment.

Table 1 contains a set of insurance claims for a scenario in which there are three patients *A*, *B*, and *C* receiving treatments from four dentists α, β, γ and δ. Fig. 4 is the corresponding social network of dentists constructed from the table and is composed of four nodes representing the four dentists and two directed links denoting the relationships of the dentists. Because dentist α provides patient *B* with the same treatment (i.e., a tooth filling) on the 17th tooth earlier than dentist γ (see entries 1 and 4 in Table 1), there is a link pointing from dentist α to dentist γ. Because dentist β provides patient *A* with the same treatment (i.e., tooth scaling) on the 11th tooth earlier than dentist α (see entries 2 and 7 in Table 1), and dentist β provides patient *C* with a tooth filling treatment on the 23th tooth earlier than dentist α (see entries 3 and 5 in Table 1), there is a link pointing from dentist β to dentist α. Note that there are "two" identical treatments on the same tooth of the same patient between dentists α and β, but there is only "one" identical treatment between dentists α and γ. To reflect the above different conditions, the link between dentists α and β is twice as wide as the link between dentists α and γ. However, dentist δ is isolated (i.e., no link connects the node to another in either direction) because there are no other dentists providing the same treatment on the same tooth for the same patient as dentist δ.

The construction of a link should consider not only whether the two dentists provide the same treatment on the same tooth for the same patient but also whether the time gap is within the year warranty for the treatment. For example, there is no link between dentists β and γ, though they both fill the 15th tooth of patient *C* (see entries 8 and 9 in Table 1). The reason is that the time gap (i.e., over two years) between the two treatments is beyond the year warranty (i.e., two years) of the tooth filling treatment.

3.2. *Trustworthiness evaluation*

The trustworthiness of a person can be quantified as a value [24,25]. The higher the trustworthiness score of a person is, the higher the trustworthiness of this person will be. Generally, a good dentist will not perform unnecessary treatment on the tooth of a patient if the patient's tooth is treated well by other good dentists. Similarly, a patient will most likely not receive the same treatment on the same tooth within the year warranty of this treatment if the treatment is performed by a good dentist. In the proposed social network of dentists, a link is established only when the two connected dentists claim to have provided the same treatment on the same tooth of the same patient within the year warranty of the treatment. By using the trustworthiness score of a dentist, we can observe whether a link relationship exists in their claims.

To be precise, we first divide the claims into two types: one is the claims that do not incur a link relationship with the claims of other dentists, and another is the claims that do incur such a link relationship. For the first type, the corresponding dentist may provide an excellent treatment on the tooth of the patient such that this patient does not need to visit other dentists to treat the same tooth. Thus, we increase the trustworthiness score for this dentist. For the second type, both dentists provide dental filling treatments on the same tooth of the same patient, and the time gap between the two treatments is within the year warranty of the treatment. Actually, it is difficult to distinguish which dentist files the fraudulent claim; we can only infer that these two dentists are suspected of filing the fraudulent claim. For these two possible cheating dentists, we depreciate their trustworthiness scores. Furthermore, the more such links a dentist has, the higher the degree of suspicion (or the lower the trustworthiness score) for that dentist. We compute the trustworthiness score of a dentist by analyzing the link relationships from the claims as defined below.

Definition 1. Suppose dentist u has N_u^{diff} claims for difficult-to-commit treatments. These N_u^{diff} claims are divided into two types: $N_u^{diff,NoLK}$ claims not incurring a link relationship with other claims and $N_u^{diff,LK}$ claims incurring a link relationship with other claims. The score of claim $N_u^{diff,NoLK}$ is set to one, i.e., $Score(u_i^{diff,NoLK}) = 1$, while the score of claim $N_u^{diff,LK}$ is set to negative one, i.e., $Score(u_j^{diff,LK}) = -1$. Let $Tr(u)$ denote the trustworthiness score of dentist u, as given:

Table 1
Data retrieved from insurance claims.

No.	Patient	Dentist	Treatment	Position	Date of treatment
1	B	α	tooth filling	17	20080206
2	A	β	tooth scaling	11	20080315
3	C	β	tooth filling	23	20080317
4	B	γ	tooth filling	17	20080620
5	C	α	tooth filling	23	20080730
6	A	δ	tooth filling	16	20080811
7	A	α	tooth scaling	11	20080813
8	C	β	tooth filling	15	20080913
9	C	γ	tooth filling	15	20101010

$$Tr(u) = \sum_{i=1}^{N_u^{diff,NoLK}} Score(u_i^{diff,NoLK}) + \sum_{j=1}^{N_u^{diff,LK}} Score(u_j^{diff,LK})$$

Note that there are three conditions for a claim incurring a link relationship with the claims of other dentists. The first condition is that a dentist first treats a patient and then the patient visits another dentist and receives the same treatment on the same tooth. In such a condition, the claim of the first dentist is called the first-hand claim. The second condition is that a dentist is the second dentist to treat a patient who had received the same treatment on the same tooth by a previous dentist; after receiving the treatment from the second-hand dentist, this patient does go to another dentist to treat the same tooth. The claim of the second dentist is called the second-hand claim. However, if the patient still goes to another dentist to receive the same treatment on the same tooth as that provided by the second-hand dentist, the claim of the second-hand dentist will be called the first-&-second-hand claim. In summary, the claims incurring a link relationship with the claims of other dentists can be further classified into three sub-types. The first sub-type is claims that are only first-hand claims, the second is claims that are only second-hand claims, and the third is claims that are both first-hand and second-hand claims. It is worth nothing that first-hand and second-hand claims are both suspected of being fraudulent claims. Thus, one will be subtracted from the trustworthiness score of the dentist if the dentist has such a claim. However, if the claim of a dentist is a first-&-second-hand claim, it means that the dentist provides the same treatment on the same tooth of the same patient that was provided by two other dentists. Clearly, the suspicion of filing fraudulent claims for this type of claim is twice that of the first-hand or second-hand claims because a first-&-second-hand claim can be divided into a first-hand claim and a second-hand claim. Thus, two will be subtracted from the trustworthiness score of a dentist if the dentist has a first-&-second-hand claim.

Example 1. Assume that dentist u has applied 100 claims, 20 of which incur link relationships with the claims of other dentists. Suppose that there are 4 first-hand claims, 6 s-hand claims, and 10 first-&-second-hand claims. By Definition 1, the trustworthiness score of dentist u is:

$$\begin{aligned} Tr(u) &= \sum_{i=1}^{80} Score(u_i^{diff,NoLK}) + \sum_{j=1}^{20} Score(u_j^{diff,LK}) \\ &= 1 \times 80 + ((-1) \times 4 + (-1) \times 6 + (-2) \times 10)) = 50. \end{aligned}$$

Example 2. Suppose dentist α has 1000 claims, 300 of which incur link relationships. For the 300 claims, 120 are first-hand claims, 80 are second-hand claims, and 100 are first-&-second-hand claims. Dentist β has 10 claims, 3 of which incur link relationships. For the 3 claims, 2 are second-hand claims, and the remaining claim is a first-&-second-hand claim. Then, the trustworthiness score of dentist α is 300 (i.e., $700 + ((-1) \times 120 + (-1) \times 80 + (-2) \times 100))$) and that of dentist β is only 3 (i.e., $7 + ((-1) \times 2 + (-2) \times 1)$).

In these examples, the dentists who have many claims generally have higher scores than those dentists who have fewer claims. It is unfair to calculate a dentist's trustworthiness score using the number of claims. Indeed, it is fairer to evaluate a dentist's trustworthiness score based on the ratios of the number of claims with and without link relationship against the total number of claims.

Definition 2. Assume dentist u has N_u^{diff} claims for difficult-to-commit treatments. The trustworthiness score of dentist u is revised to be

$$1/N_u^{diff} \times (\sum_{i=1}^{N_u^{diff,NoLK}} Score(u_i^{diff,NoLK}) + (\sum_{j=1}^{N_u^{diff,LK}} Score(u_i^{diff,LK}))$$

According to Definition 2, dentist α in Example 2 will obtain a trustworthiness score of 0.3 (i.e., 300/1000), as does dentist β (= 3/10).

In Definition 2, we depreciate the trustworthiness scores of two connected dentists because both of them are suspected of filing fraudulent claims. However, it is possible that the first-hand dentist genuinely provided adequate treatment to the patient, but the patient suffered the same disease within the year warranty for various reasons (such as poor sanitary habits). Thus, it is likely that this patient consults with the second-hand dentist and receives the same treatment on the same tooth. Clearly, the likelihood that both the first-hand and second-hand dentists genuinely provide adequate treatment for the same patient is proportional to the time gap between these two treatments. The longer the time gap between the two treatments, the higher the possibility will be that the two dentists are genuinely providing adequate treatment. Therefore, we should also consider the time gap between the first-hand and the second-hand treatments for the same patient when calculating the trustworthiness score of the dentists. Then, for the first-hand, second-hand, and first-&-second-hand claims, the score of the corresponding claims should be revised to include a temporal factor such that the (negative value) scores of these claims are inversely proportional to the time gap between two related claims.

Definition 3. Assume that $u_j^{diff,LK}$ denotes the jth claim for the difficult-to-commit treatments of dentist u that incurred a link relationship and that $Score(u_j^{diff,LK})$ denotes the score of $u_j^{diff,LK}$. Let the time gap between the treatments of claim $u_j^{diff,LK}$ and its first-hand or second-hand treatment be $TDiff(u_j^{diff,LK})$. Then, the score of the claim is revised as

$$\begin{aligned} &1/N_u^{diff} \times (\sum_{i=1}^{N_u^{diff,NoLK}} Score(u_i^{diff,NoLK}) \\ &+ \sum_{j=1}^{N_u^{diff,LK}} (Score(u_j^{diff,LK})/TDiff(u_j^{diff,LK}))) \end{aligned}.$$

Note that the time gap is counted in months in this paper; for example, $TDiff(u_j^{diff,LK})$ is one if its time gap is within one month; $TDiff(u_j^{diff,LK})$ is two if its time gap is within two months.

Example 3. Assume that dentist α has 10 claims for difficult-to-commit treatments, three of which, denoted as C_1, C_2 and C_3, incur link relationships. Suppose claim C_1 is a first-hand claim whose treatment is performed one month earlier than the subsequent treatment by another dentist. Claim C_2 is a second-hand claim, whose treatment is performed six months after a treatment performed by another dentist. Claim C_3 is a first-&-second-hand claim with the corresponding treatment performed four months after the treatment performed by a first dentist and three months earlier than the treatment performed by a third dentist. By Definition 3, the trustworthiness score of dentist α is 21/40 (i.e., $1/10 \times (7 + ((-1)/1 + (-1)/6 + (-1)/3 + (-1)/4))$).

As discussed before, we depreciate the trustworthiness score of a dentist if the dentist has a first-hand claim. We are guessing that the dentist applied for a reimbursement for a treatment that he/she did not provide to the patient because the patient needed to consult with the second-hand dentist for the same treatment. However, it is possible that the first-hand dentist genuinely provided adequate treatment on the patient's tooth and the second-hand dentist submitted the fraudulent claim. Therefore, we also depreciate the trustworthiness score of a dentist if that dentist has a second-hand claim. We guess that the second-hand dentist applied for a reimbursement for a treatment that he/she did not provide because the first-hand dentist performed the treatment properly. However, there is still the possibility that the second-hand dentist genuinely provided adequate treatment to the patient because the first-hand dentist may not have cured this patient. For the above reasons, it is not fair to decrease the trustworthiness score of a dentist only considering the amount, ratio, and time gap of his/her first-hand, second-hand, and first-&-second-hand claims. That is, in addition to the link properties of a node, the personality and reputation of the corresponding dentist should also be considered [26]. The personality and physic of a dentist can be input into the social network manually. However, this manual input is subjective and cannot cover all of the dentists in an area. For example, for Taichung city in Taiwan, there are over 5000 dentists. According to the opinions of experts in detecting fraudulent claims, the difference between the number of second-hand and first-hand claims for a dentist can be a hint as to the personality and physic of the dentist. If a dentist has significantly more first-hand claims than second-hand claims, we guess that this dentist fails to provide adequate treatment to most of his/her patients, so that many of these patients must seek subsequent treatment from the second-hand dentists. However, if a dentist has more second-hand than first-hand claims, we can infer that this dentist provides adequate treatment to most of his/her patients, so that most of his/her patients do not need to seek the same treatments elsewhere. Thus, we use the difference between the number of first-hand and second-hand claims as an indicator to reflect the properties of a dentist.

Definition 4. Let $FHand(u)$ denote the number of first-hand claims and $SHand(u)$ denote the number of second-hand claims for dentist u. The personality and physic of a dentist is approximated by the value of $SHand(u) - FHand(u)$.

Note that the number of first-hand and second-hand claims for dentists vary. The dentists who have many claims will dramatically gain or lose more in their trustworthiness score than those dentists with fewer claims. To remedy this flaw, we use the ratio for the difference between the first-hand and second-hand claims of a dentist against the sum of the first-hand and second-hand claims of that dentist as an indicator of the personality and physic of that dentist.

Definition 5. Assume dentist u has $FHand(u)$ first-hand claims and $SHand(u)$ second-hand claims. The indicator to reflect the personality and physic of this dentist is $(SHand(u) - FHand(u))/(SHand(u) + FHand(u))$.

In a social network, the trustworthiness of a node should consider the properties of the node and the interaction conditions of the node with other nodes in the social network [26]. By analyzing the claims, we can derive the interaction condition and the properties of the corresponding dentist of a node (see Definition 3 and Definition 5). The two metrics have their own weight in the trustworthiness scores of dentists. Without loss of generality, we denote the weights of the two metrics as σ and δ, where $\sigma + \delta = 1$. The final trustworthiness score of dentist u, denoted as $Tr(u)$, is computed as follows:

$$Tr(u) = \sigma \times 1/N_u^{diff}\left(\sum_{i=1}^{N_u^{diff,NoLK}} Score(u_i^{diff,NoLK}) + \sum_{j=1}^{N_u^{diff,Lk}} (Score(u_j^{diff,Lk})/TDiff(u_j^{diff,LK}))\right) + \delta \times (SHand(u) - FHand(u))/(SHand(u) + FHand(u)).$$

The exact values of σ and $\delta$are undecided until now. They are decided retrospectively by the empirical data such that the computed trustworthiness of the dentists match the pre-known facts (i.e., seven fraudulent dentists in the empirical data) as possible. Then, the trustworthiness of other dentists is computed with the weights accordingly.

4. Analysis and discussion

Since of confidential issue and privacy legislation, the comprehensive and full-scale data is difficult to retrieve, especially for the healthcare data. For conducting simulations, synthetically generated dataset is used first. To synthesize the dataset, all important factors, influencing the data generation, distribution, and interaction, should be considered. In this paper, we consider the probability of fraudulence, the visiting rate of patients, the probability of visiting different dentists for a patient, and so on. The limitation of the synthesized data is dependent on the computing power and the duration of each simulation. The more factors under consideration, the more time and higher computing power will be. Some other miner factors, such the dynamic personality of the dentists, the smarter detection along the time, the cognition of patients for their own right, and so on are not considered in the simulation. For the sake of simplicity, only the major factors are considered during the data generation. For a strictly confidential data, given artificial data is better than no data. In addition, the synthetically generated data can be closer to the real data, and we can explore the nature, and the consequences, of that relationship along the time. In the next subsection, we synthesize a dataset under some reasonable assumptions to conduct the simulation and then demonstrate the effectiveness of the proposed method.

4.1. Simulations

To demonstrate the effectiveness of the proposed equation to evaluate the trustworthiness of dentists, we use a data generator to generate the claims data according to some scenarios and perform a simulation using the proposed equation for trustworthiness evaluation. We generate 500 dentists beforehand, who are classified into five categories, including (1) fraudulent dentists, denoted as F, who always file fraudulent claims; (2) less-trusted dentists, denoted as L, who frequently file fraudulent claims; (3) normal dentists, denoted as N, who sometimes file fraudulent claims; (4) good dentists, denoted as G, who seldom file fraudulent claims; (5) excellent dentists, denoted as E, who never file fraudulent claims. Since not everyone would like to cheat in the claiming and the detection of fraudulent claims is not so sensitive, the population distribution of the five categories is assumed to follow the standard normal distribution. That is, the 500 dentists are assigned to one of the

Table 2
The parameters of simulation.

	F	L	N	G	E
Probability	2.5%	7.5%	80%	7.5%	2.5%
Fraud rate	20%	10%	5%	3%	0%

Table 3
The preference relationship.

Patient Visit Dentists (Probability)	P_1	P_2	P_3	...	P_{50000}
70%	D_2	D_{33}	D_6	...	D_1
20%	D_{142}	D_{320}	D_{222}	...	D_{499}
9%	D_{486}	D_{55}	D_{60}	...	D_{500}
1%	D_8	D_{133}	D_{24}	...	D_{491}

five categories based on 500 trials with a random number x with $x \sim ND(0, 1)$. Their categories are decided by the value of the trials as follows:

$$\begin{cases} if x \leq -1.96, x \in \text{fraudulent dentist(denoted as} < F); \\ if -1.96 < x \leq -1.281, x \in \text{less-trusted dentist(denoted as}L); \\ if -1.281 < x \leq 1.281, x \in \text{normal dentist(denoted as}N); \\ if 1.281 < x \leq 1.96, x \in \text{good dentist(denoted as}G); \\ if x > 1.96, x \in \text{excellent dentist(denoted as}E). \end{cases}$$

Table 2 also provides the fraud rate for each category. Without loss of generality, the fraud rates are assigned by rule of thumb according to the categories of their personality.

We next generate 50,000 patients, each of which has 32 teeth numbered from 11 to 42. To emulate the real world, the scenarios for the simulation are described as follows.

(1) In the real world, many patients are treated by a specific dentist because of location, loyalty, habit, or other reasons. Without loss of generality, for each patient, we randomly select three dentists as his/her preference, and the patient will visit them with a probability of 70%, 20%, and 9%, respectively. However, patients may visit an unfamiliar dentist with a small probability because of an emergency, travel, etc. The patient will still have some very small probability, i.e., one percentage point in this paper, of visiting some other unfamiliar dentist. Table 3 shows the preference relationship between the 500 dentists and the 50,000 patients, showing their visiting relationships as well as their individual probability. For example, in Table 3, patient P_1 will visit dentists D_2, D_{142}, D_{486}, and D_8 with probability of 70%, 20%, 9%, and 1%, respectively;
(2) The personality and fraud rate of the dentist that the patient visits are fixed in the simulation. The distribution of the personality and fraud rate of the dentist is predefined in Table 2;
(3) Each patient needs a dental filling treatment with probability 0.2% for teeth every day; in other words, the patient needs to visit the dentist 7.3 times (=0.2% × 365) on average each year;
(4) The number of teeth to be filled during a dental filling treatment for a patient is in the range of one to three, their associated probabilities being 70%, 25%, and 5%, respectively. For the sake of simplicity, the tooth position for the tooth to be filled is a random number that is uniformly distributed in the range from 11 to 42;
(5) A fraudulent dentist will randomly select teeth that were filled in the past to apply for a reimbursement. The fraudulent claims will contain at most two fraudulent teeth in one patient visit, and the probability of a fraudulent claim for one or two teeth is 90% and 10%, respectively.

In scenario 3, a patient may need to visit a dentist 7.3 times a year, which is relatively high than expected. In general, the reasonable value for a patient to visit the dentist for filling operation may be 0.73 times a year, or approximately 43.8 (= 32/0.73) years, all teeth need one filling operation. Our simulation, expanding six years (shown later), accelerates the period of the filling operation ten times to facilitate the simulation. Since the personality of a dentist may change with time, the simulation need to shorten the experiments expansion, assuming a dentist keeps in the same category of the fraudulent claim in the simulation. Thus, the simulation adopts the scenario that a patient ten times frequently visits a dentist for filling operations.

According to all the above scenarios, the process of generating the claims data is as follows:

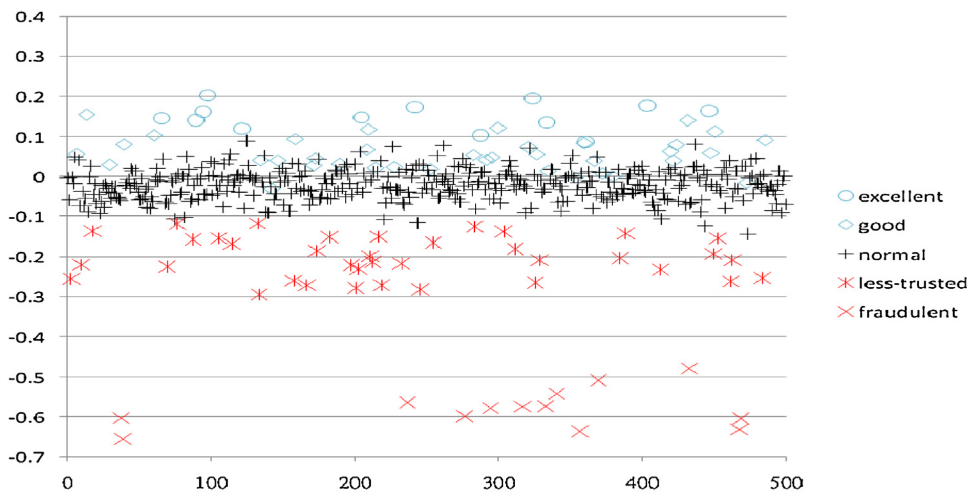
(1) For each day, the data generator selects a random number for each patient to determine whether the patient will visit a dentist for dental filling treatment. For each patient, the data generator has a probability of 0.2% of picking him or her to receive the dental filling treatment (Scenario 3). If a patient is selected to visit a dentist, the data generator will generate one, two, or three teeth to be filled with the probabilities 70%, 25%, and 5%, respectively (Scenario 4). Furthermore, the data generator will randomly generate a number from 11 to 42 to select the tooth to be filled with the probability of a uniform distribution (Scenario 4);
(2) This data generator plays Russian roulette to assign a preferred dentist to the selected patient according to his/her preference relationship shown in Table 3 (Scenario 1). In addition, the generator will randomly generate a genuine or fraudulent claim for the dental filling treatment with the probability associated with the personality of the dentist assigned to the patient for this visit (Scenario 2);
(3) If the selected patient is assigned to a fraudulent dentist in this visit, the data generator will further select a random number to determine if one or two teeth are included in the fraudulent claim with probability 90% and 10%, respectively (Scenario 5). Moreover, the data generator will generate the tooth positions of the teeth in the fraudulent claim. The tooth position number generation is a little complex because the generator will collect all of the tooth positions where the patient has genuinely received a dental filling treatment from the first day to the current day. The data generator will then randomly select one (or two) tooth positions from the collection as the tooth position in the fraudulent claim;
(4) The data generator generates the claims data patient by patient and then day by day for a period of six years (or 2,190 days = 365 × 6 days).

Table 4 shows a sample from the claims data generated by the data generator; these data are used to evaluate the effectiveness of the proposed trustworthiness equation. For example, on the first day, patient P_6 is selected to visit dentist D_{132} for a dental filling treatment on teeth numbered 18 and 19. Because dentist D_{132} is a fraudulent dentist and is selected to file a fraudulent claim for this treatment, the data generator generates the tooth position number 33, which was filled in the past, as the tooth in the fraudulent claim.

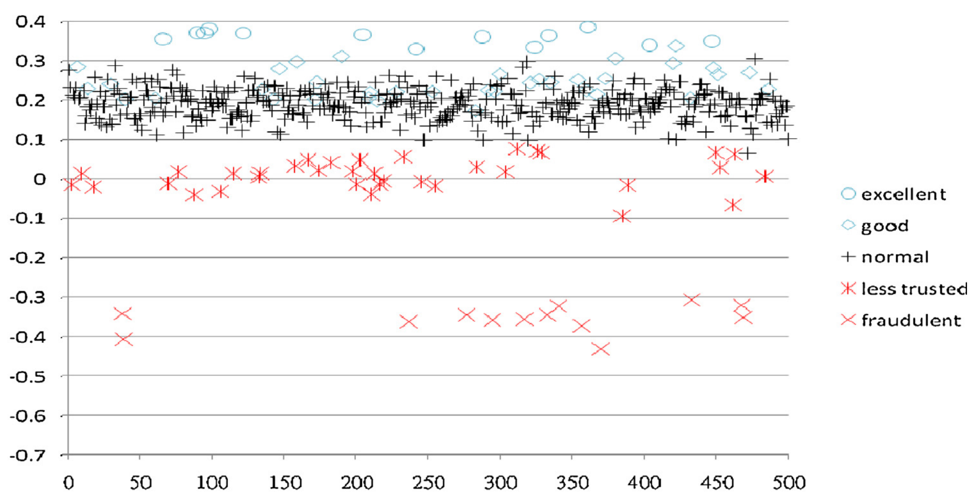
In this simulation, we select two intervals for testing the generated claims. The first interval is from the beginning of the third year to the end of the fourth year, the second interval is from the beginning of the fifth year to the end of the sixth year. Both intervals start after the middle of the six year period. We believe that the claims for these two intervals demonstrate the stability of the generated claims, avoiding the *cold-start* claims. The concern is that the claims from the beginning of the simulation cannot be second-hand claims because there are no claims preceding them.

Table 4
A part of the generated claims data.

Day	Patient	Dentist	Genuine 1	Genuine 2	Genuine 3	Fraud 1	Fraud 2
1	P_6	D_{132}	18	19		33	–
1	P_{5003}	D_{55}	40			12	22
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2190	P_{44005}	D_1	29	32	36		



(a) Trustworthiness scores of the dentists from the third year to the fourth year



(b) Trustworthiness scores of the dentists from the fifth year to the sixth year

Fig. 5. (a) Trustworthiness scores of the dentists from the third year to the fourth year. (b) Trustworthiness scores of the dentists from the fifth year to the sixth year.

Table 5
The result of the ZeroR classifier.

The Matrix		Fraudulent Dentists		
		Yes	No	
Zero	No	109	7	Positive Predictive Value: 109/116 = 0.94
	Yes	0	0	Negative Predictive Value: 0.00
		Sensitivity: 1.00	Specificity: 0.00	Accuracy = 0.94

The trustworthiness scores of the 500 dentists in the first and second intervals are evaluated according to the proposed trustworthiness equation, as illustrated in Fig. 5(a) and (b). In the first interval (Fig. 5(a)), it can be seen that the trustworthiness scores of the fraudulent and less-trusted dentists are obviously lower than those of the normal, good, and excellent dentists, and their scores reflect their personalities. Thus, our trustworthiness equation applied to the claims data in the first interval can differentiate

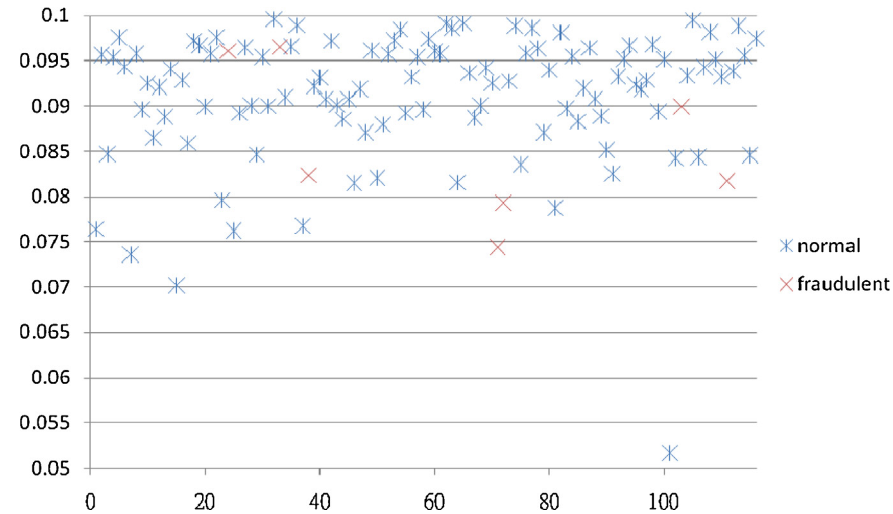


Fig. 6. Trustworthiness scores of the 116 dentists in the real world.

the dentists with different personalities. Fig. 5(b) shows the trustworthiness scores of the 500 dentists in the second interval. This interval, like the first, does not have the cold-start problem, but it does have the *hot-non-ending* problem, whereby we cannot fully know whether a dentist is a first-hand dentist for a patient because the subsequent treatment for the patient may not have occurred by the end of the simulation. For example, assume that patient *A* consults with dentist α to fill one tooth near the end of the sixth year. We cannot determine whether dentist α is a first-hand dentist because we currently have no claims data about whether other dentists will treat patient *A* to fill the same tooth in the future. Therefore, dentists in the second interval have fewer scores subtracted because of the hot-non-ending problem. We guess that the trustworthiness scores of the dentists in the second interval are higher than those of the dentists with the same personality in the first interval. Fig. 5(b) shows the trustworthiness scores of the 500 dentists in the second interval. We can see that the fraudulent and less-trusted dentists can still be differentiated from the dentists in the other three categories, and the excellent dentists have higher trustworthiness scores than the other dentists. Nevertheless, the trustworthiness scores of the dentists in the second interval are higher than those in the first interval. The claims data in the second interval with the hot-non-ending problem is similar to the claims data in the real world that address reimbursement for recent treatments because it is still unknown whether subsequent treatments occur. This simulation's results show that the proposed trustworthiness equation can still detect fraudulent dentists whether or not there is a hot-non-ending problem in the claims.

4.2. Empirical studies

To demonstrate the effectiveness of our trustworthiness equation in the real world, we gather real claims data that were filed by dentists from January 2005 to December 2005 in one area of a city in Taiwan. There are 116 dentists in the area, and their average cases of claims, payment of reimbursement, number of patients in a month are 361 cases, 412 thousand in NT dollars, and 255 patients, respectively. For the 116 dentists, 7 dentists had been detected as filing fraudulent claims by the insurer using the traditional detection method (i.e., statistical and manual analysis). We applied the trustworthiness equation to the data. Using the information about the seven fraudulent dentists, we tune the weights of σ and δ such that the average trustworthiness scores of the seven fraudulent dentists are the smallest.

Fig. 6 shows the final trustworthiness scores of the 116 dentists calculated by the proposed trustworthiness equation after tuning the weights of σ and δ. It can be seen that five of known fraudulent dentists have lower trustworthiness scores than the other normal dentists, but there are still two fraudulent dentists with higher trustworthiness scores. The ZeroR classifier simply predicts the majority class and it is generally used to evaluate a baseline accuracy [27,28]. In Table 5, the ZeroR model "Fraudulent Dentists = No" suggests an accuracy of 0.94.

We investigated the claims data for these two dentists and found that the patients for the two fraudulent dentists are highly loyal and seldom visit other dentists. Thus, the two fraudulent dentists have fewer links (i.e., social relationships) with other dentists so there will be fewer subtractions from their scores. In this type of situation, the proposed trustworthiness equation will not predominate because the correctness of the equation is based on the social relationships between the dentists. The solution to the above situation is to use both the traditional method and the proposed trustworthiness equation simultaneously to detect fraudulent dentists.

We also see that there are some normal dentists with low trustworthiness scores. It is guessed that these dentists may understand the traditional detection method and file sophisticated claims that are hard to detect using the traditional method. As a result, these dentists pass the detection process of the insurer. However, the proposed equation will identify these suspicious dentists if they have many social relationships with other dentists. The occurrence of these social relationships cannot be prevented by the suspicious dentists because they cannot completely prevent their patients from consulting other dentists. Clearly, the proposed method can identify most fraudulent dentists in terms of the difficult-to-commit claims. It is easy to on-line determine whether the easy-to-commit claims, like extracting a tooth twice, is fraudulent one. However, to on-line identify the difficult-to-commit claims, like the filling operations, is difficult, since no enough evidence can be relied on for such difficult-to-commit claims in the claiming data. One feasible and harmonious way is to identify the suspicious dentists and then investigate the patients and their patient records across several dentists for confirmation. Though it is classified as a retrospective solution, it is still an effective and non-disturbing-people solution.

Because of our confidentiality agreement, we could not ask the insurer to investigate the genuineness of the claims for the dentists who were not detected by the insurer as fraudulent but had low trustworthiness scores similar to those of the known fraudulent dentists. Therefore, the correctness of the proposed equation cannot be further proved. However, we believe that the proposed trustworthiness equation based on social relationships is a new way to detect fraudulent dentists that cannot be detected using the traditional statistical detection method. If an insurer can detect fraudulent dentists using both the traditional method and our method, we believe that the detection of the fraudulent dentists will be more accurate.

In this paper, we proposed a metric based on the social network among patients and dentists. The medical operation on the patients by the dentists is utilized to evaluate the trustworthiness of each dentist. The metric returns a range of numerical values as their suspicious scores. The higher the suspicious score, the higher possibility the dentist has fraudulent claims. A threshold of suspicious degree, classifying the trusted and untrusted dentists, is hard to be defined in advance. There is another problem, imbalanced data; that is, the fraudulent dentists are the minority against the normal dentists. For solving the problem of imbalanced data, several techniques, like over-sampling and under-sampling, have been proposed to increase the performance of the classifier [29]. Indeed, we are aiming for proposing an approach to evaluate suspicious degree of dentists, rather than the construction of a classifier; the techniques for increasing and evaluating the performance of the classifier, like cross validation, Receiver Operating Characteristic (ROC) curve [20], and over sampling [30], are beyond the scope of this paper.

Regarding the performance of the proposed method, let's recall Fig. 3, the social network of dentist (the circled one in the right) is constructed by the claim. For each claim related to one specific tooth of a patient, it will relate to one or two dentists. In the first case, it means that the patient always visits the same dentist for his/her tooth, and then no link is added to the social network. In the second case, it indicates that the patient visits two different dentists for his/her same tooth, and then one link between two nodes is added to the social network. Thus, for n claims, there at most n links are added to the social network. That is, the time complexity to construct the social network is $O(n)$. Note that while encountering a new claim of a dentist, the proposed approach needs to get the historical consulting of the corresponding patient to confirm this dentist being the first-hand or second-hand one and then compute the suspicious degree according to the medical operation type, i.e., whether it is a difficult-to-commit treatment. Finally, the resultant suspicious degree is accumulated to that dentist. The above three computations are along with a new claim, and can be seen as a constant since of the index technique provided by database. Thus, the time complexity to compute the suspicious degree of all the dentists are also $O(n)$, where n is the number of claims. Regarding the space complexity of the social network, the network at most has n nodes if all patients visit different dentists for each of their tooth (which is rarely found in a real case). Thus, the space complexity is also $O(n)$ for n claims.

5. Conclusions

Fraudulent claims cause serious damage to health insurance funds. Previous detection methods are ineffective and time-consuming and allow fraudulent dentists to obtain health insurance funds by filing fraudulent claims. In this paper, we proposed a trustworthiness evaluation based on social networks to evaluate the trustworthiness of dentists. The simulation results demonstrate that the proposed trustworthiness equation can effectively identify the less-trusted and fraudulent dentists. In addition, the empirical results show that we can discover most fraudulent dentists, although some cannot be detected because their patients' loyalty prevents them from forming social relationships between the fraudulent dentists and other dentists. This flaw can be solved by using the traditional detection methods along with our trustworthiness equation. This paper provides a new direction for investigating the genuineness of claims data. If the insurer can detect fraudulent dentists using the traditional method and the proposed method simultaneously, the detection will be more transparent and ultimately reduce the losses caused by fraudulent claims.

Kose et al. [31] devised an interactive machine-learning-based framework (named eFAD) for detecting fraudulent behaviors in the healthcare insurance industry. Based on the knowledge of earlier transactions by the same actors, eFAD is effective in detecting the abnormal behaviors with fragmented nature, e.g., two transactions with exactly the same content, however, one of them could be part of a fraud. In addition, eFAD provides the visualization tool to facilitate a fact-finding process, to save time. For future work, it would be worthy of considering both individual records and social networking behaviors. By the comprehensive investigation, we shall understand the behaviors deeply so that we probably enhance the accuracy of fraud detection.

References

[1] The Judicial Yuan of the Republic of China, http://jirs.judicial.gov.tw/eng/, 2008 (Accessed: 16 June 2016).
[2] U. S. Department of Justice, Federal Bureau of Investigation, Financial crimes report to the public, https://www.fbi.gov/stats-services/publications/fcs_report2006/financial-crimes-report-to-the-public-fiscal-year-2006#Health, Fiscal Year 2006. (Accessed: 16 June 2016).
[3] Thompson LH. Health insurance: Vulnerable payer lose billions to fraud and abuse (Rep. to the Chairman of the Subcommittee on Human Resources and Intergovernmental Operations). Washington, DC: US General Accounting Office; 1992.
[4] Economist. Health-care fraud: The $272 billion swindle; 2014 (Accessed: 16 June 2016). www.economist.com/news/united-states/21603078-why-thieves-love-americas-health-care-system-272-billion-swindle.
[5] Derrig RA. Insurance fraud. J Risk Insur 2002;69:271–87.
[6] Sparrow MK. Fraud control in the health care industry: Assessing the state of the art. Office of Justice Programs, National Institute of Justice: US Department of Justice; 1998.
[7] Chen W.C, Medical Care Payment. Bureau of National Health Insurance, Taiwan. http://www.nhi.gov.tw. (Accessed: 30 June 2014).
[8] Frieden J. Health care fraud detection enters the information age. Bus Health 1992;10(7):29.
[9] Hales DN, Sridharan V, Radhakrishnan A, Chakravorty SS, Siha SM. Testing the accuracy of employee-reported data: an inexpensive alternative approach to traditional methods. Eur J Oper Res 2008;189(3):583–93.
[10] Herb W, Tom M. A scientific approach for detecting fraud. Best's Rev 1995;95(4):78–81.
[11] Major JA, Riedinger DR. EFD: a hybrid knowledge/Statistical-Based system for the detection of fraud. J Risk Insur 2002;69(3):309–24.
[12] Chan CL, Lan CH. A data mining technique combining fuzzy sets theory and Bayesian classifier – an application of auditing the health insurance fee. In: Arabnia HR, editor. Proceedings of the International Conference on Artificial Intelligence. 2001. p. 402–8.
[13] Sokol L, Garcia B, Rodriguez J, West M, Johnson K. Using data mining to find fraud in HCFA health care claims. Top Health Inform Manage 2001;22(1):1–13.
[14] Viaene S, Ayuso M, Guillen M, Van Gheel D, Dedene G. Strategies for detecting fraudulent claims in the automobile insurance industry. Eur J Oper Res 2007;176(1):565–83.
[15] Williams GJ, Huang Z. Mining the knowledge mine: the hot spots methodology for mining large real world databases.London: Springer-Verlag; 1997. p. 340–8.
[16] Yang WS, Hwang SY. A process-mining framework for the detection of healthcare fraud and abuse. Expert Syst Appl 2006;31(1):56–68.
[17] Bhattacharyya S, Jha S, Tharakunnel K, Westland JC. Data mining for credit card fraud: a comparative study. Decis Support Syst 2011;50(3):602–13.
[18] Ravisankar P, Ravi V, Rao GR, Bose I. Detection of financial statement fraud and feature selection using data mining techniques. Decis Support Syst 2011;50(2):491–500.
[19] Kou G, Peng Y, Wang G. Evaluation of clustering algorithms for financial risk analysis using MCDM methods. Inf Sci 2014;275:1–12.
[20] Han J, Kamber M, Pei J. Data Mining: Concepts and Techniques. Waltham: Elsevier; 2011.
[21] Ngai EWT, Hu Y, Wong YH, Chen Y, Sun X. The application of data mining techniques in financial fraud detection: a classification framework and an academic review of literature. Decis Support Syst 2011;50(3):559–69.

[22] Jing Y, Baluja S. Visualrank: applying pagerank to large-scale image search. IEEE Trans Pattern Anal Mach Intell 2008;30(11):1877–90.
[23] Haveliwala TH. Topic-sensitive pagerank: a context-sensitive ranking algorithm for web search. IEEE Trans Knowl Data Eng 2003;15(4):784–96.
[24] Kim HJ, Lee KM. A quantitative trust model based on multiple evaluation criteria. In: Proceedings of the 9th international conference on Knowledge-Based Intelligent Information and Engineering Systems – Volume Part I. Berlin: Springer-Verlag; 2005. p. 1036–43.
[25] Uggirala A, Gramopadhye AK, Melloy BJ, Toler JE. Measurement of trust in complex and dynamic systems using a quantitative approach. Int J Indust Ergon 2004;34(3):175–86.
[26] Wu F, Li HH, Kuo YH. Reputation evaluation for choosing a trustworthy counterparty in C2C e-commerce. Electron Commer Res Appl 2011;10(4):428–36.
[27] Agrawal A, Misra S, Narayanan R, Polepeddi L, Choudhary A. A lung cancer outcome calculator using ensemble data mining on SEER data. In: Proceedings of the Tenth International Workshop on Data Mining in Bioinformatics, Article No. 5. 2011.
[28] Lee K, Palsetia D, Narayanan R, Patwary MMA, Agrawal A, Choudhary A. Twitter trending topic classification. In: Proceedings of theIEEE 11th International Conference on Data Mining Workshops. 2011. p. 251–8.
[29] Chawla NV. Data mining for imbalanced datasets: an overview. In: Maimon O, Rokach L, editors. Data mining and knowledge discovery handbook (Vol. 2), New York: Springer; 2005. p. 853–67.
[30] Li X, Han J, Yin Z, Lee JG, Sun Y. Sampling cube: a framework for statistical olap over sampling data. In: Proceedings of the 2008 ACM SIGMOD International Conference on Management of Data. 2008. p. 779–90.
[31] Kose I, Gokturk M, Kilic K. An interactive machine-learning-based electronic fraud and abuse detection system in healthcare insurance. Appl Soft Comput 2015;36:283–99.