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The Impact Of Healthcare Fraud And Abuse Regulations On Administration Practices

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Abstract

Insurance companies or third party payers make inappropriate payments due to mistakes, misuse, and fraud. The magnitude of this problem warrants its classification as a high-priority concern for health systems. Conventional approaches to identifying instances of healthcare fraud and abuse are laborious and ineffective. The integration of automated techniques with statistical expertise has resulted in the development of a new multidisciplinary field known as Knowledge Discovery from Databases (KDD). Data mining is a fundamental component of the Knowledge Discovery in Databases (KDD) process. Data mining enables third-party payers, such as health insurance companies, to extract valuable insights from a large volume of claims and select a smaller fraction of claims or claimants that need further evaluation. We conducted a comprehensive analysis of research that used data mining techniques to identify instances of health care fraud and abuse. These studies included both supervised and unsupervised data mining methods. The majority of existing research have mostly concentrated on algorithmic data mining, neglecting the specific application of fraud detection in the field of health care supply or health insurance policy. Further research is required to establish a correlation between sound and evidence-based methods of diagnosing and treating fraudulent or abusive activities. Based on the existing research, we ultimately suggest following seven broad methods for data mining of health care claims.

Keywords: *healthcare, data mining, knowledge discovery in databases (KDD), Business Intelligence (BI), insurance claim, fraud detection.*

1. Introduction

1.1. Defining Fraud and Abuse

Insurance companies or third party payers make inappropriate payments due to errors, misuse, or fraud. Abuse refers to the behaviors of a provider that lead to needless expenses for the payer, either directly or indirectly. Abuse encompasses any action that deviates from the objectives of delivering patients with treatments that are medically essential, adhere to professionally acknowledged standards, and are reasonably priced (Centers for Medicare and Medicaid treatments, 2012).

Health care fraud refers to the deliberate act of deceiving in order to get illegitimate benefits (Busch, 2007). Contrary to errors and abuse, fraudulent practices are often classified as criminal acts according to the law. Nevertheless, there is a lack of universal agreement over the precise definition of fraud and abuse in the context of healthcare services or health insurance. To get more information and illustrations of fraudulent activities and misuse, refer to the publication by Rashidian, Joudaki, and Vian (2012).

Approximately 10% of the healthcare system's spending is squandered as a result of fraudulent activities and misuse (Gee, Button, Brooks, & Vincke, 2010). Hence, the magnitude of health care fraud and abuse is significant enough to warrant it being a top concern for health systems.

1.2. Advancing Data Mining Techniques for Enhanced Detection of Health Care Fraud and Abuse

Conventional approaches of detecting health care fraud and abuse use a small number of auditors who are responsible for processing a large volume of paper-based health care claims. In practice, they allocate limited time to each claim, prioritizing certain aspects of a claim while disregarding the overall behavior of a provider (Rashidian et al., 2012). This approach is characterized by a significant expenditure of time and a lack of efficiency. The aforementioned study conducted by Copeland, Edberg, Panorska, and Wendel in 2013, Aral, Güvenir, Sabuncuoğlu, and Akar in 2012, and Ortega, Figueroa, and Ruz in 2006, indicates that it remains the prevailing situation in several low-income and middle-income nations.

The use of electronic health data and the increasing adoption of computerized systems have created new prospects for enhanced identification of fraudulent activities and misuse. The advancements in machine learning and artificial intelligence have led to increased focus on automated techniques for detecting fraud. The integration of automated techniques with statistical expertise has given rise to a burgeoning multidisciplinary field known as Knowledge Discovery from Databases (KDD). Data mining is the fundamental component of the Knowledge Discovery in Databases (KDD) process.

Data mining enables third-party payers, such as health insurance companies, to extract valuable insights from a large volume of claims. It allows them to identify a smaller sample of claims or claimants that need additional examination and inspection for potential instances of fraud and abuse (Rashidian et al., 2012). The data mining technique contributes to a more streamlined and productive IT-based auditing system.

We conducted a comprehensive analysis of research that successfully improved the identification of health care fraud and abuse via the use of data mining methods. Our objective was to find several methodologies of data mining and use data mining algorithms for the purpose of detecting health care fraud. Our analysis excludes financial fraud, a phenomenon that is not exclusive to health care professionals. Furthermore, our research specifically excludes the examination of fraud detection in areas such as credit card fraud, money laundering, telecommunication fraud, computer intrusion, and scientific fraud.

2. Data mining methods

Data mining may be classified into several categories. The outcome of data mining is contingent upon the specific types of data being analyzed, the specific types of information being uncovered, and the specific procedures (algorithms) being used. Machine learning specialists often categorize data mining approaches into "supervised" and "unsupervised" methods (Phua, Lee, Smith, & Gayler, 2010; Li et al., 2008; Bolton & Hand, 2002). Supervised approaches aim to uncover the correlation between input variables (attributes or features) and an output (dependent) variable (or goal attribute). Unsupervised learning techniques are used in situations when there is no existing knowledge on the dependant variable that may be used.

Supervised approaches, such as regression analysis, discriminant analysis, neural networks, Bayesian networks, and Support Vector Machine (SVM), are often used for classification and prediction tasks. Unsupervised techniques are often used for descriptive tasks, such as extracting association rules using algorithms like Apriori, and for segmentation tasks, such as clustering and anomaly detection.

3. Supervised data mining methods

Supervised data mining in the field of health care fraud and abuse detection refers to the use of approaches that rely on samples of records that are already known to be fraudulent or non-fraudulent. These two sets of data are used to create models that enable us to categorize fresh observations into one of the two sets of data. Supervised approaches need trust in accurately categorizing the records. Moreover, they are valuable in identifying preexisting patterns of fraudulent activity and misuse. Therefore, it is necessary to continually update the models in order to include new forms of fraudulent activities and adapt to changes in legislation and situations (Rashidian et al., 2012). Supervised methods used for detecting health care fraud and abuse include decision tree (Shin, Park, Lee, & Jhee, 2012; Liou, Tang, & Chen, 2008; William & Huang, 1997), neural networks (Liou et al., 2008; Ortega et al., 2006; He, Graco, & Yao, 1997), genetic algorithms (He et al., 1999), and Support Vector Machine (SVM) (Kirlidog & Asuk, 2012; Kumar, Ghani, & Mei, 2010).

4. Unsupervised data mining techniques

Fraudsters will modify their tactics to evade detection whenever they become aware of a certain detection approach (Sparrow, 1996). As previously mentioned, supervised approaches are effective in identifying pre-existing patterns of fraud and abuse. Theoretically, we can use unsupervised methods to detect novel forms of fraud or abuse. Unsupervised approaches often evaluate the characteristics of one claim in comparison to other claims and ascertain their relationships or distinctions. Thus, it is capable of identifying and establishing sequential and associative patterns among records, as well as detecting anomalous records or grouping together comparable data. Several unsupervised methods have been used to detect health care fraud and abuse, including clustering (Liu & Vasarhelyi, 2013; Ekina, Leva, Ruggeri, & Soyer, 2013; Tang, Mendis, Murray, Hu, & Sutinen, 2011; Musal, 2010; C. Lin, C.M Lin, Li, & Kuo, 2008; William & Huang, 1997), outlier detection (Capelleveen, 2013; Tang et al., 2011; Shan, Murray, & Sutinen, 2009), and association rules (Shan, Jeacocke, Murray, & Sutinen, 2008).

In a research conducted by Sokol, Garcia, Rodriguez, West, and Johnson (2001), the authors provide a detailed explanation of the first procedures involved in processing and displaying the data. These stages must be adhered to in any data mining methodology. Typically, these preliminary stages require a substantial amount of effort before the main data mining process. The authors used Health Care Financing Administration claims pertaining to preventive treatments such as mammography, bone density evaluation, and diabetes counseling (Sokol et al., 2001). In his study, Musal (2010) used Geo-location data and unusually elevated consumption rates of services as markers of fraudulent conduct.

5. Hybrid Methods for Data Mining

Several research have used hybrid approaches that combine supervised and unsupervised techniques. For more details, please refer to Table 1. Major and Riedinger (2002) conducted a study where they evaluated an electronic fraud detection tool. This program matched the characteristics of individual providers to those of their peers in order to discover any abnormal activity by the providers. Unsupervised learning is used to create novel rules and enhance the process of identification (Major & Riedinger, 2002). A research used a three-step process to identify insurance fraud. They used unsupervised clustering techniques to analyze insurance claims and generated a diverse set of labeled groups. Subsequently, they used an algorithm that relied on a supervised classification tree to create rules for assigning each record to clusters. Williams and Huang (1997) determined the most efficient guidelines for identifying abusive actions in the future.

6. Summary

Our analysis reveals that the words KDD and data mining are subject to varying interpretations across various research. These approaches include a variety of distinct techniques and may be used for various sets of challenges (Maimon & Rokach, 2010). The use of practical guidelines may enhance the adoption and utilization of the approaches while mitigating mistakes and misapplications of the techniques. Although there is a constraint, the research indicate that both supervised and unsupervised approaches are valuable in identifying various fraud tactics and schemes (Capelleveen, 2012).

The majority of the literature that was discovered mostly emphasized the technical methodologies used in knowledge discovery in databases (KDD) and data mining. However, there was a lack of emphasis on the practical significance of these discoveries for healthcare administrators and decision makers. One study that stands out from the others is the research conducted by Lin et al. (2008). This study is a perfect example of how to give practical recommendations for managers to address health care fraud based on their results. In order to enhance the use of KDD and data mining techniques, future research should prioritize the examination of the policy ramifications of their discoveries.

Fraud detection is a component of a broader initiative aimed at eliminating health care fraud, abuse, and waste (Rashidian et al., 2012). Fraud detection should be aware of the potential risks that health care delivery policies might introduce, which may amplify the likelihood of fraudulent activities and misuse (Capelleveen, 2012). Fee for service payments may lead to an increase in the number of services provided (Chaix-Couturier, Durand-Zaleski, Jolly, & Durieux, 2000). This might potentially serve as a risk factor for both misuse and fraud in the field of healthcare.

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