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Examining Predictive Modeling–Based Approaches to Characterizing Health Care Fraud

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Caveat and Disclaimer

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Examining Predictive Modeling–Based Approaches to Characterizing Health Care Fraud

Abstract

Background: Health care fraud may represent hundreds of billions of dollars in spending that could be better spent on patient care. There is often insufficient detail on the underlying methodologies and data samples that lead to fraud estimates, which may be due to different purposes of these reports or the need to obscure the details of fraud detection methods to prevent fraudulent operators from responding to existing methods.

Objectives: The objective of this study was to provide a systematic evaluation and synthesis of the methodologies and data samples used in current peer-reviewed studies on characterizing health care fraud.

Data sources: The academic databases searched were Academic Search Complete, Business Source Complete, EconLit, Medline (EBSCO), OneSearch, ProQuest Business Collection, ScienceDirect and Web of Science. Governmental and commercial sources were also used for background research.

Synthesis of methods: This examination was conducted using a systematic review methodology to identify relevant studies and determine their relevance. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement was used to guide reviewing the literature. Study criteria for eligibility were collected by applying specific search terms: health care, health insurance, Medicare, Medicaid, Obamacare, Affordable Care Act or health services; fraud, cheat, falsification, corruption or kickback; detect, detection, prevent, prevention, deterrence, audit or auditing. Results were restricted to scholarly journals, academic journals, working papers and conference proceedings. Study selection occurred through two independent reviews of each study for inclusion or exclusion. Disagreements between reviewers were resolved through discussion by the entire research team.

Results: Our search terms resulted in 450 articles that were potentially appropriate for inclusion in our report. The results of independent reviews ended with 27 studies considered as relevant to include after the application of our inclusion criteria. Variables are identified from the literature to synthesize each method of fraud detection used.

Limitations: One limitation of this study is that the strength of the evidence is reliant on the quality and number of studies previously performed on the topic. Another limitation is the quality of studies with regard to their applicability to different types of insurers. Finally, the majority of studies could not provide proof of intent to commit fraud.

Conclusions: A limited number of validated methods are used to detect health care fraud. The literature on this topic is spread among several academic fields. The majority of available studies utilize public or social health insurance systems such as Medicare or Medicaid to study fraud. The main gaps we identified are validation of existing methods and proof of intent to commit fraud in the studies analyzed.

Implication of key findings: Our insurer agnostic approach examines the availability and effectiveness of health care fraud analytic methods across different types of health insurers, posing great value for members of the health sectors. The tools identified may be of value to health actuaries. Actuaries that are working on insurance products where fraud or abuse is a concern will be able to use the results as a benchmark for fraud management and an indicator of best practices. Those considering or currently involved in work that could be considered as “nontraditional” would benefit from the educational material produced in the project.

Executive Summary

What Is Health Care Fraud?

This report examines the approaches used to determine and characterize health care fraud. "Fraud denotes practices that are tantamount to theft by deception, defined under the regulations as 'an intentional deception or misrepresentation made by a person with the knowledge that the deception could result in some unauthorized benefit to himself or to some other person'" (Gosfield 2011, p. 1:3). Public programs such as Medicare are heavily impacted by fraudulent activities. "The National Health Care Anti-Fraud Association (NHCAA) estimates that the financial losses due to health care fraud are in the tens of billions of dollars each year" (The Challenge of Health Care Fraud n.d.). This amount represents what is or has been reported as fraud and may be skewed by the sensitivity of the subject as well as the lack of expertise in identifying it. Accurate estimation of health care fraud is important for improved public policy making, ranking resource allocation, and in reducing pressure and cost of compliance for law-abiding providers, facilities and their patients. Public insurers such as Medicare and Medicaid and private insurers use a range of automated detection systems and human experts to identify and investigate fraudulent claims (CMS Fraud Prevention System 2017) .

Methods for Detecting Health Care Fraud

A detailed summary of fraud detection methodology alongside administered approaches in identified peer-reviewed studies are found throughout this report. Many methodologies can be used in detecting health care fraud. Data mining and regression are presented as the dominant approaches to health care fraud methodology among claims-level, provider-level and facility-level analyses. Characterizing the level of analysis and comparing this across studies posed challenges because of the heterogeneity of studies as well as differences in standards of communications across the journal types considered. Generally, the validity and reliability of any method is important for accurately noting fraud. Measures of accuracy and overall rate of fraud for the methods surveyed, including sensitivity, specificity and prevalence, were noted where applicable.

Results of the Project

The two main results of this project are a comprehensive list of studies that used a predictive method to investigate health care fraud and a comparative analysis of these studies. Our review of available literature for health care fraud detection resulted in 450 studies that were potentially eligible for inclusion in our study. Only 27 studies met the inclusion criteria on further review by the research team. These studies included in the review had to involve health care claims. In addition, they needed to include an analysis of fraud or fraud along with abuse and/or waste. Finally, all these studies used some form of analytic methodology to detect fraud that could be implemented by other researchers or practitioners, either in the same data set or in other contexts.

We utilized 24 variables to perform an in-depth analysis of the 27 studies to obtain results described in the report. For example, we found that the studies were conducted by researchers working in a number of disciplines, including health services research, risk management and insurance, computing and information systems, and health economics. We also assessed the country where studies were performed. Many of the studies were performed in the U.S., but the health care fraud literature is international, with approximately half the studies using data from other countries. As another example, we assessed the bias in the studies by examining both the funding source for the study and potential for bias generated by the researcher's employment and other disclosures. Common features included in the studies such as recommendations, pros and cons of the methodology, assumptions and biases were populated in a spreadsheet, a link to which can be found in the Appendix.

Implications for the Detection and Deterrence of Health Care Fraud

This report shows the vast array of disciplines, fields and countries looking into the characterization of health care fraud and its deterrence. The majority of studies available utilize public and social health insurance systems, showing gaps in the literature among private health insurance systems. The main divides of the results include the validation of existing methods, differences between those studies that presented prevalence and rates of fraud and those that did not, differences in prevalence and rates of fraud analyses that did present these results, and proof of intent to commit fraud posed as challenging among studies. Further details regarding the results of the study are available in the body of the report and in the spreadsheet link in the Appendix.

One of the most important implications of the review relates to the information that was missing from the majority of studies. The vast majority of studies did not report their validity in terms of sensitivity or specificity. This makes it challenging to determine the accuracy of the methods or to make recommendations about their usefulness. In addition, the majority of studies also did not include a calculation of prevalence or fraud rate estimation. This makes conclusions about the overall rate of fraud difficult to substantiate based on evidence from the current peer-reviewed research literature.

Our study also identified a number of gaps that may be important areas for future investigations of health care fraud. One such gap includes the technical definition of fraud as including proof of intent to commit fraud. Almost none of the studies identified in this review examined fraud that included proof of intent. The majority of the studies reviewed included new methods rather than the validation of existing methods of fraud detection. Replication of these studies with repeated use of the same measure in the same or different contexts would add to the evidence regarding the validity and generalizability of fraud detection methods. This may be an especially important concern considering the burden of claims verification and program integrity efforts on patients and providers in the health care system.

This report does validate the importance of fraud detection as a major function of health insurers and as an area of future research. Clearly, fraud represents a cost to the health care system with no benefit, so efforts such as those described in the studies reviewed are an important part of a more efficient health care system. Health insurers likely will continue to play a major role in these efforts, given their access to health care claims data needed to apply most fraud detection methodologies. Improvements and wider applications of these methods are an important approach to improving the overall functioning of the U.S. health care system.

1. Introduction

1.1 Rationale

One of the pressing concerns in the health care system is the potential for "fraud, waste, and abuse" (U.S. GAO n.d.).This concern has become even more significant with the many changes occurring in the health care and health finance system with the implementation of the Affordable Care Act (ACA). The ACA relies in part on funding obtained from program integrity efforts, such as the Recovery Audit Contractors, and the expansion of this program, to expand coverage to underserved populations. The ACA also introduced a number of new health insurance programs that could be targets for fraud and abuse such as the new health insurance exchanges (marketplaces) and new populations covered by the Medicaid program. Thus, the success of the ACA and future health care reform efforts relies to a significant extent on the degree to which fraudulent claims can be identified and deterred.

Available health care fraud analyses in health insurance have traditionally been provided by government agencies, as well as independent researchers. Measuring the extent of health care claims fraud is also important for directing government budget monies to where they are most needed and for maintaining the viability of many federal programs. There are often not sufficient details on the underlying methodologies and data samples that lead to these estimates, which may be due to different purposes of these reports or the need to obscure the details of fraud detection methods to prevent fraudulent operators from responding to existing methods[1]. Many health care fraud detection methods are, or may be, proprietary, which makes it virtually impossible to assess the overall state of the fraud detection literature using publicly available data sources and publications.

Prior studies have speculated whether health care has a rate of fraud similar to that of other lines of insurance; if so, health care fraud would represent hundreds of billions of dollars in spending that could be better spent on patient care (The Challenge of Health Care Fraud n.d.). At least one prior review has also examined the question of what methods exist to detect and deter health care fraud and concluded that no evidence exists to support the use of these methods (Rashidian, Joudaki and Vian 2012). However, prior reviews may not have provided a comprehensive and systematic review of available methods to detect health care fraud, leading to a potential gap in the literature. In particular, the Rashidan et al. article focused on four clinically focused databases: Medline, Embase, CINAHL and PsycINFO. A use of a wider array of academic databses covering a larger number of fields is likely to identify a wider variety of methodologies for detection of health care fraud and provide new insights into the current state of understanding in this important area.

1.2 Objectives

The main objectives of this paper are to identify, detail and synthesize existing methodologies for detecting and preventing health care fraud through a systematic literature review. The focus is on studies that attempt to apply a methodology to identify fraud that is committed with the intention of defrauding health insurance provided by health insurance companies, employers and government bodies. This review is designed to serve several purposes: an educational primer on health care fraud for actuaries; an analysis of potential fraud indicators and how available predictive modeling methodologies can use these indicators

[1] This is not an exhaustive list and does not represent an endorsement of any agency, organization or fraud detection method.

for managing health care fraud; and a discussion of the health policy implications of health care fraud given its impact on cost.

This review is designed to support third-party payers in a variety of settings, with a focus on the U.S. health care system. Our insurer agnostic approach examines the availability and effectiveness of health care fraud analytic methods across different types of health insurers. The topic is expected to be of great importance to the health section given that many members work on Medicare, surrounding insurance programs and with additional focus on social insurance programs. It is also expected to be of value to actuaries working for private health insurance programs and consultants, since private health insurers have the latitude to explore a wide variety of approaches to detecting and combating health fraud.

The review is also of value because of its public policy implications. Health care spending represents approximately one-sixth of the U.S. economy (Folland, Goodman and Stano 2016). Methods to reduce fraud, along with waste and abuse, are key to improving the efficiency of the health care system. Our project was designed in part to allow the health section members to participate in the active discussion about the magnitude and prevention of health care fraud. In general, this review will assist actuaries and other health care stakeholders to optimally direct their resources toward effective methods for detecting and preventing fraud. This resource allocation is expected to increase the return on investment for administrative funds spent on claims administration costs.

The development and validation of predictive models for fraud detection may also be a promising area for future exploration to the extent that the existing literature has gaps in providing evidence in different categories of methods and in different subareas of health insurance. This project was designed to identify those gaps as a starting point for future studies. Those gaps are discussed at greater length in sections 4 and 5 of our report.

2. Methods

2.1 Protocol and Registration

This examination was conducted by using systematic review methodology to identify studies and determine relevance. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement was used to guide the performance of reviewing the literature (Moher et al. 2009). PRISMA consists of a 27-item checklist and a four-phase flow diagram, which are used to guide reviews and ensure their quality.

There are four steps in the screening process: 1) to identify the universe of all studies through structured database searches, 2) to screen the studies identified, 3) to determine which studies are eligible for inclusion in the study based on the focus of the project and 4) then to include and synthesize all relevant studies in the analysis. The protocol utilized in this study was based on agreement between the research team and the funder in the study proposal. All decisions regarding the study design were ultimately the responsibility of the research team. This study was not registered in a database of systematic reviews before the initiation of the study, mainly because the project did not propose inclusion of a meta-analysis of results identified by the review (Moher et al. 2009).

2.2 Eligibility Criteria

Study criteria for eligibility were collected by applying specific search limits to prespecified academic databases noted in section 3.3. Results were restricted to peer-reviewed scholarly journals, academic journals, working papers and conference proceedings. The articles were published from January 2001 to December 31, 2015. The searches were also limited to keywords in the bibliographic citation and abstract and not within the full text article if possible. As a result, reports, studies and other publications from government and private sources that were not published in peer-reviewed journals were excluded from our review. These references are used selectively within this report to provide background and other supporting material. This exclusion was justified on the basis of limiting the scope of our report to studies that had been vetted through a peer-reviewed process and to enhance objectivity.

The key terms used in study extraction were divided into two segments. In segment 1, the following concept keywords were used: health care, health care, health insurance, Medicare, Medicaid, Obamacare, affordable care act, health services, fraud, cheat, falsification corruption and kickback. It is important to note that proximity syntax can vary among databases. For example, some use N5, NEAR/5 or W/5. The concept keywords in segment 2 consisted of detect, detection, prevent, prevention, deterrence, audit and auditing. Segments 1 and 2 were combined to conduct the study extraction. The results of this extraction process are shown in the results in Figure 1. Additional information about the search strategy is available in the Appendix.

Because this study was designed as a review of methodologies for detection and deterrence of health care fraud, we use this as a guideline to determine eligibility in independent reviews for further selections. Studies were considered eligible if they proposed a method for health care fraud detection. Studies were considered ineligible if they did not relate to health or health care, if they did not contain a methodology for detecting or deterring fraud, or if they did not relate to fraud, waste and abuse. Studies that included an analysis of fraud along with abuse or general waste were considered eligible for the study. However, those that considered only waste but not fraud or abuse that would include the possibility of fraud also were not eligible for inclusion in the study.

2.3 Data Sources

The academic databases searched were Academic Search Complete, Business Source Complete, EconLit, Medline (EBSCO), OneSearch, ProQuest Business Collection, ScienceDirect and Web of Science. The database extractions were conducted on May 12, 2016. Studies were included that had been published through December 31, 2015. For identified studies, the abstract information was extracted. The full text of the publication was later extracted for the abstracts deemed potentially includable in the study. Two non-English language publications were translated into English for the purpose of the review (Mesa et al. 2009; Victorri-Vigneau et al. 2009). One working paper published before the end of the inclusion period identified as part of the review was included in the final, published format from the journal, despite the fact that the journal publication appeared in print after the end of the inclusion period (Fang and Gong 2016, 2017). The number of abstracts drawn from each database is shown in Figure 1.

2.4 Database Search

For each database, each segment as described in section 3.2 was run separately and the number of abstracts were recorded. The first and second segments were additionally combined, and abstract counts after removing duplicates were recorded. The results were then exported to RIS format and imported to EndNote Basic in separate database folders. When all database searches were complete, the duplicates were placed in the "All My References" default folder. The search resulted in 450 abstracts potentially eligible for inclusion in the review.

Figure 1
Database Searches

Academic Search Complete	•Segment 1 = 273 •Segment 2 = 991,578 •Combined segments 1 and 2 = 80
Buisness Source Complete	•Segment 1 = 189 •Segment 2 = 110,789 •Combined segments 1 and 2 = 75
EconLit	•Segment 1 = 35 •Segment 2 = 17,446 •Combined segments 1 and 2 = 6
Medline (via EBSCOHost)	•Segment 1 = 287 •Segment 2 = 1,628,700 •Combined segments 1 and 2 = 119
OneSearch (Primo Central Index)	•Segment 1 = 604 •Segment 2 = 2,359,751 •Combined segments 1 and 2 = 153
ProQuest Buisness Collection	•Segment 1 = 191 •Segment 2 = 100,765 •Combined segments 1 and 2 = 54
ScienceDirect	•Segment 1 = 19 •Segment 2 = 90,145 •Combined segments 1 and 2 = 12
Web of Science	•Segment 1 = 126 •Segment 2 = 1,970,421 •Combined segments 1 and 2 = 37

2.5 Study Selection

Study selection occurred through independent reviews conducted by multiple individuals who reviewed each study for inclusion or exclusion. Two reviewers (Bin Qiu and RLW) independently reviewed the 450 identified abstracts for relevance to the report based on the eligibility criteria. Each reviewer scored the abstracts as either "relevant," "potentially relevant" or "not relevant." Agreements between the reviewers on "relevant" studies were included in the final set of articles reviewed as full-text publications. Agreements between the reviewers on "not relevant" studies were excluded from the review. Disagreements between the reviewers and articles deemed as "potentially relevant" by both reviewers were reviewed by the entire research team for relevance (BQ, RLW, RDL and JA)[2]. The research team

[2] Note that SDS joined the research team after the studies were identified, and therefore was not part of the article selection process.

members independently reviewed these results and after discussion came to a final agreement on inclusion or exclusion of these studies in the final review. The results of these reviews ended with 27 studies considered as relevant for inclusion, as shown in Figure 2.

The 27 abstracts identified as relevant for inclusion were then extracted and assessed as full-text publications by three members of the research team for final inclusion (RLW, RDL and JA). After independent review and discussion of the results, the articles were deemed as either included or excluded from the final review. All of the articles were deemed as included in the review based on the application of the criteria in section 2.2.

2.6 Data Collection Process

Data were collected through analysis of the 27 studies identified for inclusion in the final report. These studies were split evenly among the two primary investigators and the research coordinator (RDL, JA and SDS). Each chose nine of the 27 articles to analyze on an in-depth basis, aiming to fill a predetermined data collection sheet containing 24 variables characterizing the aspects of the studies pertinent to our review. These variables are described in section 2.7. The variables were prepared in an Excel spreadsheet and populated accordingly (see the Appendix).

2.7 Variables (Data Items)

Twenty-four variables were generated in this analysis in six different areas as shown in Figure 3. These variables were designed by the research team to capture the essential elements of each study. They provide a basis for analyzing the methods for fraud detection presented in each article and for comparing the results across different articles.

2.8 Risk of Bias in Individual Studies

As a part of the variable analysis of each study, two variables were selected in terms of identifying bias: funding source and potential for bias. Potential for bias was assessed through the disclosure statement in the article as well as the authors' stated affiliation and connections between that affiliation, the funding source and the data source used for the study.

2.9 Summary Measures

The principal summary measures used in our analysis were sensitivity and specificity as accuracy measures of the methods surveyed and the overall rate of fraud as measured by the prevalence. Prevalence was used as the measure of the rate of fraud in the studies. We summarized these methods across the studies reviewed; in certain cases, these measures were calculated based on findings presented in the report (e.g., an accuracy rate of 900 fraudulent claims correctly out of 1,000 reviewed is equivalent to a true positive rate of 90%). However, we did not summarize other accuracy measures such as "overall accuracy" or area under the Receiver Operating Characteristic curve that were described in a small number of studies in addition to, or as a substitute for, sensitivity and specificity. Calculations by authors of this report are noted in the results of Tables 9 and 10. Counts and descriptive variables were used to summarize differences in study characteristics such as country where the study was performed and the type of journal where the study was published.

2.10 Synthesis of Results

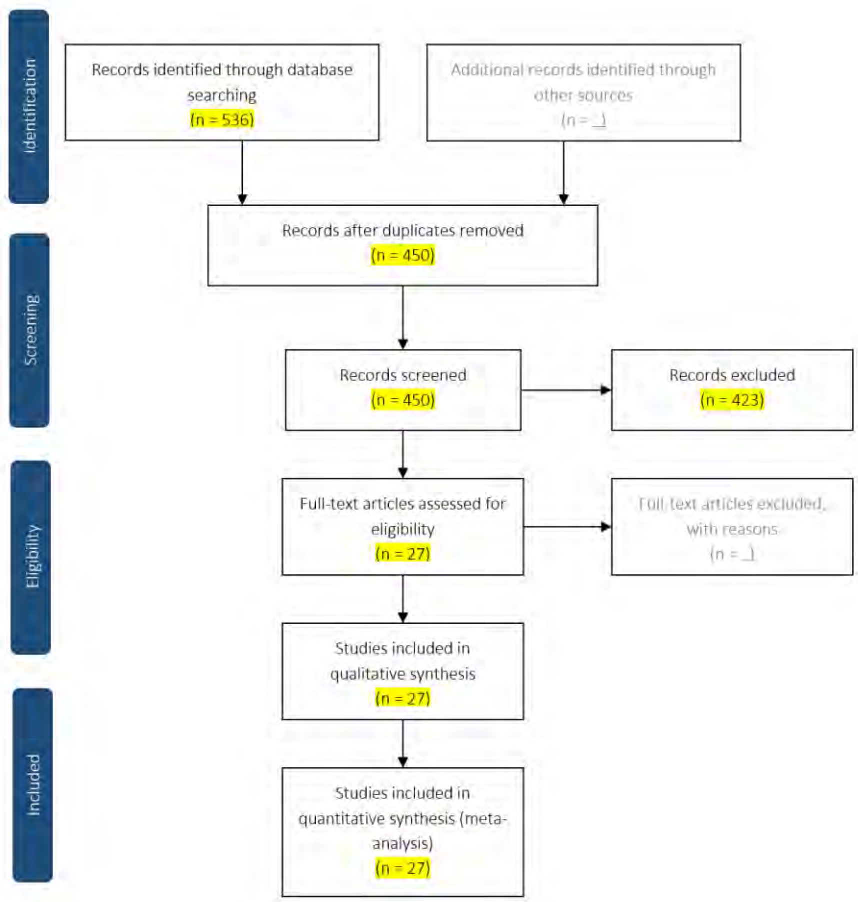
The results from included studies were summarized in the results section and comparisons were performed across these studies. However, the results examined in this review were not synthesized through a meta-analysis or other method for combining studies.

2.11 Risk of Bias across Studies

The main risk of bias across studies relates to publication bias and bias related to the subject area of health care fraud. Publication bias refers to the possibility that positive findings are more likely to be submitted for publication than studies with negative findings or statistically insignificant results (Ioannidis 1998). Publication bias is difficult to assess without access to unpublished studies. The risk of bias related to the subject area of fraud is also difficult to assess because of the proprietary nature of many fraud detection systems, which may be business secrets or the subject of criminal or civil investigation.

Figure 2

Selection of Included Studies



2.12 Additional Analyses

No additional analyses were performed on the data beyond those presented in this section. No such analyses were planned before the initiation of the study.

3. Results

3.1 Study Selection

Figure 2 shows our selection of studies for inclusion in the systematic review. We utilized the search strategy described in sections 3.3–3.5 to identify the records for inclusion in our study. Our initial search resulted in 536 abstracts from the identified databases. After removal of duplicates, we obtained abstracts for 450 studies that were potentially eligible for inclusion in our study.

We screened the records as described in section 3.5, resulting in 27 studies assessed for eligibility in our study. We then assessed these full-text articles for eligibility for synthesis in our qualitative and quantitative analyses. We found that all 27 studies met the eligibility criteria as described in section 2.5 and thus include all of them in our study.

Figure 3

Variables

Article characteristics

- Article title
- Authors
- Journal
- Year
- Academic field (Health Services Research, Risk Management and Insurance, Health Economics, or Computer Information Systems)

Data

- Population
- Claim type (medical, drug or both)
- Country
- Outcome of interest

Methodology

- Approach
- Scope (fraud only, fraud and waste and/or abuse, primarily not fraud)
- Level of analysis
- Specific methodology

Results and Conclusions

- Results
- Author's recommendation for future studies
- Conclusions from the paper

Assessment of Bias

- Funding source
- Potential for bias

Assessment of the Study and Implications

- Pros of the methodology
- Cons of the methodology
- Applicable areas/samples
- Data characteristics/features
- Assumptions
- Possibility of extension

3.2 Study Characteristics

The characteristics of the studies included in our review were generally heterogeneous. Table 1 shows the list of 27 studies that are included in our final review. Table 2 shows the years the studies were published, as well as the academic fields that the journals that published the studies represent. The year of publication varied over the 16-year window we considered (2001–2016), with the number of studies growing in each three-year window. The earliest study period, 2001–2004, was expanded into a four-year period because of the small number of studies in the early period we reviewed. The field of publication also varied for the studies considered as shown in Table 2, with the plurality of studies coming from the field of health services research. Interestingly, a relatively small number of studies came from the field of risk management and insurance despite the fact that the vast majority of health care claims are paid by third-party payers, both in the U.S. and in other developed countries (National Health Expenditure Data 2014).

The studies were also diverse in terms of the countries represented as shown in Table 3. The plurality of studies were conducted in the U.S., with a number of studies conducted in Turkey as well as in other European, Middle Eastern, Asian and North and South American countries and Australia. Of note is the fact that the study country could not be identified for one of the studies in the review. We attempted to contact the authors of this study; however, the contact email account was inactive and could not be reached. The countries were diverse in part because of our decision to include non-English-language studies—the studies conducted in France (Victorri-Vigneau et al. 2009) and in Chile (Mesa et al. 2009) are non-English-language papers that were translated into English for the purpose of this review.

Table 1

Studies Included in the Final Review

Title	Authors	Year	Journal	Number*
A prescription fraud detection model	Aral, Karca Duru; Güvenir, Halil Altay; Sabuncuoğlu, İhsan; Akar, Ahmet Ruchan	2012	*Computer Methods and Programs in Biomedicine*	1
A process-mining framework for the detection of healthcare fraud and abuse	Yang, Wan-Shiou; Hwang, San-Yih	2006	*Expert Systems with Applications*	2
Detecting hospital fraud and claim abuse through diabetic outpatient services	Fen-May, Liou; Ying-Chan, Tang; Jean-Yi, Chen	2008	*Health Care Management Science*	3
The effects of the fraud and abuse enforcement program under the National Health Insurance program in Korea	Kang, H.; Hong, J.; Lee, K.; Kim, S.	2010	*Health Policy*	4
Physician Medicare fraud: characteristics and consequences	Pande, Vivek; Mass, Will	2013	*International Journal of Pharmaceutical and Healthcare Marketing*	5
What are the characteristics that explain hospital quality? A longitudinal PRIDIT approach	Lieberthal, Robert D.; Comer, Dominique M.	2014	*Risk Management and Insurance Review*	6
Creating and validating a tool able to detect fraud by prescription falsification from health insurance administration databases [original written in French]	Victorri-Vigneau, Caroline; Larour, Katia; Simon, Dominique; Pivette, Jacques; Jolliet, Pascale;	2009	*Thérapie*	7
A survey on statistical methods for health care fraud detection	Li, Jing; Huang, Kuei-Ying; Jin, Jionghua; Shi, Jianjun	2008	*Health Care Management Science*	8
Computer-aided auditing of prescription drug claims	Iyengar, Vijay S.; Hermiz, Keith B.; Natarajan, Ramesh	2014	*Health Care Management Science*	9

Title	Authors	Year	Journal	Number*
Internal control differences between community health centers that did or did not experience fraud	Dietz, Donna K.; Snyder, Herbert	2007	*Research in Healthcare Financial Management*	10
On stratified sampling and ratio estimation in Medicare and Medicaid benefit integrity investigations	Edwards, Don	2011	*Health Services and Outcomes Research Methodology*	11
Improving fraud and abuse detection in general physician claims: A data mining study	Joudaki, Hossein; Rashidian, Arash; Minaei-Bidgoli, Behrouz; Mahmoodi, Mahmood; Geraili, Bijan; Nasiri, Mahdi; Arab, Mohammad	2015	*International Journal of Health Policy and Management*	12
Overpayment models for medical audits: multiple scenarios	Ekin, Tahir; Fulton, Lawrence V.; Musal, R. Muzaffer	2015	*Journal of Applied Statistics*	13
Predicting health care fraud in Medicaid: A multidimensional data model and analysis techniques for fraud detection	Thornton, Dallas; Mueller, Roland M.; Schoutsen, Paulus; Hillegersberg, van Jos	2013	*Procedia Technology*	14
Leveraging big data analytics to reduce healthcare costs	Srinivasan, Uma; Arunasalam, Bavani	2013	*IT Professional*	15
Detecting fraud in health insurance data: Learning to model incomplete Benford's law distributions	Lu, Fletcher; Boritz, J. Efrim	2005	*Machine Learning: ECML 2005, Proceedings*	16
A scoring model to detect abusive billing patterns in health insurance claims	Shin, Hyunjung; Park, Hayoung; Lee, Junwoo; Jhee, Won Chul	2012	*Expert Systems with Applications*	17
Outlier detection in healthcare fraud: A case study in the Medicaid dental domain	van Capelleveen, Guido; Poel, Mannes; Mueller, Roland M.; Thornton, Dallas; van Hillegersberg, Jos	2016	*International Journal of Accounting Information Systems*	18
An interactive machine-learning-based electronic fraud and abuse detection system in healthcare insurance	Kose, Ilker; Gokturk, Mehmet; Kilic, Kemal	2015	*Applied Soft Computing*	19
An adaptation of the Minimum Sum Method	Gilliland, Dennis; Feng, Wenning	2010	*Health Services and Outcomes Research Methodology*	20
EFD: A hybrid knowledge/statistical-based system for the detection of fraud	Major, John A.; Riedinger, Dan R.	2002	*Journal of Risk and Insurance*	21
Fraud in the health systems of Chile: a detection model [original written in Spanish]	Mesa, Francisco R.; Raineri, Andrés; Maturana, Sergio; Kaempffer, Ana María	2009	*Pan American Journal of Public Health*	22
Detecting Medicare abuse	Becker, David; Kessler, Daniel; McClellan, Mark	2005	*Journal of Health Economics*	23
Cost-based quality measures in subgroup discovery	Konijn, Rob M.; Duivesteijn, Wouter; Meeng, Marvin; Knobbe, Arno	2015	*Journal of Intelligent Information Systems*	24
A fraud detection approach with data mining in health insurance	Kirlidog, Melih; Asuk, Cuneyt	2012	*Procedia—Social and Behavioral Sciences*	25
Detecting potential overbilling in medicare reimbursement via hours worked	Fang, Hanming; Gong, Qing	2017**	*American Economic Review*	26
Multi-stage methodology to detect health insurance claim fraud	Johnson, Marina Evrim; Nagarur, Nagen	2015	*Health Care Management Science*	27

Title	Authors	Year	Journal	Number*

* The studies are numbered from 1 to 27 for ease of reference.
** The original version was published as National Bureau of Economics Research working paper in 2016.

Table 2
Study Year and Field

Study Characteristic	*N*
Year	
2001–2004	1
2005–2007	4
2008–2010	6
2011–2013	7
2014–2016	9
Field	
Health services research	12
Computing and information systems	10
Health economics	2
Risk management and insurance	2
Unidentified	1

Table 3
Countries Where Studies Were Conducted

Country	Number of Studies
Australia	1
Canada	1
Chile	1
France	1
Iran	1
Republic of Korea	2
the Netherlands	1
Taiwan	2
Turkey	3
U.S.	12
U.S., Taiwan and Australia	1
Unidentified	1

The studies analyzed a variety of health care claims in examining health care fraud. Table 4 shows the types of claims used in each study. The majority of the studies reviewed examined fraud in medical claims, meaning claims for outpatient or inpatient services, and others examine drug claims and/or dental claims. Most of these medical studies looked purely at medical claims, although a small number used medical and drug claims or medical and dental claims. For those studies that examined drug claims, the majority looked only at drug claims, although a number also used medical claims and/ or dental claims. There was also one study that looked strictly at dental claims. Two of the studies used claim types that could not be identified based on the way the study was written. One study used clinical data in addition to claims data to examine fraud.

Table 4
Claim Type Used in Each Study

Claim Type	Number of Studies
Dental only	1
Dental, drug and medical	1
Drug and medical	3

Claim Type	Number of Studies
Drug only	5
Medical only	15
Unidentified	2

The level of analysis and approach also varied widely in the studies we examined. The majority of the studies used claims analysis, analysis of provider-level data or analysis of facility-level data as shown in Table 5. However, characterizing the level of analysis and comparing this across studies was challenging because of the heterogeneity of studies as well as differences in standards of communications across the journal types considered. The most common approach to the study of health care fraud was data mining, which represented 14 out of the 27 studies we considered (Table 6). The approach characterizes the main way that fraud was assessed. We characterized any study that utilized the features of the data to examine outliers or otherwise identify suspicious or fraudulent claim patterns as a data-mining approach.

Specific methods within the category of data-mining approach are also identified wherever possible. A characterization of the methods used is shown in Tables 7 and 8. These methods are not mutually exclusive—four of the studies used two or more of these methods. In addition, many papers may have applied two or more methodologies as part of their overall approach. For example, a large number of papers used a literature review as a methodology to supplement an analytic approach such as data mining.

Table 5

Level of Analysis

Level of Analysis	Number of Studies
Claims level	12
Provider level	6
Facility level	5
Other	4

Table 6

Approach Used in the Studies Examined

Approach	Number of Studies
Data mining	14
Statistical analysis	2
Regression	2
Literature review	1
Electronic fraud detection	1
Stratified sample and interviews	1
Validation by expert opinion	1
Fraud detection tool	1
Classification of excluded physicians	1
Survey	1
Monte Carlo simulation; random sampling	1
Multistage approach including examination of providers, demography and claims followed by scoring system for fraudulent claims	1
Conversion of Medicare billing codes to hours worked	1
Anomaly detection analysis support vector machine algorithm	1
PRIDIT	1
Unidentified	1
* Some studies use more than one of the identified approaches	

Table 7

Methodologies Used in the Studies Examined

Methodology	Number of Studies
Box plot	2
Classification trees	2
Clustering	6
Examination by experts	6
Linear regression	6
Literature review	10
Logistic regression	2
Neural network	2
Peak analysis	1
Random samping	4
Significance testing	7
Suspicion scoring	7
Unidentified	3
* Some studies use more than one of the identified methods	

Table 8

Methodology by Study Number

Study Number	Box Plot	Classification Trees	Clustering	Examination by Experts	Linear Regression	Literature Review	Logistic Regression	Neural Network	Peak Analysis	Random Sampling	Significance Testing	Suspicion Scoring	Unidentified
1				x		x						x	
2			x			x				x			
3		x					x	x					
4					x								
5					x	x					x		
6			x			x							
7												x	
8													x
9				x		x						x	
10											x		
11										x	x		
12			x	x		x							
13						x					x		
14													x
15					x								
16												x	
17		x										x	
18	x		x	x	x	x			x				
19			x	x		x				x			
20	x									x			
21											x		
22				x			x				x		
23					x						x		
24													x
25						x							
26					x							x	
27			x					x				x	
Totals	2	2	6	6	6	10	2	2	1	4	7	7	3

3.3 Risk of Bias within Studies

The risk of bias in the studies considered was examined based on the funding source as well as characteristics of the authors and the studies that may lead to biased results. Those variables are shown for each of the 27 papers as shown in the spreadsheet accompanying this report (see the Appendix for link to the Excel spreadsheet). One common source of bias is that a large number of studies were funded by government sources; nine used data from a public insurance program. In these cases, the authors were also examining a public (government-run) insurance program, often the same one that was funding the study. Similarly, several of the authors of studies had an affiliation with the public insurer that provided data for the study; this was the case for five of the studies reviewed. In addition, many of the studies received funding from a private source such as an insurance company or received data from a private insurance company that may have biased the results of the study; this was the case for seven of the 27 studies reviewed.

3.4 Results of Individual Studies

The individual studies included in the report are generally too heterogeneous to be summarized using one or more summary measures. For a number of studies, the accuracy in terms of sensitivity (i.e., true positive rate) and specificity (i.e., true negative rate) was presented. Individual studies that reported accuracy in terms of sensitivity and specificity are shown in Table 9. Individual studies that reported prevalence are shown in Table 10.

Table 9

Individual Studies That Reported Sensitivity and Specificity

Study Title	Study Number	Sensitivity Reported	Specificity Reported
A prescription fraud detection model*	1	77.4%	89.2%
A process-mining framework for the detection of healthcare fraud and abuse	2	64%	67%
Detecting hospital fraud and claim abuse through diabetic outpatient services	3	100% (all models)	Logistic regression: 86.5% Neural networks: 92.1% Classification trees: 98.7%
Creating and validating a tool able to detect fraud by prescription falsification from health insurance administration databases	7	Groups 1 and 2** 69.4% Group 1 only 47.2%	Groups 1 and 2 99.5% Group 1 only 100%
Improving fraud and abuse detection in general physician claims: a data mining study	12	Abuse: 85.39% Fraud: 50%	Abuse: 84% Fraud: 99.37%
An interactive machine-learning-based electronic fraud and abuse detection system in healthcare insurance	19	93.5%–88.5%	53.8%–82.4%
Fraud in the health systems of Chile: a detection model	22	99.71%	99.86%
Multi-stage methodology to detect health insurance claim fraud	27	Otolaryngologists: 87% General practitioners: 85% Neurologists: 86% Ophthalmologists: 87%	Otolaryngologists: 86% General practitioners: 86% Neurologists: 88% Ophthalmologists: 83%
* Specificity is calculated as True Negative Rate/(True Negative Rate + False Positive Rate) as reported in the study. Sensitivity was reported in the study as the true positive rate. **Selected patients sorted into groups: G1 = repetition of several prescription uses at least three times throughout the year; G2 = two repetitions			

Table 10

Individual Studies That Reported Prevalence

Study Title	Study Number	Prevalence Reported
Improving fraud and abuse detection in general physician claims: a data mining study	12	54% of physicians are suspected of abuse 2% of physicians are suspected of fraud
A scoring model to detect abusive billing patterns in health insurance claims	17	6% of clinics are suspicious
Outlier detection in healthcare fraud: a case study in the Medicaid dental domain	18	5% of providers require further analysis
EFD: a hybrid knowledge/statistical-based system for the detection of fraud	21	4.12% are reported to fraud unit
Fraud in the health systems of Chile: a detection model	22	8.60% of medically authorized leaves were fraudulent

3.5 Synthesis of Results

The studies listed were not combined using a meta-analysis or other method. Instead, we utilized a qualitative approach to analyzing and combining the results of the studies as appropriate.

3.6 Risk of Bias across Studies

The risk of bias across studies was relatively minor given our assessment of the included studies. In the case of our review, publication bias is relatively less of a concern than it would be in other lines of inquiry. This is the case because not all studies reported specific numerical or analytic results. Those that did often did not report statistical significance values. A greater concern is bias related to the subject area of health care fraud. It is possible that the subject of fraud is less likely to result in publications because of the possibility that such publication would allow fraudulent operators to adjust their behavior to avoid detection. Additionally, any successful method could be considered as a trade secret and therefore treated as proprietary rather than publishable work. The tendency of our studies to focus on public (government-run) health insurance programs may reflect this bias.

3.7 Additional Analysis

We assessed additional variables through our analysis: authors' recommendations for future studies, conclusions, pros and cons of the methodology, applicable areas and samples for the method, data characteristics and features, assumptions and possibility of extension. Those results are shown in the spreadsheet link in the Appendix, which links to a separate Excel file. Many common features of the studies on the selected variables were found and are summarized in Table 11.

Table 11

Common Features of the Studies

Features	*N*
Additional recommendations/conclusions	
Improve cost or cost-effectiveness of fraud detection and prevention	4
Validate results	3
Replicate results in other settings	14
Pros of the methodology	
Ease of implementation/simplicity	11
Flexibility	10
Use of common/standard methods or common/available software	5

Features	*N*
Able to handle large numbers of variables	2
Facilitates auditing/resource allocation to fraud detection	4
Cons of the methodology	
Dimensionality/large amount of data required	6
Challenging or opaque method	10
Required data not always available	2
Computationally expensive model/long run times	2
Use of subjective measures	3
Exclusion of types of health care professionals	4
Missing data	2
Difficult to generalize	6
Reliance on expert opinion	4
Methods not described in the paper	3
Restrictive assumptions	3
Requires a validation sample	2
Assumptions	
Fraud results in outliers/common patterns exist in regular care	5
Data accuracy	10
Managers/directors are able to provide meaningful data	2
Payments are either totally legitimate or totally fraudulent	2
Validity of expert opinion	3

4. Discussion

4.1 Summary of Evidence

The main finding of this review is that the strength of the evidence for the performance and accuracy of health care fraud detection methods is of varying quality. There is evidence that a number of the methods in the studies identified by this review perform well in terms of standardized outcomes. It is also the case that many of the studies did not present reflecting the accuracy of their methods as results of their studies. Those studies that report accuracy did so in a manner that was inconsistent across studies. For the methods that were tested and validated, the accuracy is generally high, although the acceptability of the results may vary by the setting where the methods are implemented. Even for those studies that do report accuracy and/or prevalence, there is still not a clear way to qualify the results given many of them are done with samples and the fact that it is difficult or impossible to compare accuracy and prevalence rates across samples and different health care contexts.

The relevance of this study differs for key groups. Health care providers may want to consider the applicability of these findings to their practice. Those providers may benefit from additional training in fraud detection methods to understand how their clinical practice interacts with the health care finance system. Providers can also use this evidence to refine their billing practices to improve their collection of revenue and reduce the rejection of claims. Health insurance practitioners can use this study to implement additional fraud and abuse detection systems or to provide a benchmark for the performance of their existing systems. They may also wish to use this research to refine existing fraud detection systems. Finally, policymakers can use this evidence to estimate the rate of fraud in the systems that they run or regulate. In particular, policymakers should consider making additional investments in fraud rate estimation, as this is one of the gaps in the literature identified in the review.

4.2 Limitations

One of the major limitations of our study is that we focused on the available evidence for health care fraud and fraud detection methodologies. This is a limitation that is common to all systematic reviews; however, it may be a particularly challenging problem for the study of fraud. Fraud is by its nature difficult to detect because of the efforts of those engaged in fraudulent or abusive behavior to conceal their actions. In addition, court proceedings for fraud can take many years to settle, leading to difficulties in studying fraud using standard academic or research methods. In a similar sense, the decisions of many companies and governments to use proprietary methods to detect and deter fraud limit the scope of research that can be performed in this area.

A second major limitation related to the study of fraud is the difficulty of proving intent in any research study. The criminal definition of fraud requires intent to convict an individual (Gosfield 2011). None of the studies explicitly examined intent, although one study did specifically examine those already convicted of fraud. As a result, we chose to take a wide range of studies, including those that also dealt with abuse or waste, as well as methodological studies that could be used to detect health care fraud even if that was not the main purpose of the study.

A third limitation relates to our choice of keywords for searching. Despite our best efforts to identify a wide range of keywords, it is likely that our review does not include all relevant studies of methods for health care fraud detection. Although this is a common issue in all systematic reviews, it may be particularly problematic in fraud because of the large number and diversity of academic literatures that cover the topic. In particular, we chose not to include keywords related to auditing to confine our study to fraud detection methods. We also chose to confine our study to health care fraud, rather than more general insurance fraud. Both decisions likely mean that our review is limited to the specific topic of methods for health care fraud detection, and other studies may exist that have a bearing on this topic.

One final limitation relates to our use of the peer-reviewed academic literature. This is a standard for systematic reviews as promulgated in the PRISMA guidelines. This also means that many governmental standards for fraud detection, as well as private methods, are not incorporated in our review. A number of these methods can be found at various external websites (U.S. Office of the Inspector General n.d.; Health Care Fraud 2016; The Challenge of Health Care Fraud n.d.).

4.3 Conclusions

This report describes the results of our review of the health care fraud detection literature. Our review did result in a sizeable number of studies. In addition, the diversity of the studies reflects the overall diversity of health care practice as well as the diverse approaches to health care management in different countries. One notable difference is between public and private systems. One important conclusion to be drawn from this report is that health care fraud detection is an active area of research that is taking place in a wide array of settings by researchers in a number of different disciplines.

Our review also highlights an important lack of standardization across these studies. There is no agreed-on framework for reporting the results of health care fraud detection studies and accuracy of fraud detection methods. The most common is the use of sensitivity and specificity, although those analyses are not universally available for the studies we reviewed. The diversity of scientific disciplines may make this problem particularly acute, since each discipline may have its own standards for what constitutes a "significant" result, and how to communicate the results of studies.

One other surprising finding from our review is the lack of data on prevalence and limited exploration of the validation of those methodologies used. Few of the studies that we reviewed reported any such rate in the data analyzed. One reason may be the lack of validation of health care fraud studies; few of the studies we reviewed used validated samples to derive the results, and that may make researchers wary of reporting prevalence numbers. The prevalence of fraud, and how it differs by service type, country or public versus private insurance, is a key gap in the literature that should be addressed. Validated fraud studies on a small scale can be used to generate evidence on the prevalence of fraud that can be extrapolated or used to power larger-scale studies of health care fraud.

5. Funding

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Appendix

1 Search Statements[3]

1.1 Segment 1

("health care" OR "healthcare" OR "health insurance" OR medicare OR medicaid OR obamacare OR "affordable care act" OR "health services") **NEAR/5** (fraud* OR cheat* OR falsification OR corruption OR kickback)

Note: Proximity syntax varies among databases. Some use N5; others use Near/5 or W/5; etc.

Segment 1 revised for one search

("health care fraud" OR "health care fraud" OR "health insurance Fraud" OR "Medicaid fraud" OR "Medicare fraud" OR "Obamacare fraud")

1.2 Segment 2

(detect OR detection OR prevent OR prevention OR deterrence OR audit OR auditing)

1.3 Combined Segments 1 and 2

("health care" OR "healthcare" OR "health insurance" OR "medicare" OR "medicaid" OR "obamacare" OR "affordable care act" OR "health services") **NEAR/5** (fraud* OR cheat* OR falsification OR corruption OR kickback) AND (detect OR detection OR prevent OR prevention OR deterrence OR audit OR auditing)

2 Search Steps

1. Run each segment separately and record results number
2. Run first and second segments combined and record results number
3. Export to RIS format and input to EndNote Basic in separate database folders

After all searches completed, removed duplicates from "All My References" default folder.

[3] The search steps are written out exactly as they were performed.

3 Spreadsheet Link

Link to Excel Spreadsheet with Interactive Dashboard from SOA website:

https://www.soa.org/inventory-articles-studies.xlsx

About The Society of Actuaries

The Society of Actuaries (SOA), formed in 1949, is one of the largest actuarial professional organizations in the world dedicated to serving 28,000 actuarial members and the public in the United States, Canada and worldwide. In line with the SOA Vision Statement, actuaries act as business leaders who develop and use mathematical models to measure and manage risk in support of financial security for individuals, organizations and the public.

The SOA supports actuaries and advances knowledge through research and education. As part of its work, the SOA seeks to inform public policy development and public understanding through research. The SOA aspires to be a trusted source of objective, data-driven research and analysis with an actuarial perspective for its members, industry, policymakers and the public. This distinct perspective comes from the SOA as an association of actuaries, who have a rigorous formal education and direct experience as practitioners as they perform applied research. The SOA also welcomes the opportunity to partner with other organizations in our work where appropriate.

The SOA has a history of working with public policymakers and regulators in developing historical experience studies and projection techniques as well as individual reports on health care, retirement and other topics. The SOA's research is intended to aid the work of policymakers and regulators and follow certain core principles:

Objectivity: The SOA's research informs and provides analysis that can be relied upon by other individuals or organizations involved in public policy discussions. The SOA does not take advocacy positions or lobby specific policy proposals.

Quality: The SOA aspires to the highest ethical and quality standards in all of its research and analysis. Our research process is overseen by experienced actuaries and nonactuaries from a range of industry sectors and organizations. A rigorous peer-review process ensures the quality and integrity of our work.

Relevance: The SOA provides timely research on public policy issues. Our research advances actuarial knowledge while providing critical insights on key policy issues, and thereby provides value to stakeholders and decision makers.

Quantification: The SOA leverages the diverse skill sets of actuaries to provide research and findings that are driven by the best available data and methods. Actuaries use detailed modeling to analyze financial risk and provide distinct insight and quantification. Further, actuarial standards require transparency and the disclosure of the assumptions and analytic approach underlying the work.

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